Northwestern University
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CHICAGO RED LIGHT CAMERA ENFORCEMENT

BEST PRACTICES & PROGRAM ROAD MAP

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16. Abstract

The City of Chicago has one of the longest-running and largest red light camera (RLC) enforcement systems in the country. While numerous studies have shown that camera enforcement is an effective deterrent to reckless driving and its use improves overall roadway safety, support for its application in various cities has not been uniform. Specifically, its application in Chicago has continued to generate public debate. This study performs an assessment of Chicago's RLC program in terms of its impact on traffic safety, leading to a set of best practices in RLC enforcement, and recommendations for further improvement to the Chicago program. The aim is to provide guidance for continued RLC operation at individual camera locations, as well as for selection of locations for future implementation. By investigating available historical data and conducting statistical analyses, performance metrics and a set of guidelines were proposed to ensure the program is being implemented to the best benefit of the general public and of the City. A stakeholder engagement strategy was also designed and implemented to take into account expert and public opinion on the RLC program. The stakeholder outreach effort sought to better characterize and understand the expert and lay person perceptions of public concerns and gaps in knowledge about Chicago's RLC program.

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The authors remain solely responsible for all work, findings, conclusions and recommendations presented in this report.

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EXECUTIVE SUMMARY

Introduction

The City of Chicago has one of the longest-running and largest red light camera (RLC) enforcement systems in the country. While numerous studies have shown that camera enforcement is an effective deterrent to reckless driving and its use improves overall roadway safety, support for its application in various cities has not been uniform. Specifically, its application in Chicago has continued to generate public debate.

Motivated by these general public concerns, this study reviews Chicago's red light camera program and provides suggested guidance and recommendations for the City's administration of its RLC program going forward, particularly with regard to meeting the program's traffic safety goals. Accordingly, this study investigated and quantified the safety benefits due to RLC enforcement, while examining the relationship between RLC violators' behavior and various contributing factors.

Traffic safety is generally measured by changes in crashes, the type and severity of crashes, and changes in the cost of crashes at RLC intersections. This report sought to provide a comprehensive analysis on the effectiveness of red light cameras using data obtained from the City of Chicago and the Illinois Department of Transportation.

The safety analysis performed in this study followed a two-stage approach. The first stage included a study on crash frequency and RLC violations independently, while the second stage brought these two pieces together. The relationship between different types of traffic accidents and RLC violations was examined in order to draw conclusions and formulate recommendations that would assist decision makers to advance an overall road safety program.

This study is part of an effort to ensure the City is making best utilization of the system it has, and to support continual improvement of the program. Thus particular attention was directed towards identifying well-suited locations for cameras, and emphasizing the importance of ongoing monitoring of the system. In addition, a stakeholder engagement process provided insight into public perceptions of the enforcement system, and informed the technical analysis in formulating the study recommendations.

Background

Red Light Camera (RLC) Enforcement is intended to increase vehicular safety by reducing crashes at intersections, particularly angle crashes because of the extreme consequences to those involved. There have been a number of RLC effectiveness studies in the past, using various analysis and evaluation approaches on diverse sets of data. Though methods and datasets might have been different, findings tend to lead to similar general conclusions. Namely, more severe types of crashes, i.e. right angle related crashes, are reduced, while less severe and typically less frequent rear-end collisions might potentially increase.

The City of Chicago, with one of the largest and longest-running RLC enforcement systems in the country, currently leads the nation with over 306 RLCs at 151 intersections. The first RLC in Chicago was installed in 2003, with the number of photo-enforced intersections increasing since, especially during 2008 and 2009. According to the Chicago Department of

Transportation (CDOT), installation of RLCs was prioritized for intersections with the highest angle crash rates in order to increase safety. In general, RLC candidate intersections are identified according to a ranking system, which takes into account the number of total crashes, angle crashes, and the angle crash rate. Since angle crashes are most likely to result in serious injury or fatalities, CDOT recognized reducing the angle crash rate as the primary criterion to increase intersection safety.

Objectives

The objective of this study is to perform an assessment of Chicago's RLC program in terms of its impact on traffic safety, leading to a set of best practices in RLC enforcement, and recommendations for further improvement to the Chicago program. The aim is to provide guidance for continued RLC operation at individual camera locations, as well as for selection of locations for future implementation. By investigating available historical data and conducting statistical analyses, performance metrics and a set of guidelines were proposed to ensure the program is being implemented to the best benefit of the general public and of the City.

The problem at hand entails multiple dimensions, with primary focus on two aspects: human factors and public policy. In the study, driver behavior at intersections with and without RLC enforcement, and the resulting safety impacts both at a localized level, as well as for the overall system, were investigated. Particular emphasis was placed on the spillover effect (i.e. drivers adjusting their behavior at nearby non-RLC intersections as a result of their experience through the RLC equipped intersections). The analysis resulted in recommended guidelines to determine where it would be best to deploy RLCs, and whether or not a particular intersection was a good candidate for RLC enforcement.

A stakeholder engagement strategy was also designed and implemented to take into account expert and public opinion on the RLC program. The stakeholder outreach effort sought to better characterize and understand the expert and lay person perceptions of public concerns and gaps in knowledge about Chicago's RLC program.

Method

For the purpose of this study, 340 sites before and after the RLC system deployment (years 2008 and 2009), referred to as the treatment group, were analyzed. Another 236 sites, where no cameras were installed, served as the control group, thereby providing a basis for the comparative effectiveness assessment.

This study designed and implemented a methodology for an observational before-after assessment that considered regression-to-the-mean (RTM) as well as potential spillover effects as integral parts. Regression to the mean is the statistical tendency for locations chosen because of high crash histories to have lower crash frequencies in subsequent years even without treatment. Spillover refers to the impact of RLC enforcement on reducing crashes at non-camera intersections, through its impact on driver behavior. Both of these phenomena have not been systematically accounted for in previous studies.

The study used a state-of-the-art Empirical Bayesian (EB) statistical methodology for the observational before-after study. In this approach, EB statistical estimation methods and actual observations are used to predict the crashes in the after period had there been no RLC treatment.

Potential spillover effects at intersections without RLCs, if left unaccounted for, could lead to potentially significant underestimates of RLC safety impacts. This important issue is challenging to validate and even harder to quantify and integrate into the analysis since RLC installations, typically, take place over several years and other programs/ treatments might have affected crash frequencies at the spillover study sites. By using a two-level control approach, this study devised a robust method to estimate the magnitude of the spillover effect and incorporate it in the overall assessment.

Furthermore, the study performed an analysis of RLC violations over time to understand and quantify the contributing effect of traffic features, intersection factors, and signal configuration on the frequency of violations. Regression models were used for that purpose, using violations at 152 RLCs in the city of Chicago over a 6-year period between 2010 and 2015.

Combining the violations analysis with the safety impact assessment allowed identification of intersections where the RLC program has demonstrated the greatest impact on reducing crashes while promoting safe driving. This joint analysis, using clustering techniques and ordinal variable regressions, formed the basis for suggesting guidelines for intersection selection for RLC deployment, and, in some cases, possible discontinuation.

Stakeholder outreach involved three distinct target groups- experts, advocates, and community representatives, reflecting different points of view and inputs for recommendations. Stakeholders were engaged through one-on-one telephone interviews, to elicit and assess views regarding both RLC programs in general and the current Chicago RLC program, and to invite suggestions for evolution of the latter.

Findings

The Empirical Bayesian (EB) before-and-after analysis method was applied to the cameras commissioned in 2008 and 2009 in the City of Chicago. The results are in general agreement with the findings in the literature, that the RLC treatment reduces the angle and turn crashes (by 19% in Chicago), and increases the rear-end crashes (by 14%) with an overall reduction in crashes (by 10%). Angle and turn crashes are both *more severe*, and about *three times more frequent* than rear-end crashes (in the before RLC period), and thus the primary target of safety enforcement at signalized intersections. The study also documented significant spillover effect (positive impact on safe behavior) from RLC installation.

Regression models for the analysis of RLC violations data over time show how different observable elements affect violation behavior in the presence of RLCs and how that behavior changes over time. Higher traffic volumes, more approach lanes, higher speed limits, wider intersections, longer cycles, not allowing left turns, and longer all-red phases were found to increase the frequency of RLC violations. On the other hand, presence of a physical median, “No turn on red” sign, longer yellow phase duration along with the presence of protected left bay decrease RLC violations’ frequency. The results also reveal the existence of a learning effect whereby more drivers adopt safe behaviors over time as a result of enforcement, reflected in a significant decreasing trend of violations over time.

A clustering analysis showed that most of the cameras result in a significant improvement of safety with a relatively low number of violations. Instances where local impact on crashes is not significant (notwithstanding spillover effects onto neighboring areas) while still registering relatively high numbers of violations were flagged and recommended for additional site-specific investigation as to the desirability of passive RLC enforcement.

Reaching out to the stakeholders (advocates, experts, and community representatives) revealed a variety of opinions. There is a broad acceptance of the program among the experts and most advocates for its positive contribution to road safety. On the other hand, several community representatives, as well an anti-RLC advocacy group, view the Chicago RLC program primarily as a revenue generator. Among the community groups, even those that acknowledge the safety benefits of the RLC program indicate that the value of the program may be diminished by the perceived emphasis on revenue generation.

Recommendations

Quantitative studies conducted in this project demonstrate significant safety benefits of the current RLC program. As a result, it is appropriate to recommend continuation of the program. Most of the intersections have experienced an improvement in safety, particularly in terms of severe angle and turn crashes, albeit with an accompanying increase in less severe rear-end crashes. The safety benefits extend beyond the immediate vicinity of the RLC intersections, evidenced by a significant spillover effect. However, some intersections appear to experience no significant safety impact. Recognizing that crashes are the result of complex interactions amongst many factors, and subject to considerable randomness, these deviations should be used as opportunities for detailed investigation and learning to design and deploy more effective automated enforcement programs. The procedure developed as part of the study also helps to identify intersections, presently without enforcement, that are likely to benefit from such enforcement. Furthermore, the study team recommends extending the enforcement threshold (time-into-red that triggers a ticket) from the current 0.1 second to 0.3 or 0.4 seconds. Finally, continuous monitoring, evaluation, adaptation, and reporting to the community are recommended.

1 INTRODUCTION

The goal of this study was to assess the traffic safety impact of the Red Light Camera (RLC) enforcement in Chicago, IL. Traffic safety is generally measured by changes in crashes, the type and severity of crashes, and changes in the cost of crashes at RLC intersections. Although numerous studies had demonstrated that automated enforcement reduced red light running, a growing number of communities have deactivated their RLC programs in recent years. This study investigated and quantified the safety benefits due to RLC enforcement, while examining the relationship between RLC violators' behavior and various contributing factors. This report sought to provide a comprehensive analysis on the effectiveness of red light cameras using data obtained from the city of Chicago.

The safety analysis performed in this study followed a two-stage approach. The first stage included a study on crash frequency and RLC violations independently, while the second stage brought these two pieces together. The relationship between different types of traffic accidents and RLC violations was examined in order to draw conclusions and formulate recommendations that would assist decision makers advance an overall road safety program. Cluster analysis was performed, based on the number of violations and corresponding number of crashes by type, to identify intersection approach pairs that benefited the most through the program as well as the ones that experienced no improvement, or even deterioration in safety performance. Further analysis of within-cluster intersections' various attributes determined the impact of the RLC program (positive or negative), and these findings helped determine criteria for future removal and placement of cameras. A major portion of this study, therefore, focused on providing recommendations that would serve as guidelines to determine where it would be best to deploy RLCs, and whether a particular intersection was a good candidate or not for such enforcement.

A stakeholder engagement strategy was devised to take into account expert and public opinion on the RLC program. In this process, three groups, namely traffic safety advocates (including known program opponents), experts, and community groups were formed as representatives of different communities and interests in the field. General perception among community groups, contrary to safety experts' position, remains that Chicago RLC program is mostly a revenue generator. Stakeholders' recommendations based on telephonic/in-person interviews, were provided in this report; predominately referring to program's transparency, its reliability and accuracy monitoring. The stakeholder outreach strategy was aimed at ensuring wider public support by closing the gap in perceptions between different interested parties.

1.1 RLC Program Description: Intent, Scope, Scale

Red Light Camera (RLC) Enforcement is designed to increase vehicular safety by reducing crashes at intersections, specifically angle crashes because of the extreme consequences to those involved. There have been a number of red light effectiveness studies in the past, in which various evaluation approaches were undertaken to perform different types of analysis on diverse sets of data. Though methods and datasets might have been quite different, findings tend to lead to similar general conclusions. Namely, more severe types of crashes, i.e. right angle related crashes, are reduced, while less severe rear-end collisions might potentially increase (*1*). While numerous studies have shown that camera enforcement is an effective deterrent to reckless driving and its use improves overall roadway safety, the application in Chicago has continued to generate public debate.

The City of Chicago has one of the longest-running and largest RLC enforcement systems in the country and is currently leading the nation with over 306 RLCs at 151 intersections. The first RLC in Chicago was installed in 2003, with the number of photo-enforced intersections increasing since, especially during 2008 and 2009, and subsequently adjusted on the basis of periodic reviews. TABLE 1.1.1 provides the number of commissioned and decommissioned RLCs per year starting from 2003 till 2015. FIGURE 1.1.1 represents the spatial distribution of currently active RLCs. Two intersection approaches are being monitored at most RLC intersections. However, appropriate signage is posted at all four approaches identifying the intersection as photo-enforced. According to Chicago Department of Transportation (CDOT) installation of RLCs was prioritized for intersections with the highest angle crash rates (per million vehicles) in order to increase safety. In general, RLC candidate intersections are identified according to the ranking system, which takes into account the number of total crashes, angle crashes, and the angle crash rate. Since angle crashes are most likely to result in serious injury or fatalities, CDOT recognized reducing the angle crash rate as the primary criterion to increase intersection safety.

Accordingly, this study aims to create a framework for examining the performance of individual camera locations, as well as those intersections that currently do not have camera enforcement. Investigation of historical data and analysis conducted, establishes a set of guidelines and/or appropriate metrics to ensure the program is being implemented to the best benefit of the City and the general public.

TABLE 1.1.1 Summarized RLC Commissioning/Decommissioning Activity

Year	Commissioned	Decommissioned	Total Active
2003	2	0	2
2004	39	0	41
2005	0	0	41
2006	20	0	61
2007	76	0	137
2008	132	0	269
2009	104	0	373
2010	21	10	384
2011	2	2	384
2012	0	0	384
2013	0	0	384
2014	0	32	352
2015	0	46	306

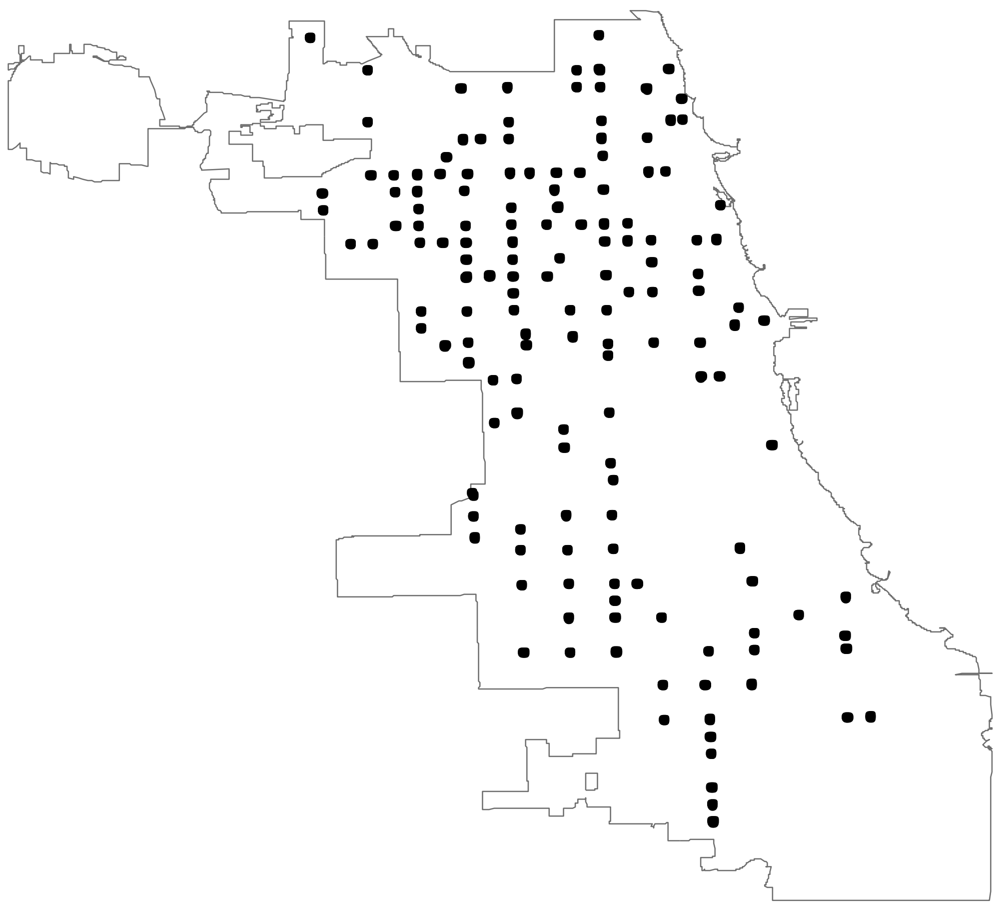


FIGURE 1.1.1 Spatial distribution of RLC intersections in Chicago, IL.

Considerable amount of relevant literature and data were gathered in order to design and conduct the study of both crashes and violations. For the purpose of this study, 340 intersection, approach pairs before and after the RLC system deployment (years 2008 and 2009), referred to as the treatment group, were analyzed. Another 236 intersection, approach pair sites, where no cameras were installed, were referred to as the control group. Data collection, for both groups, consisted of crash and violations statistics, traffic signal control related information, geometric and traffic flow data at signalized intersections. Before-after study covered two three-year periods: 2005 through 2007 for before, and 2010 through 2012 for the after period. Control group information were utilized to distinguish between the overall conditions change within the Chicago area, over the years, that could not be attributed to the RLC deployment.

The available literature has found that estimates of the safety effect of RLC programs vary considerably, even though the majority of them agree that RLCs reduce right-angle crashes and could increase rear end crashes. At the same time, previous research experience pointed towards the need for the advancement of the analysis methods. This research, hence, focused on designing the methodology for an observational before-after study, which considered regression-to-the-mean (RTM) as well as the spillover effect, as its integral parts. Both of these phenomena remained relatively unaccounted for in previous research efforts.

Therefore, the proposed Empirical Bayesian (EB) approach for the observational before-after study, attempts to overcome the limitations of previous evaluations of red-light cameras, especially the neglected spillover effect. Potential spillover effects to intersections without RLCs need to be considered, especially when determining reference/control sites; if left unaccounted for, this effect can lead to significant underestimates of RLC safety benefits. This particularly important issue is, however, rather challenging to validate and even harder to quantify and integrate into analysis since RLC installations, typically, take place over several years and other programs/ treatments might have affected crash frequencies at the spillover study sites.

Studies on the effectiveness of Red Light Cameras date back to 1981, where Maisey et al. found that angle crashes reduced, while rear-end crashes increased (*2*). Since then there has been a number of studies analyzing the effectiveness of this safety measure using three main approaches for comparison (*3*):

- A so-called naïve approach by comparing the observed crashes in the before and after periods, factoring in the duration of periods and the traffic counts (*3-6*);
- Comparison Group approach, where the changes in crashes in the comparison group are factored in into the comparison (*3; 4; 6*); and
- Empirical-Bayes (EB) approach, which combines statistical estimation methods and the actual observations to predict the crashes in the after period had there been no treatment (*3-9*).

Consistent with the findings of the 2005 Virginia study (*10*), the 2007 study (*11*) found that cameras were associated with an increase in rear-end and a decrease in red light running crashes (about 27% or 42% and about 8% or 42%, respectively, depending on the statistical method used). The same study emphasized there was significant variation by intersection and by jurisdiction: stating non-universal effectiveness of RLCs.

A detailed literature review on crash frequency models and driver behavior at RLC intersections can be found in Appendix 8.1.

2 MODELING THE SAFETY EFFECTS OF RED-LIGHT CAMERA ENFORCEMENT WITH SPILLOVER EFFECTS

The main objective of any before-after safety analysis is to reliably predict the number of crashes at a treatment site in the after period, had there been no treatment applied there. This predicted value is then compared to the actual observed number of crashes after the treatment. If there is a reduction in the number of crashes relative to the predicted 'what if there had been no treatment?' value, then the safety on that site has improved.

This analysis uses an Empirical Bayesian (EB) before-after analysis method to model the safety effects of Red Light Cameras (RLC) capturing the spillover effect. Zero-Inflated Negative Binomial (ZINB) (*12*) models are used to estimate Safety Performance Functions for crashes of different types at the intersection, approach level separately for the before and after periods.

Afterwards, two methods are proposed to capture the spillover effect of the behavior at the RLC intersections to the reference intersections. The three models (no spillover, uncontrolled spillover, and controlled spillover) are applied to the City of Chicago. The results agree with the other RLC studies in the literature.

2.1 Methodology

This study focuses on designing the methodology for an observational before-after study, which considers regression-to-the-mean (RTM) as well as the spillover effect, as integral parts. Regression to the mean is the statistical tendency for locations chosen because of high crash histories to have lower crash frequencies in subsequent years even without treatment. Commonly, these phenomena are not accounted for in such before-after RLC reports.

The proposed Empirical Bayesian (EB) approach for the observational before-after study attempts to overcome the limitations of previous RLC evaluations, more particularly the neglected spillover effect. An EB approach combines statistical estimation methods with the actual observations to predict crashes in the after period had there been no treatment. Potential spillover effects at intersections without RLCs, if left unaccounted for, can lead to significant underestimates of RLC safety benefits. This important issue is, however, very challenging to validate and even harder to quantify and integrate into analysis, since RLC installations, typically, take place over several years and other programs/treatments might have affected crash frequencies at the spillover study sites.

Agencies tend to install RLCs where the numbers of crashes are high. Since crashes are random events, comparing the sheer number of crashes before and after treatment would suffer from the 'regression-to-the-mean' bias (*3*). If an agency selects a site with a high estimated number of crashes, then it is possible to observe a significantly lower number of observed crashes in the after period. However, this reduction should not be solely attributed to the treatment itself because the number of crashes would be expected to reduce towards the mean anyway. As a result, an unbiased estimation is needed for the number of crashes at a treatment site in the after period had there been no treatment.

Two main safety metrics are used in the literature (*3*): reduction in the expected number of crashes, and the Index of Safety Effectiveness.

Reduction in the expected number of crashes is calculated as the difference between the predicted number of crashes in the after period *had there been no treatment*, and the expected number of crashes in the after period *with treatment*. A positive value indicates a reduction in crashes. Index of Safety Effectiveness is the ratio of the expected number of crashes in the after period with treatment to the predicted number of crashes in the after period had there been no treatment. A smaller value indicates a higher effectiveness.

In this project, separate Safety Performance Factors (SPFs) for the before and after periods are estimated. A pictorial flowchart below shows the estimation of SPFs for before (FIGURE 2.1.1a) and after periods (FIGURE 2.1.1b). To calculate the SPFs, the dependent variable is the number of crashes and the independent variables are the different attributes of the intersections in the corresponding time period. Complete lists of the attributes are provided in TABLE 2.2.1 and TABLE 2.2.2. Data used at this step is from the reference intersections.

(a)

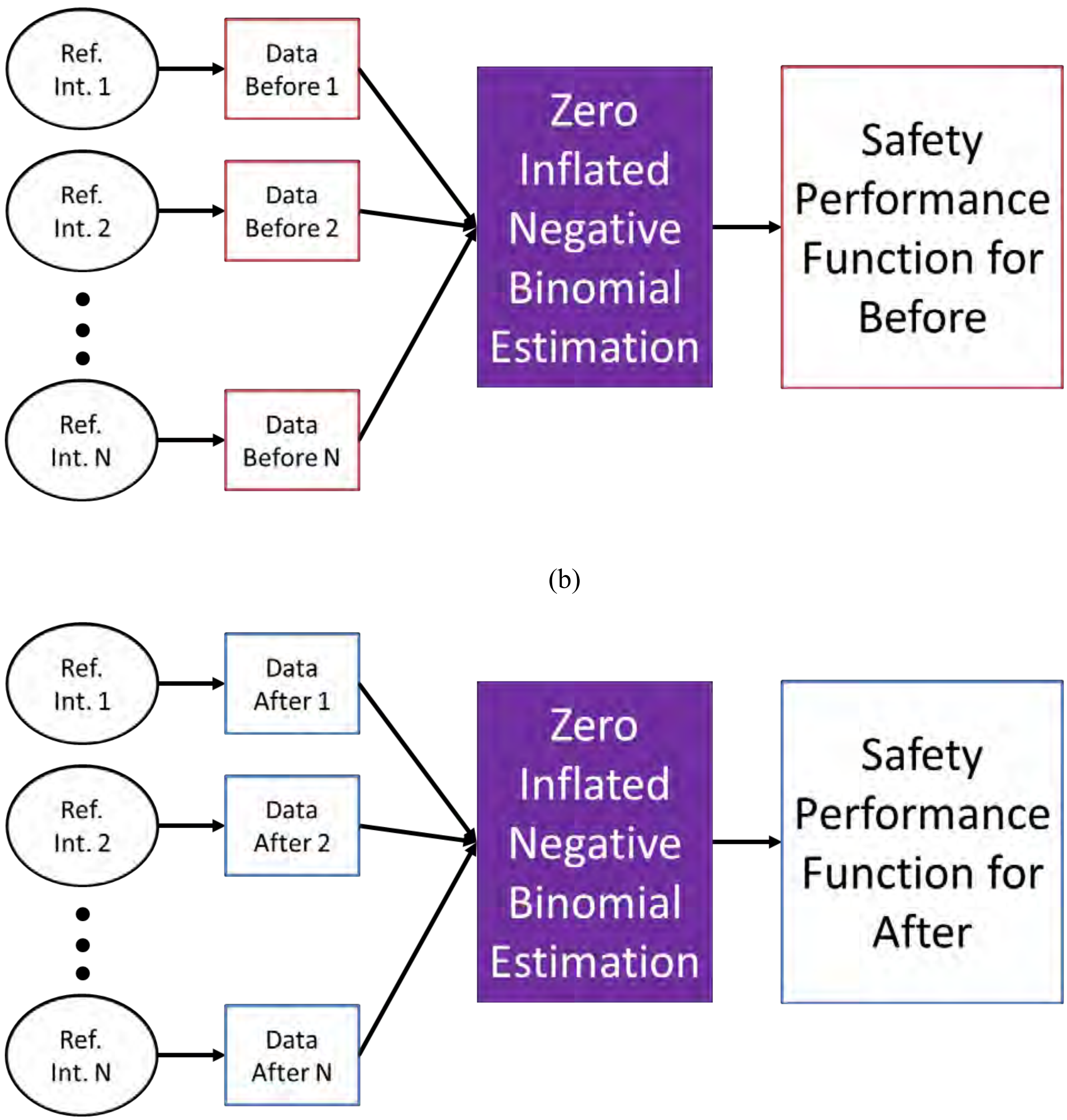


FIGURE 2.1.1 Calculation of SPFs for (a) before and (b) after period

This approach acknowledges that there are unobserved changes that happened over time such as socioeconomic factors, weather, gas prices, technological improvements and the spillover effect. The spillover effect can be described as a behavioral change, where drivers carry over their careful behavior from RLC intersections to non-RLC intersections (*7; 13-17*). Using the SPFs, obtained using the reference intersections, one can predict the number of crashes had there been no treatment at site. For this prediction, data for the treatment intersection is plugged in the SPFs. FIGURE 2.1.2 shows the overall assessment procedure for safety analysis. Detailed EB procedure with corresponding assumptions and calculations are provided and explained in the Appendix 8.2.1.

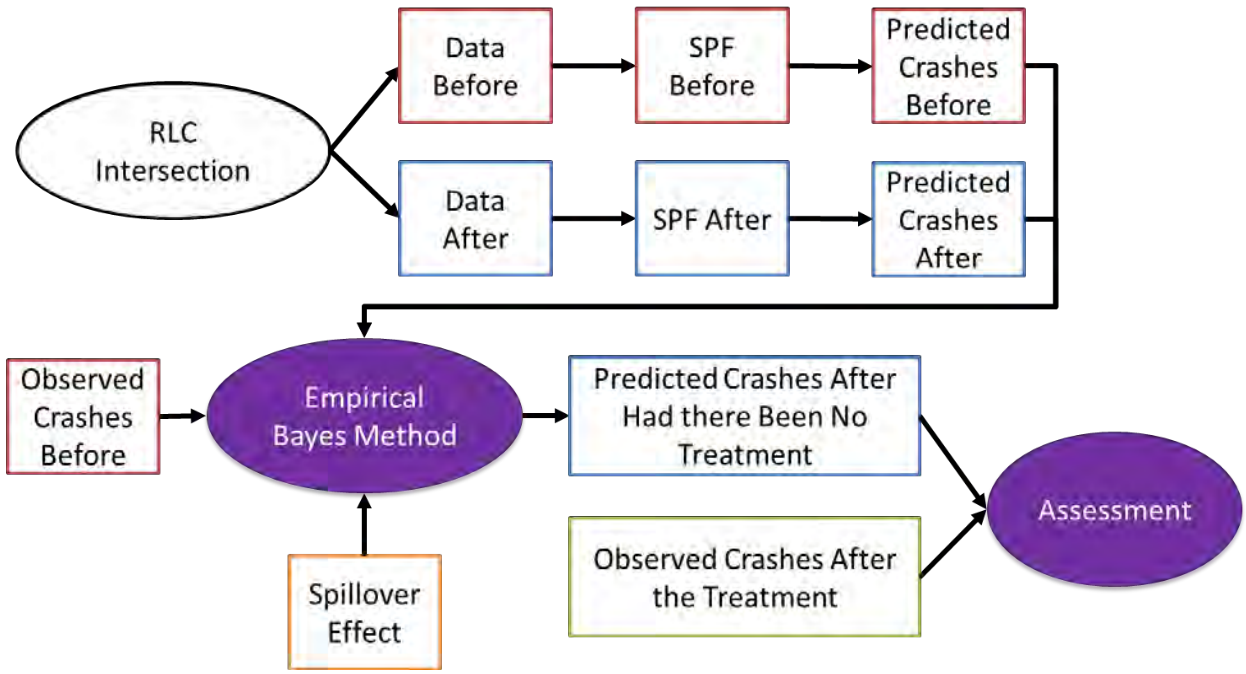


FIGURE 2.1.2 Overall assessment procedure for safety analysis.

2.2 Data

The above models were applied to the city of Chicago. While Chicago Department of Transportation (CDOT) was the main provider of the data, below is a complete list of sources:

- Data on crash location, crash type, fatalities, and injuries was provided by Illinois Department of Transportation (IDOT) to CDOT. We obtained the data from CDOT,
- Data on Annual Average Daily Traffic (AADT), number of lanes, and speed limits were collected from IDOT's website (*18*),
- Traffic signal data such as cycle length, yellow light duration, and all red duration were provided by CDOT,
- Additional data including left turn arrows on traffic lights, turning restrictions, turning bays, and medians were collected manually using Google Street View (*19*).

The selected periods are:

- Before: 2005-2007 (3 years),
- After: 2010-2012 (3 years).

The RLCs are selected based on the following criteria:

- Commissioned in 2008 or 2009,
- Not decommissioned in the after period (2010-2012),
- Four-legged intersections,
- Partial or complete AADT data available for the approaches,
- 85 intersections fit the above criteria,
- These correspond to 340 approaches; 172 of them have Red Light Cameras installed.

The reference intersections were selected based on the following criteria:

- An RLC was never installed,
- Four-legged signalized intersections,
- Partial or complete AADT data available for the approaches,
- The AADT and the number of crashes at the intersection approaches are within 10% of the treatment approaches,
- The intersection is at least 0.75 miles away from the nearest treatment intersection,
- 103 intersections were selected,
- 103 four-legged intersections correspond to 412 approaches. 236 of them fit the full set of criteria above.

The crashes were selected based on the following criteria:

- The crash is intersection-related (a binary provided in the IDOT data),
- The crash resulted in one or more of the following (KABC): <u>K</u>illing, <u>A</u>-type (incapacitating), <u>B</u>-type injury (non-incapacitating), or <u>C</u>-type (possible) injury.

The following crash types are selected:

- All KABC crashes: any crash that fits the above criteria,
- KABC Angle & Turn crashes: any crash that fits the above criteria and its 'Collision Type Code' is 'angle' or 'turning',
- KABC Rear End crashes: any crash that fits the above criteria and its 'Collision Type Code' is 'rear-end'.

FIGURE 2.2.1 displays the location of the treatment and reference intersections.

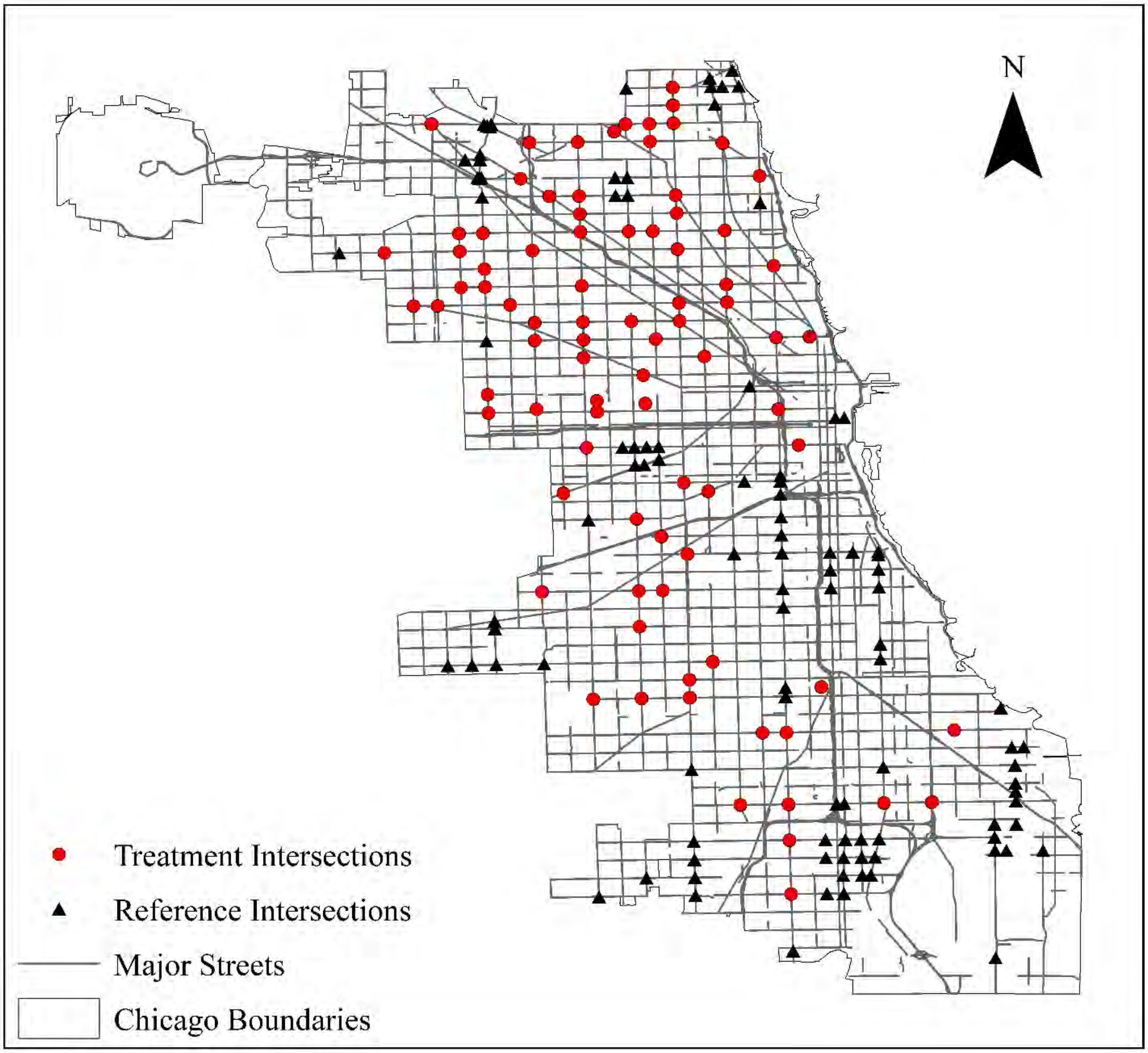


FIGURE 2.2.1 Location of treatment (RLC) and reference intersections.

The crash and AADT data were mapped to the closest intersection and approach using GIS tools. The AADT data is provided on an annual basis on street sections for both directions of traffic (*18*). As a result, it was not possible to obtain the AADT for every approach but for opposing approaches as a sum: North and South bound, or East and West bound. Same limitations apply for speed limits. The signal information on yellow and all red durations were also provided by CDOT in the same fashion. Since average values are used for the before and after periods, not all three years of AADT data are necessarily required. The averages are taken based on the available years. When Google Street View (*19*) was used, data could be collected individually for all four approaches.

After the data collection was finalized, the approach and orientation dependencies were transformed into point-of-view dependencies. See FIGURE 2.2.2 for details.

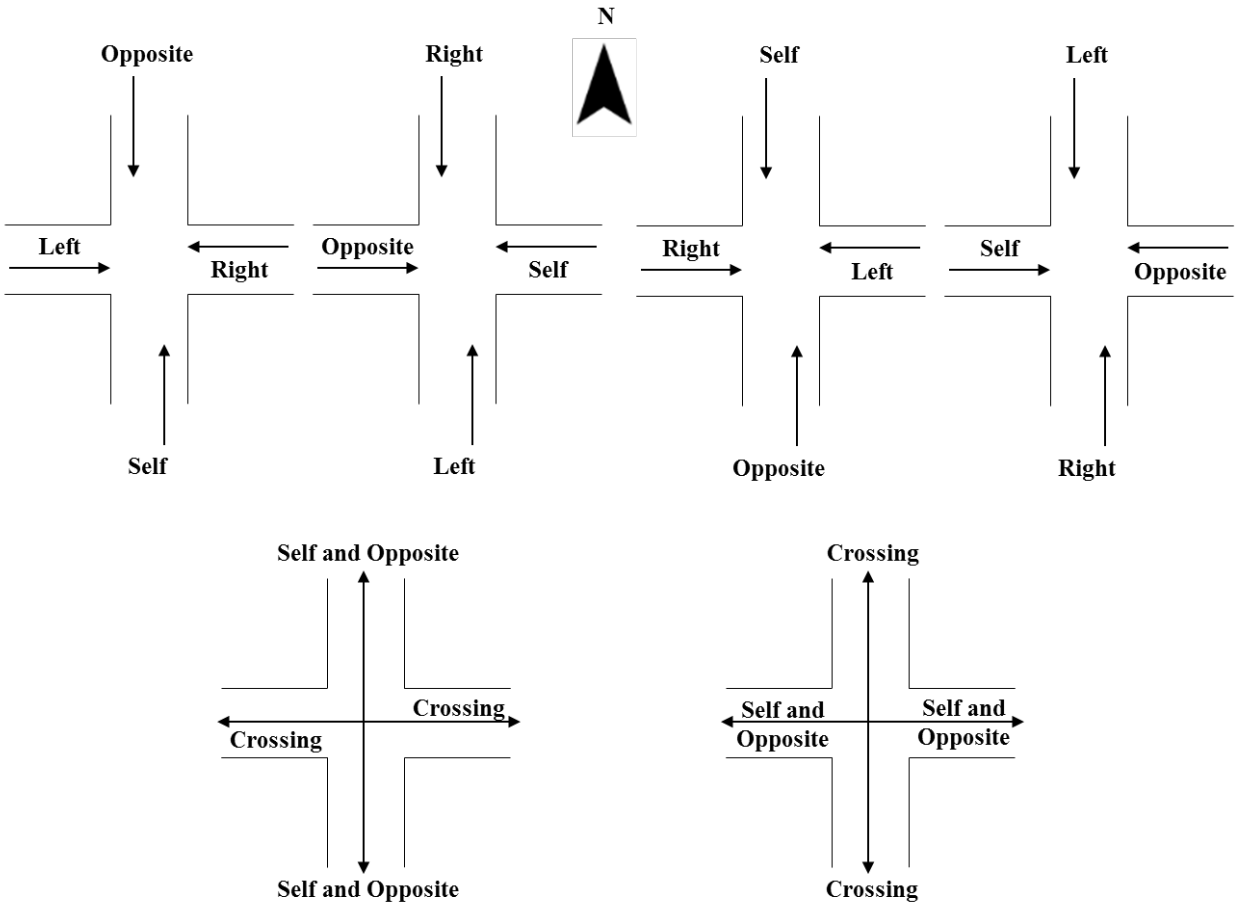


FIGURE 2.2.2 Point-of-view based approach and orientations. "Self" denotes the reference approach for specific measurements on arriving vehicles.

See TABLE 2.2.1 and TABLE 2.2.2 for the summary statistics of the reference in before and after period and TABLE 2.2.3 and TABLE 2.2.4 for the summary statistics of the treatment in before and after period respectively.

TABLE 2.2.1 Summary Statistics of Reference Variables in 2005-2007 (236 observations)

Variable	Mean	Std. Dev.	Min.	Max.
All Crashes	3.62	3.58	0.00	18.00
Angle & Turn Crashes	1.85	2.12	0.00	12.00
Rear End Crashes	0.60	1.03	0.00	7.00
AADT - Self and Opposite	16,675	14,635	2,850	206,167
AADT - All Approaches	33,330	21,828	12,250	230,550
AADT/lane - All Approaches	5,615	2,149	2,042	19,213
Speed Limit - Self	31.36	4.13	25.00	55.00
Cycle Length (sec)	81.24	16.40	65.00	130.00
Yellow - Self and Opposite	3.05	0.21	3.00	4.00
All Red - Crossing Approaches	1.41	0.49	1.00	2.00
All Red - Self and Opposite	1.42	0.49	1.00	2.00
Left Turn Allowed - Opposite Approach	0.97	0.17	0.00	1.00
Permissive Left Turn Arrow - Left Approach	0.27	0.44	0.00	1.00
Permissive Left Turn Arrow - Self	0.28	0.45	0.00	1.00
Protective Left Turn Arrow - Left Approach	0.02	0.14	0.00	1.00
Protective Left Turn Arrow - Opposite Approach	0.02	0.14	0.00	1.00
Protective Left Turn Arrow - Right Approach	0.02	0.14	0.00	1.00
Protective Left Turn Arrow - Self	0.03	0.16	0.00	1.00
Permissive or Protective Left Turn Arrow - Self	0.31	0.46	0.00	1.00
Right Turn Allowed - Opposite Approach	0.99	0.09	0.00	1.00
Right on Red Prohibition - Left Approach	0.39	0.49	0.00	1.00
Right on Red Prohibition - Self	0.38	0.49	0.00	1.00
Median - Opposite Approach	0.14	0.34	0.00	1.00
Median - Self	0.14	0.35	0.00	1.00

TABLE 2.2.2 Summary Statistics of Reference Variables in 2010-2012 (236 observations)

Variable	Mean	Std. Dev.	Min.	Max.
All Crashes	2.72	4.14	0.00	19.00
Angle & Turn Crashes	1.14	2.07	0.00	10.00
Rear End Crashes	0.58	1.20	0.00	10.00
AADT - Self and Opposite	15,439	14,068	2,500	198,950
AADT - All Approaches	30,779	20,829	8,750	222,480
AADT/lane - All Approaches	5,288	1,988	1,900	15,891
Speed Limit - Self	30.74	3.91	25.00	55.00
Cycle Length (sec)	81.24	16.40	65.00	130.00
Yellow - Self and Opposite	3.05	0.21	3.00	4.00
All Red - Crossing Approaches	1.41	0.49	1.00	2.00
All Red - Self and Opposite	1.42	0.49	1.00	2.00
Left Turn Allowed - Opposite Approach	0.97	0.17	0.00	1.00
Permissive Left Turn Arrow - Left Approach	0.27	0.44	0.00	1.00
Permissive Left Turn Arrow - Self	0.28	0.45	0.00	1.00
Protective Left Turn Arrow - Left Approach	0.02	0.14	0.00	1.00
Protective Left Turn Arrow - Opposite Approach	0.02	0.14	0.00	1.00
Protective Left Turn Arrow - Right Approach	0.02	0.14	0.00	1.00
Protective Left Turn Arrow - Self	0.03	0.16	0.00	1.00
Permissive or Protective Left Turn Arrow - Self	0.31	0.46	0.00	1.00
Right Turn Allowed - Opposite Approach	0.99	0.09	0.00	1.00
Right on Red Prohibition - Left Approach	0.39	0.49	0.00	1.00
Right on Red Prohibition - Self	0.38	0.49	0.00	1.00
Median - Opposite Approach	0.14	0.34	0.00	1.00
Median - Self	0.14	0.35	0.00	1.00

TABLE 2.2.3 Summary Statistics of Treatment Variables in 2005-2007 (340 observations)

Variable	Mean	Std. Dev.	Min.	Max.
All Crashes	3.61	5.03	0.00	29.00
Angle & Turn Crashes	1.71	2.84	0.00	19.00
Rear End Crashes	0.68	1.28	0.00	9.00
AADT - Self and Opposite	20,942	8,497	7,000	54,825
AADT - All Approaches	41,883	10,676	22,550	74,925
AADT/lane - All Approaches	6,716	1,547	2,819	9,813
Speed Limit - Self	31.03	3.39	25.00	45.00
Cycle Length (sec)	86.02	16.55	65.00	150.00
Yellow - Self and Opposite	3.05	0.21	3.00	4.00
All Red - Crossing Approaches	1.63	0.48	1.00	2.00
All Red - Self and Opposite	1.63	0.48	1.00	2.00
Left Turn Allowed - Opposite Approach	0.98	0.13	0.00	1.00
Permissive Left Turn Arrow - Left Approach	0.56	0.50	0.00	1.00
Permissive Left Turn Arrow - Self	0.56	0.50	0.00	1.00
Protective Left Turn Arrow - Left Approach	0.00	0.05	0.00	1.00
Protective Left Turn Arrow - Opposite Approach	0.00	0.05	0.00	1.00
Protective Left Turn Arrow - Right Approach	0.00	0.05	0.00	1.00
Protective Left Turn Arrow - Self	0.00	0.05	0.00	1.00
Permissive or Protective Left Turn Arrow - Self	0.56	0.50	0.00	1.00
Right Turn Allowed - Opposite Approach	1.00	0.05	0.00	1.00
Right on Red Prohibition - Left Approach	0.46	0.50	0.00	1.00
Right on Red Prohibition - Self	0.46	0.50	0.00	1.00
Median - Opposite Approach	0.20	0.40	0.00	1.00
Median - Self	0.20	0.40	0.00	1.00

TABLE 2.2.4 Summary Statistics of Treatment Variables in 2010-2012 (340 observations)

Variable	Mean	Std. Dev.	Min.	Max.
All Crashes	3.10	5.58	0.00	28.00
Angle & Turn Crashes	1.18	2.40	0.00	15.00
Rear End Crashes	0.89	1.87	0.00	11.00
AADT - Self and Opposite	19,718	8,337	5,625	58,750
AADT - All Approaches	39,436	11,204	17,400	81,850
AADT/lane - All Approaches	6,390	1,614	3,292	11,150
Speed Limit - Self	30.65	3.00	25.00	40.00
Cycle Length (sec)	86.02	16.55	65.00	150.00
Yellow - Self and Opposite	3.05	0.21	3.00	4.00
All Red - Crossing Approaches	1.63	0.48	1.00	2.00
All Red - Self and Opposite	1.63	0.48	1.00	2.00
Left Turn Allowed - Opposite Approach	0.98	0.13	0.00	1.00
Permissive Left Turn Arrow - Left Approach	0.56	0.50	0.00	1.00
Permissive Left Turn Arrow - Self	0.56	0.50	0.00	1.00
Protective Left Turn Arrow - Left Approach	0.00	0.05	0.00	1.00
Protective Left Turn Arrow - Opposite Approach	0.00	0.05	0.00	1.00
Protective Left Turn Arrow - Right Approach	0.00	0.05	0.00	1.00
Protective Left Turn Arrow - Self	0.00	0.05	0.00	1.00
Permissive or Protective Left Turn Arrow - Self	0.56	0.50	0.00	1.00
Right Turn Allowed - Opposite Approach	1.00	0.05	0.00	1.00
Right on Red Prohibition - Left Approach	0.46	0.50	0.00	1.00
Right on Red Prohibition - Self	0.46	0.50	0.00	1.00
Median - Opposite Approach	0.20	0.40	0.00	1.00
Median - Self	0.20	0.40	0.00	1.00

2.3 Model Estimates and Results

Note that while separate models provided the best fit for all KABC and rear-end KABC crashes, a combined model with an indicator (dummy) variable for the after period provided the best fit for KABC angle & turn crashes. For the rest of this section, the term KABC will be omitted. TABLE 2.3.1 presents the results obtained in the analysis. From the model results, it can be seen that the AADT, signal configurations, left turn arrows, movement restrictions, and median play a significant role in the number of crashes. An arrow pointing up means that the explanatory variable tends to increase the crashes, whereas an arrow pointing down means that the explanatory variable tends to decrease them. A dash means that the variable has no effect. For instance, high AADT-self increases angle and turn crashes whereas it had no significant impact on rear-end crashes.

TABLE 2.3.1 Impact of different intersection attributes on crashes

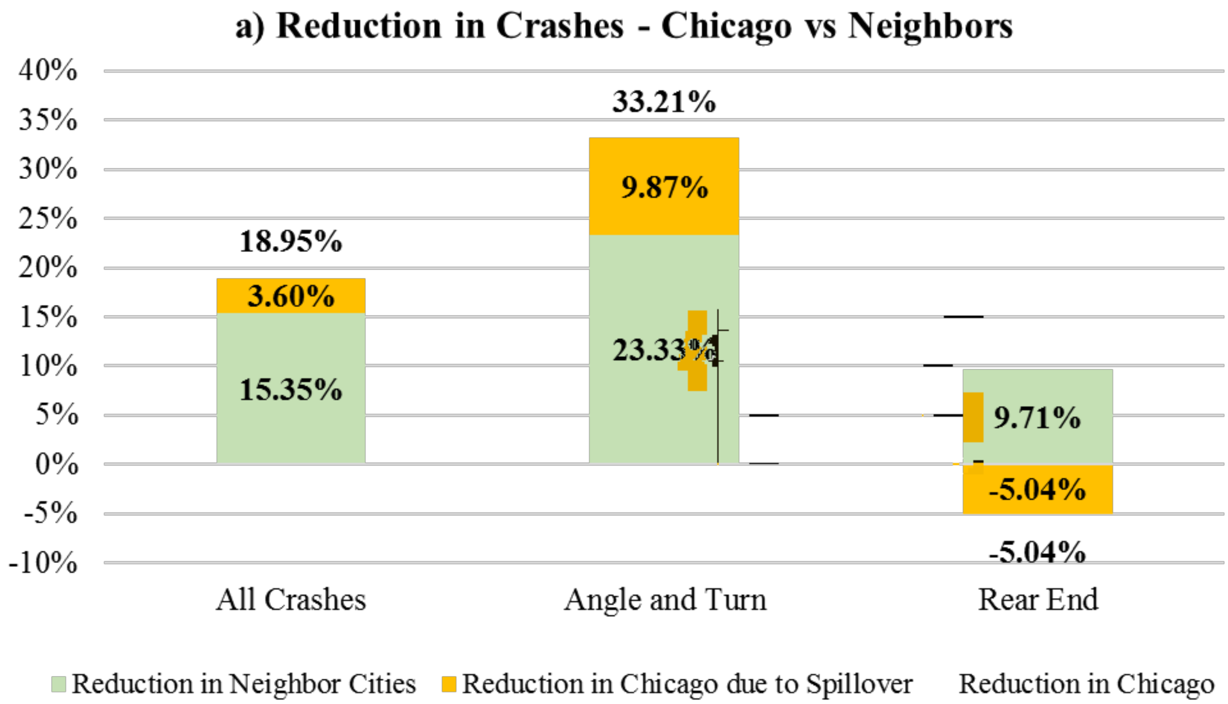
Explanatory Variables	All Before	All After	Angle & Turn	Rear-End Before	Rear-End After
AADT - Self	↑	–	↑	↑	–
AADT - Total	–	↑	–	–	↑
AADT Total / Lane	–	–	–	–	↓
Speed Limit - Self	–	–	–	↑	–
Cycle Length (sec)	↓	↓	↓	–	–
Yellow - Self	–	↓	–	–	–
All Red - Crossing	–	↑	–	–	–
All Red - Self	–	↓	–	–	–
Left Turn Blocked - Opposite Approach	↓	–	–	–	–
Permissive Left Turn Arrow - Left Approach	–	–	↑	–	↓
Permissive Left Turn Arrow - Self	–	↑	–	↑	↑
Protective Left Turn Arrow - Left Approach	↓	–	↓	–	–
Protective Left Turn Arrow - Opposite Approach	–	↑	–	–	–
Protective Left Turn Arrow - Right Approach	–	↓	–	–	–
Protective Left Turn Arrow - Self	–	↓	–	–	↓
Permissive or Protective Left Turn Arrow - Self	–	–	–	↓	–
Right Turn Blocked - Opposite Approach	↓	–	–	–	–
Right on Red Prohibition - Left Approach	–	↓	–	–	–
Right on Red Prohibition - Self	↓	↑	↓	–	–
Median - Opposite Approach	↑	–	–	–	–
Median - Self	–	–	–	↑	↑

Since the reference intersections are subject to a potential spillover, one can look at the changes in crashes at locations that are far enough from the RLC intersections but still close enough to the general area. The underlying assumption is that the driver population is essentially the same (or similar) in those areas, however their driving behavior is not influenced by the RLC's due to the considerable distance away from them, and the knowledge that no RLC's are deployed in those communities (that lie outside the City of Chicago). Considering that significant variables, as well as the coefficient values are potentially different for the safety performance functions in the before and after period, one can plug in the variables of the reference sites in the after period into both functions. If nothing else had changed, the two models would be statistically the same i.e. would result in the same expected crash values.

If these values are different, then the ratio U between the two (before SPF vs. after SPF with the same variables) captures the reduction in crashes at the reference intersections due to the unobserved factors. Therefore, if one assumes that this entire reduction is due to the spillover, U would yield the "uncontrolled" spillover effect, which can be seen as an upper bound to the actual spillover effect.

If the percentage reduction in crashes for specific crash type is A in the study area, and B in the neighboring area, then $A - B$ can be seen as the 'pure' reduction due to spillover. In order to calculate the correction factor for "controlled" spillover effect (i.e. controlling for the effect of other, unobserved variables) for specific crash type, crash data from the neighboring cities in Illinois are collected:

- Arlington Heights,
- Cicero,
- Glenview,
- Lombard,
- Naperville,
- Niles,
- Schaumburg.



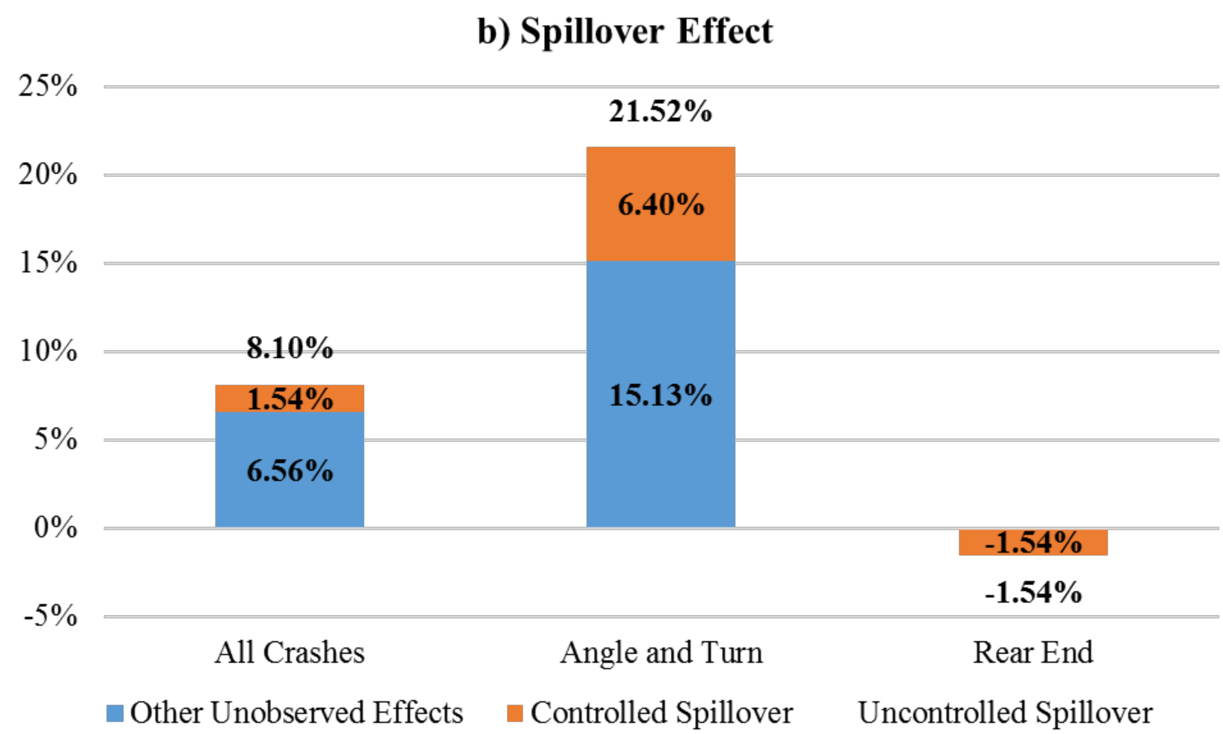


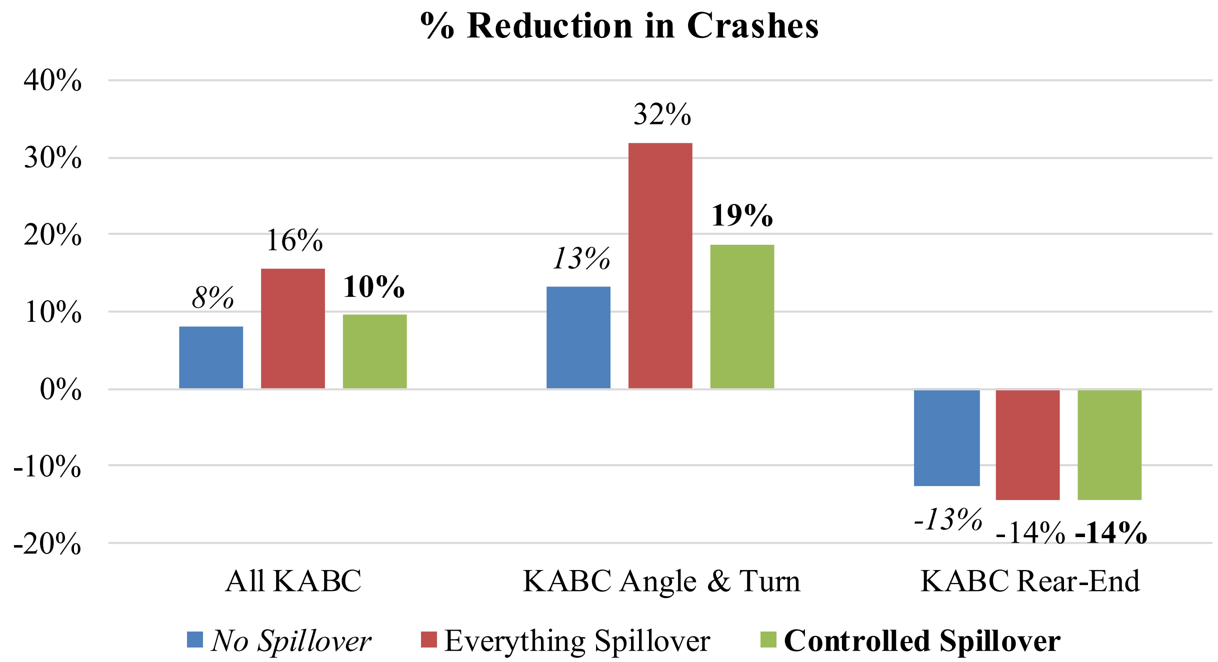
FIGURE 2.3.1 a) Reduction in crashes in the neighbor cities and Chicago, b) Uncontrolled and controlled spillover effects.

Since the intersection-based crash data was not available for the neighbor cities, we used the overall crash reduction normalized by the change in vehicles miles traveled (VMT) in the before and after periods when calculating B percentage reduction in crashes in neighboring areas for specific crash types (*20*). To make the comparison fair, we used the observed number of crashes at the reference intersections in Chicago normalized by the VMT in Chicago. FIGURE 2.3.1a presents the values B, A $(A - B)$. These values are used in the calculation of C - controlled spillover effect for specific crash type. As an example, for all crashes FIGURE 2.3.2:

$$\begin{aligned} C = \frac{(A - B)}{A} \times U &= \frac{18.95\% - 15.35\%}{18.95\%} \times 8.10\% \\ &= 18.99\% \times 8.10\% \\ &= 1.54\% \end{aligned} \tag{2.3.1}$$

FIGURE 2.3.1b presents the spillover effect results for all type of crashes. As we have observed an increase in rear-end crashes in Chicago, whereas a decrease in the neighbor cities, we assume that the entire increase in rear-end crashes is due to spillover effect.

FIGURE 2.3.2 present the safety effects with no, uncontrolled, and controlled spillover effects. Please note that in FIGURE 2.3.2, the *italic,* normal, and **bold** fonts correspond to *no,* uncontrolled, and **controlled** spillover effects respectively. For all crashes, there is an 8% reduction without factoring in the spillover effect. If one attributes all the unobserved changes to the spillover effect, the reduction goes up to 16%. TABLE 8.2.6 in Appendix 8.2.2 provides the actual numbers that were obtained and used to generate the figure. Mitigating that effect using the control provided in Equation (2.3.1), the overall reduction is 10%. The improvement in angle & turn crashes is even higher: 13%, 32%, and 19% respectively. On the other hand, there is a 13% increase in rear-end crashes without the spillover effect, and 14% with the spillover effect.



Absolute Reduction in Crashes

	All KABC			KABC Angle & Turn			KABC Rear-End		
Crashes without RLC	*1,147*	1,248	**1,165**	*461*	587	**492**	*267*	263	**263**
Crashes with RLC	*1,054*	1,054	**1,054**	*400*	400	**400**	*301*	301	**301**
Absolute Reduction	*93*	194	**111**	*61*	187	**92**	*-34*	-38	**-38**

FIGURE 2.3.2 Before-After study results using ZINB with no, uncontrolled, and controlled spillover effects.

2.4 Conclusion

An Empirical Bayesian (EB) before-after analysis method was adapted to model the safety effects of Red Light Cameras (RLC). The Safety Performance Functions were estimated using Zero-Inflated Negative Binomial (ZINB) models separately for the before and after periods at the intersection, approach level.

In order to capture the spillover effect, two methods were proposed. Both methods use the difference in outputs of the before and after models. These differences are due to the unobserved factors such as socioeconomic factors, weather, gas prices, technological improvements and the spillover effect. Since the contribution of each factor is not known, the first method assumes that the spillover effect is the sole factor and disregards the other factors. This overestimated effect can be seen as an upper bound to the actual spillover effect. The second method then mitigates this factor by factoring in the reduction in crashes in the neighbor cities.

The three models are applied to the Red Light Cameras commissioned in 2008 and 2009 in the City of Chicago. The results agree with the findings in the literature that the RLC treatment reduces angle and turn crashes, and increases rear-end crashes with an overall reduction in crashes. However, because both severity and frequency of angle and turn crashes are considerably higher than rear-end occurrences, the overall safety improvement is substantial.

3 DETERMINANTS OF RED-LIGHT CAMERA VIOLATION BEHAVIOR

This analysis aims to understand the effect of traffic features, intersection factors, and signal configuration on the frequency of RLC violations by using regression models (statistical tools which estimate the relationships between variables) that analyze violations at 152 RLCs in the city of Chicago, Illinois over a 6-year period between 2010 and 2015. The analysis informs the overall study objectives by providing insight into observable elements and factors that affect the performance and effectiveness of RLC enforcement, and could more generally lead to safer traffic behavior at intersections. Coupled with the safety analysis described in the previous Chapter, these factors are an important consideration in the guidance provided to the City in terms of identifying locations that are more or less likely to benefit from enforcement.

The following section provides a description of the data set and variables used in the analysis followed by the methodology behind the developed regression models. Afterwards, the estimated models are discussed.

3.1 Data

Information related to 152 RLCs at 85 four-legged intersections were retrieved from the data set provided by the Chicago Department of Transportation. Locations of the RLC intersections are shown in FIGURE 3.1.1. Note that not all cameras used in the analysis presented earlier could be used here due to incomplete data over the duration of interest. The time period covered lies between 2010 and 2015. In this date range, all of the violations were provided with date-time stamp for all the cameras, except for maintenance and black-out periods where violations were not detected. Black-out periods correspond to times when the cameras were not enforcing due to parades or construction projects. The dataset included: date-time, speed of the vehicle while violating, associated vehicular lane and posted speed limit. Information related to signal timing contains the all red duration, yellow time, cycle length, total number of lanes on the approach.

Necessary additional information was readily available through online resources. Google Maps was used to manually obtain intersection geometry and configuration related information. These included intersection traverse distance, type of median, presence of dedicated left turn arrow, right turn on red prohibition sign, left and right turn bays. Annual Average Daily Traffic (AADT) was obtained from an online data portal provided by the city of Chicago; however, we corrected AADT for monthly traffic patterns as published by the Illinois Department of Transportation for the different years.

The data set includes 10,944 observations (152 x 72), for 152 red-light cameras (panels) over 72-month period. Due to maintenance and short black-out periods of some cameras, violations were not detected for specific time periods. For a better estimate of the models, the missing values were imputed before using the data to build the regression models (*22*). More details on the algorithm used to predict the missing data can be found in Appendix 8.3.1.

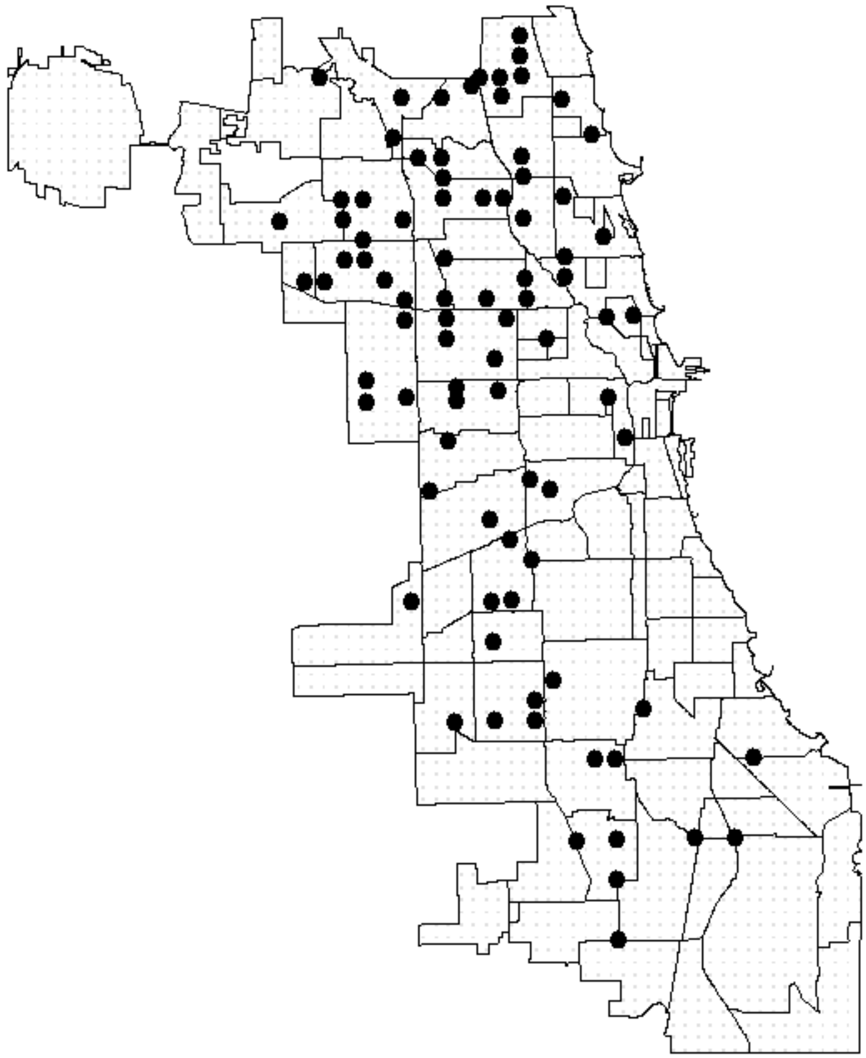


FIGURE 3.1.1 Locations of 85 RLC intersections studied.

3.2 Variables in the Regression Models

In the regression model, the number of RLC violations per month was defined as the dependent variable which was tested to be affected by traffic features, intersection factors, and signal configuration. To test for different RLC violation behaviors, four classes of violations were defined: All violations, Rolling-Right-On-Red (RROR), High speed, and One-second-into-red. All violations include all observed RLC violations for an approach by a specific camera. RROR violations include cases where a vehicle turned right without a full stop while signal is red. Violations were inferred as RROR when the violator was driving at a speed below 20 mph and in the farthest right lane. High-speed violations include cases where a vehicle runs an RLC with speed that is more than 10 percent above the speed limit. One-second-into-red includes cases where a vehicle runs an RLC within 1 sec after the signal had turned red. TABLE 3.2.1 presents the number of violations in each class.

TABLE 3.2.1 Number of Violations per Violation Class (2010-2015)

Violation Class	Number
All	1,353,862
Rolling-Right-On-Red	372,333
High-Speed	282,038
One-Second-Into-Red	656,184

TABLE 3.2.2 presents the number of violations under one second into red at 0.1 second intervals. Because the City's current policy is to not issue tickets for instances where the vehicle enters within the first 0.1 second into the red phase, there are no violations under 0.1 seconds in the Table. Furthermore, the numbers of violations at larger intervals are, in general, higher. It should be noted that 48.5% of the overall violations are within one second into red.

TABLE 3.2.2 Number of Violations at 0.1 Second Intervals

Time Into Red	Count	Cumulative Count
= 0.1 sec	50,924	50,924
0.1-0.2 sec.	59,513	110,437
0.2-0.3 sec.	42,504	152,941
0.3-0.4 sec.	34,964	187,905
0.4-0.5 sec.	37,065	224,970
0.5-0.6 sec.	53,164	278,134
0.6-0.7 sec.	87,115	365,249
0.7-0.8 sec.	99,275	464,524
0.8-0.9 sec.	97,348	561,872
0.9-1.0 sec.	94,312	656,184

TABLE 3.3.1 presents a summary of the variables (and corresponding nomenclature) included in the statistical regression model. Three directions of movement were defined for the variables relative to the movement of a vehicle approaching an RLC: self, crossing and opposite. Self indicates that the variable, for example speed limit, describes the approach on which the vehicle is moving towards an intersection. Crossing describes the approach that is crossing (perpendicular to) the self-approach on an intersection. Opposite describes the approach that is opposite of the self-approach.

3.3 Methodology

To model frequency of RLC violations in Chicago IL, regression models using serially correlated (time-dependent) panels are used. Panel data analysis (often referred to as longitudinal or cross-sectional time series data) was chosen since RLC violations were observed over a long period of time (6 years). The simple structure of the model is as follows:

$$y = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_N x_N + \nu \tag{3.3.1}$$

where y is the frequency of RLC violations, $x_1, x_2 \ldots x_N$ are explanatory variables (AADT, road geometry, and signal timing variables), $\beta_1, \beta_2 \ldots \beta_N$ are the coefficients (effects) of the explanatory variables, ν is the error term. The values of the model coefficients were estimated using the Generalized Least Squares (GLS) method built in the statistical software STATA. More detail on the serially correlated panels is found in Appendix 8.3.2.

TABLE 3.3.1 Description of Variables in Regression Models

Variable	Description	Mean	S.D
Dependent Variable			
All vio.	Continuous: All RLC violations per month time period	129.66	118.28
RROR	Continuous: RROR violations per month time period	16.17	40.89
High-speed Violations	Continuous: High-speed violations per month time period	27.18	48.56
1-into-red violations	Continuous: One-sec-into-red violations per month time period	63.19	67.04
Explanatory Variables			
AADT/lane - self	Continuous: Average Annual Daily Traffic per lane, corrected for monthly traffic patterns in the (self) direction	6.37	2.13
AADT/lane - crossing	Continuous: Average Annual Daily Traffic per lane, corrected for monthly traffic patterns in the (crossing) direction	6.16	2.27
N. lanes - self	Continuous: Number of lanes in (self) direction	3.25	1.01
N. lanes - crossing	Continuous: Number of lanes in (crossing) direction	3.12	1.04
Speed limit - self	Continuous: Speed limit in (self) direction	30.53	2.64
Speed limit - crossing	Continuous: Speed limit in (crossing) direction	30.46	2.83
Traverse Distance - self	Continuous: Intersection traverse distance in (self) direction	99.00	19.95
Traverse Distance - crossing	Continuous: Intersection traverse distance in (crossing) direction	101.63	19.54
Left-turn bay – self	Binary: Indicator of existing left-turn bay in (self) direction	0.90	0.30
Left-turn blocked	Binary: Indicator of prohibited left turn movement in (self) direction	0.02	0.14
Left-turn arrow – oppst.	Binary: Indicator of existing left turn arrow for opposite approach	0.57	0.50
ROR prohibition - self	Binary: Indicator of existing “NO TURN ON RED” sign	0.48	0.50
Right-turn bay - self	Binary: Indicator of existing right-turn bay in (self) direction	0.08	0.27
Median - self	Binary: Indicator of existing median (physical or yellow line)	0.22	0.41
Cycle length	Continuous: Length of signal cycle in seconds	86.67	16.83
Yellow phase	Factor: Length of yellow phase in seconds (3 or 4 sec)	3.05	0.21
All-red phase	Factor: Duration of all-red phase in seconds (1 or 2 sec)	1.65	0.48
Month	Factor: Indicator of the month for the time period (1 - 12)	-	-
Year	Factor Indicator of the year for the time period (2010 – 2015)	-	-

3.4 Model Estimates for All RLC Violations

The estimated model for all RLC violations shows that variables which have a positive effect (increase) on the frequency of RLC violations are *AADT/lane self*, *N. lanes self*, *speed limit*, *traverse distance-crossing*, *blocked left turn*, *cycle length*, and *all-red phase* of 2 sec compared to 1 sec. On the other hand, variables which have a negative effect (decrease) on the frequency of RLC violations include AADT/lane – crossing, *N. lanes – crossing*, *traverse distance – self*, *left-turn bay, left-turn arrow – oppst*, *ROR-prohibition*, *median*, and a *yellow phase* of 4 seconds compared to 3. Furthermore, the model shows a monthly trend in the frequency of violations where frequency is highest in *Summer* and lowest in *Winter*, and an annual learning curve where violations decrease continuously from 2010 to 2015. The model estimates can be found in TABLE 8.3.1 in Appendix 8.3.4.

The model coefficients are interpreted as follows: a one-unit increase in the explanatory variable leads to a coefficient value increase in frequency of violations on the average assuming all remaining variables are constant. Take *N. lanes – self* for example, an increase of 1 lane leads to an increase of 26.13 RLC violations on the average assuming all other variables are constant.

See TABLE 3.5.1 for a summary of the model results. An arrow pointing up means that the explanatory variable tends to increase the violations, whereas an arrow pointing down means that the explanatory variable tends to decrease them. A dash means that the variable has no effect. Starting with traffic features, *AADT/lane – self* and *N. lanes – self* can be interpreted as exposure variables whose positive coefficients indicate that higher traffic leads to higher chances of RLC violations. The negative coefficients of *AADT/lane – crossing* and *N. lanes – crossing* indicate that drivers are more likely to stop when the perceived risk of an angle collision is greater. The positive coefficients of *Speed limit – self/crossing* reflect that drivers generally expect longer yellow intervals at higher-speed intersections, because stopping requires higher decelerations that increase the risk of a rear-end collision.

As for intersection factors, the negative coefficient of *Traverse distance -self* indicates that a longer distance to traverse an intersection makes it harder for drivers to pass through an intersection in time, hence, less likely to violate. On the other hand, the positive coefficient of *Traverse distance -crossing* indicates that a wider intersection would make drivers more confident to pass through it before crossing traffic starts moving increasing the chances of a violation. *Left-turn bay - self* has a negative coefficient indicating that drivers are less likely to violate RLC after impatiently waiting behind a vehicle turning left if turn bay exist. *Left-turn blocked - self* has a positive coefficient which could mean that drivers are more confident in passing through an intersection, risking a violation, without worrying about crossing traffic from one direction. *Left-turn arrow – oppst* has a negative coefficient indicating that drivers are less likely to violate, and risk a crash, when the number of left-turning vehicles are high in the opposite direction. This is under the assumption that a left-turn arrow is installed when the number of turning vehicles is high. *Right-On-Red prohibition* and *median* have negative coefficients indicating that when installed, violation frequency decreases.

Regarding the effect of signal timing, the positive coefficient of *cycle length* shows that higher cycle length could make people impatient and more likely to violate a RLC. The negative yellow phase coefficient indicates that fewer violations are associated with the longer phase of 4 seconds than with 3-second intervals. This is expected as, all else being equal, a longer yellow increases the probability that a driver can safely enter the intersection before the signal turns red. *All-red phase*, while being important for safety, can be interpreted as an exposure variable whose positive coefficient indicates a higher probability of a violation occurring at intersections with a 2-second all-red duration than at those with 1-second all-red intervals. Keeping in mind that longer all-red phases are generally programmed for higher-risk intersections, to clear the intersection before releasing stopped vehicles, incoming drivers at the onset of yellow may perceive a lower risk of angle collision, and thus "go for it" instead of attempting to stop.

Predicted vs. actual values of total RLC violations are plotted in FIGURE 3.4.1 for the 72-month time periods using the serially correlated model. The plot shows that the model (black bars) picks up the annual and monthly trends in RLC violations; however, it tends to smooth out the spikes in numbers as expected of a linear regression model. It is worth noting that the annual and monthly trends of actual violation numbers are consistent and decreasing over the years, reflecting a certain learning process by drivers.

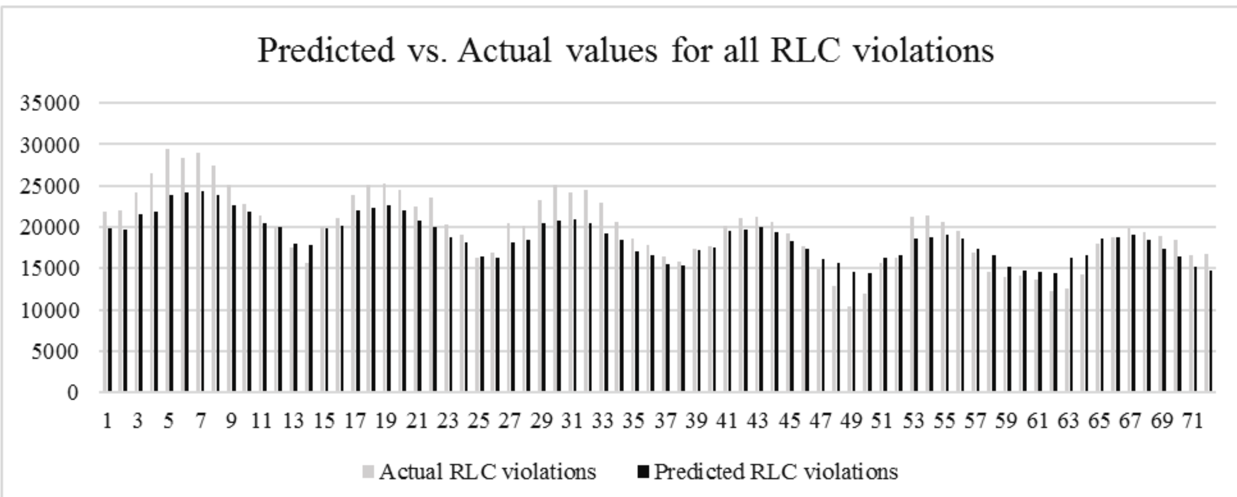


FIGURE 3.4.1 Predicted vs. actual values of total RLC violations using serially correlated model.

3.5 Model Estimates for Different Categories of RLC Violations

In addition to the total RLC violations model, separate models were estimated for three categories of RLC violations to test whether the explanatory variables have different relative effects on different types of violations. The three categories are Rolling-Right-On-Red (RROR), High speed, and One-sec-into-red. RROR violations includes cases where a vehicle turned right without a full stop while the signal is red. Violations were inferred as RROR when the violator was driving at a speed below 20 mph and in the farthest right lane. High-speed violations include cases where a vehicle runs an RLC at a speed that is more than 10 percent above the speed limit. One-sec-into-red includes cases where a vehicle violates a red signal within 1 second after that signal had turned red.

Generally, the violation behavior is similar for the different categories of violations in terms of effect sign (increasing/decreasing) although having different magnitudes. The different coefficient magnitudes capture the different frequencies of violation classes and the different behavior of violators for those classes. Furthermore, some variables were insignificant for specific classes while significant for others. Note that the classes of violations are not mutually exclusive nor collectively exhaustive. For example, a high speed violation can also be a 1-sec-into-red. Additionally, some violations were not classified into any of the three categories defined earlier, but are included in the all-violations model.

3.5.1 Rolling-Right-On-Red Violations Model

Two models were estimated, for RROR and Non-RROR violations, respectively, with the latter essentially being all violations that do not fit the RROR criteria provided earlier. The two models, when combined with an all-violations model, allow us to examine statistically, using the Chow test (*23*), whether the underlying behaviors are different (for RROR as opposed to those that are not RROR), and thus affected differently by the explanatory variables. The model estimates can be found in TABLE 8.3.2 in Appendix 8.3.5.1. See TABLE 3.5.1 for a summary of the model results. An arrow pointing up means that the explanatory variable tends to increase the violations, whereas an arrow pointing down means that the explanatory variable tends to decrease them. A dash means that the variable has no effect.

In terms of effect directionality, i.e. increasing/decreasing violation frequency, most variables have similar effect for both RROR and Non-RROR violations. In terms of effect magnitude, however, the explanatory variables have different magnitudes for the two models. For example, *N. lanes – self* has a higher positive effect on frequency of RROR violations compared to for Non-RROR violations. On the other hand, the two models show similar annual and monthly trends for violation frequencies.

An exception to the general behavior is the effect of *AADT/lane* on RROR violations, whereby higher traffic in the direction of movement (*AADT/lane – self*) decreases the frequency of an RROR violation, whereas higher crossing traffic (*AADT/lane – crossing*) increases the chances of an RROR violation. As discussed earlier, AADT is considered an exposure variable. Higher traffic in one's direction usually results in longer green time, and hence less opportunity (need) for turning on red (compared to a situation with less green time). RROR violations occur when drivers turn on red when the crossing traffic is moving. Higher crossing volumes require more green time, hence longer red for the approach under consideration (the *self* approach), thereby increasing the likelihood of drivers rolling-right-on-red, as confirmed by the positive coefficient of (*AADT/lane – crossing*). Another interesting difference is the influence of the all-red duration, which is insignificant in the RROR model, possibly because one extra second is a small fraction of the overall red during which RROR violations may occur.

3.5.2 High-speed Violations Model

Two significantly different models were estimated for High-speed violations and Non-High speed RLC violations. As explained earlier, high speed refers to traversing red-light cameras with a speed that is more than 10% above the speed limit, while non-high-speed refers to traversing a red-light-camera with a speed below that threshold. As in the case of RROR, statistical significance of the difference in behavior across these two categories was tested using the Chow test (*23*). TABLE 8.3.3 in Appendix 3.5.2 shows the model estimates, while TABLE 3.5.1 presents a summary of the model results. An arrow pointing up means that the explanatory variable tends to increase the violations, whereas an arrow pointing down means that the explanatory variable tends to decrease them. A dash means that the variable has no effect.

Except for insignificant ones, the explanatory variables have similar direction of effect, i.e. increasing/decreasing violation frequency for both models. In terms of effect magnitudes, significant variables have different magnitudes for both models. Additionally, the two models have similar annual and monthly trends although having different magnitude of effect.

Interestingly, the models show that speed limit has an insignificant effect on frequency of high-speed RLC violations. This could indicate that high-speed violators tend to accelerate through an intersection at red regardless of the speed limit. The *Left-turn bay – self* and *Left-turn blocked* variables are also insignificant for high-speed violations, which could mean that most High-speed violations are through movements (non-turning-left violations).

3.5.3 One-sec-into-red Violations Model

Two models were estimated for One-sec-into-red violations and Non-One-sec-into-red violations. The One-sec-into-red violation captures situations where a driver might be in a yellow-phase dilemma zone, in which the driver is unable to come to a complete stop nor enter the intersection in time before the signal turns red. The Chow test (*23*) showed that the coefficients estimated for the two models are significantly different. The model estimates are found in TABLE 8.3.4 in Appendix 3.5.3. See TABLE 3.5.1 for a summary of the model results. An arrow pointing up means that the explanatory variable tends to increase the violations, whereas an arrow pointing down means that the explanatory variable tends to decrease them. A dash means that the variable has no effect. The estimates show that both models have similar direction of effect (increasing/decreasing) for the significant variables, whereas the models have different effect magnitudes. As in the case of the previous violation classifications, the monthly trend is similar for both models.

The all-red variable has insignificant effect in the Non-one-into-red model. This indicated that violations outside the dilemma zone, which are less likely to be by mistake, occur during the regular red-light phase and not during all-red phase. Another interesting difference is that the annual trend is different for both models. The trend shows that one-sec-into-red violations are increasing over the years from 2010-2015, which is unlike the general behavior as seen in the previous models. This could mean that drivers' behavior is becoming riskier when trying to cross an intersection in the dilemma zone.

TABLE 3.5.1 Summary Results for Four Models

Explanatory Variables	All Violations	RROR 20	High Speed	1-Into-Red
AADT - Self	↑	↓	↑	↑
AADT - Crossing	↓	↑	↓	↓
Number of Lanes - Self	↑	↑	↑	↑
Number of Lanes - Crossing	↓	↑	↓	↓
Speed Limit - Self	↑	↑	-	↑
Speed Limit - Crossing	↑	↑	-	-
Width - Self	↓	↓	↓	↓
Width - Crossing	↑	↑	↑	↑
Left Turn Arrow - Opposite Direction	↓	↓	↓	↓
Left Turn Bay - Self	↓	↓	-	-
Left Turn Blocked - Self	↑	↑	-	↑
Right on Red Prohibition - Self	↓	↓	↓	↓
Right Turn Bay - Self	-	↑	↑	↑
Median - Self	↓	-	-	↓
Cycle Length	↑	↑	↓	↑
Yellow Length (4 sec) - Self	↓	↓	↓	↓
All-red Length (2 sec) - Self	↑	-	↑	↑
Month	Varies			
Year	↓	↓	↓	↑

3.6 Conclusion

While understanding the safety implications of RLC enforcement is essential, as reflected by the previous analysis and existing literature, another important (and overlooked) subject is to better understand how different elements affect violation behavior in the presence of RLCs, and how that behavior changes over time. This analysis aims at answering those questions by using regression models for panel data to infer the effect of traffic features, intersection factors, and signal configuration on the frequency of Red-light Camera (RLC) violations and the change of frequency over time.

To that end, the study analyzed RLC violations at 152 cameras at 85 intersections in the city of Chicago, IL over 72-month period (2010 – 2015) using regression models for serially correlated (time-dependent) panel data. The models were estimated by the Generalized Least Squares (GLS) method.

Results showed that variables which have a positive effect (increase) on the frequency of RLC violations are higher traffic volume per lane, more lanes and higher speed limit along the approach, the distance to be traversed by crossing traffic (indicating the width of the roadway), blocked left turn from the approach, longer cycle length, and an *all-red* phase of 2 sec compared to 1 sec. On the other hand, variables that have a negative effect (decrease) on the frequency of RLC violations include the volume incoming from the crossing approach, and the number of lanes of the crossing approach, the presence of a left turn bay on the main (self) approach, presence of a left-turning arrow in the opposite direction (which suggests substantial incoming conflicting turning traffic), RTOR prohibition, the existence of a median, and a yellow phase of 4 seconds compared to 3.

Furthermore, accounting for annual and monthly effects, the models showed that RLC violations were continuously decreasing over the studied years, thus indicating a positive change in safe behavior. This kind of learning effect on the part of drivers in response to enforcement is an encouraging result, also reflected in the spillover effect observed in the crash analysis performed in the previous chapter. However, the fact that one-second-into-red violations did not decrease is an indication of the existence of a genuine dilemma zone that even risk averse, rule-abiding drivers may not be able to negotiate. This is one consideration underlying our recommendation to increase the enforcement threshold (time-into-red that triggers a ticket) from the current 0.1 second to 0.3 or 0.4 seconds. Additionally, monthly effects were significant, indicating other unobserved variables in the data, like weather, could affect number of RLC violations per month.

In addition to the total RLC violations model, separate models were estimated for three classifications of RLC violations to test whether the explanatory variables have different effects on the different classification of violations. The three classifications are Rolling-Right-On-Red (RROR), High speed, and One-sec-into-red. Generally, the violation behavior is similar for the different classes of violations in terms of effect sign (increasing/decreasing) although having different magnitudes. The different coefficient magnitudes capture the different frequencies of violation classes and the different behavior of violators for those classes. Furthermore, some variables were insignificant for specific classes and significant for others.

The findings of this analysis can help policy makers and researchers understand the interactions of different elements with RLC violation behavior. While the introduced models try to explain violation behavior in the city of Chicago, the methodology can be used to build models to explain RLC violation behavior in other areas. However, the general direction of effects (positive/negative) of the considered factors confirms results found in literature for other cities. One limitation of this type of analysis is the absence of individual driver variables, as well as situational variables that may help explain factors related to driver perception, possible inattention or distraction (e.g. cell phone use), and so on. Thus the analysis is by necessity limited to observable factors present in the data, or that can be measured independently. However, this does not invalidate the significance of the findings, and their relevance and utility for both engineering and policy applications. For future work, a survey could be conducted to collect drivers' insights on how the significant factors found in this study affect their driving behavior at RLCs. Drivers' insights would improve the interpretation of results discussed in the study. In addition, models in this study could be extended using virtual reality tools, like driving simulators, to test for effect of unobserved elements in this study.

4 EVALUATION AND SCORING

This chapter describes a screening method for evaluating the performance of the Red Light Cameras based on the number of violations and the safety improvements. Statistically, the correlation between the number of crashes and violations, or between the reduction in number of crashes and violations was found to be low. As a result, a clustering analysis was performed. The objective was to identify *intersection, approach* pairs that benefited the most from the program, as well as those that experienced no measurable improvement, or even possible deterioration in safety performance. The two selected performance criteria are:

- Reduction in angle and turn crashes at the intersection level
- Number of all violations

As a reminder, these cameras are installed on 85 intersections in the years 2008 and 2009. The before period covers 2005-2007, whereas the after period covers 2010-2012. Hence, the reduction in angle and turn crashes captures the improvement between those two periods. On the other hand, the number of violations reflects the period 2010-2012.

The rationale for selecting the angle and turn crashes is as follows. As shown in Chapter 2, the RLC treatment causes in general a decrease in angle and turn crashes and an increase in rear-end crashes. As a result, the reduction in all crashes is mitigated by the increasing rear-end crashes. Since rear-end crashes are less severe in nature, and less frequent, this could be an acceptable trade-off. Hence, the reduction in angle and turn crashes is selected as one of the primary performance criteria. Intersection totals instead of approach-based values are used in this analysis because the existence of camera influences the entire intersection from a behavioral standpoint.

The second criterion is the number of all violations. The primary motivation for implementing RLC enforcement is to improve safety, locally and overall. Thus effectiveness of enforcement is naturally measured by its safety impact relative to the effort in catching, and eventually discouraging, violations. The number of violations ticketed can thus be viewed as an "input" to a safety program, the output being the improvement in safety (reduction in crashes). Over time, an effective program will see reductions in both. While overall program effectiveness is the primary concern, individual locations can also be assessed in terms of their local impact relative to the extent to which violations are occurring at that location. A large number of violations with no corresponding reduction in crashes would suggest that complementary, or alternative enforcement techniques should be considered. On the other hand, a small number of violations with a large reduction in crashes at a location would indicate highly effective performance in terms of discouraging unsafe behaviors.

The approach developed in this Chapter is therefore intended as a methodology to help the City accomplish two objectives: (1) evaluate existing intersections where RLC enforcement has been deployed, and thus help identify those where discontinuation of the RLC should be considered; and (2) assess intersections where no RLC's are presently deployed that are likely to be potentially good locations for such enforcement. However, the methodology is intended primarily as a screening technique, in the sense that individual intersections must be examined and subjected to engineering judgment that considers special factors-- such as sight distance, heavy turning movement patterns at certain times of the day, frequent parking maneuvers in the vicinity, and presence of pedestrians and bicycles-- before reaching a final decision. Furthermore, for intersections where RLC enforcement is deemed not especially effective, alternative means of improving safety should be examined.

4.1 Model Estimates and Results

In this study, a K-Means clustering algorithm is performed (*24*). Please refer to Appendix 8.4.1 for mathematical details of K-Means clustering. See TABLE 4.1.1 and FIGURE 4.1.1 for the distribution of the 170 cameras into four clusters. There are 104 cameras in Cluster A, where there is a significant reduction in the number of angle and turn (AT) crashes. This cluster also has a relatively low number of violations. See FIGURE 4.1.2 and FIGURE 4.1.3 for the distribution of the number of all violations and the absolute reduction in angle and turn crashes respectively.

TABLE 4.1.1 Summary of Clusters

Cluster	Number of Cameras	Avg. Number of All Violations	Avg. Abs. Reduction in AT Crashes	Description
D	7	17,600	-3.29	Safety Reduction, High Violations
C	43	3,960	-2.50	Safety Reduction, Low Violations
B	16	4,531	0.08	No Change in Safety, Low Violations
A	104	4,994	3.02	Safety Improvement, Low Violations

There are 16 cameras in Cluster B, where the number of violations is relatively low. However, the AT crash reduction varies between -0.5 and 0.5. From the crash reduction point of view, these intersections should be monitored closely.

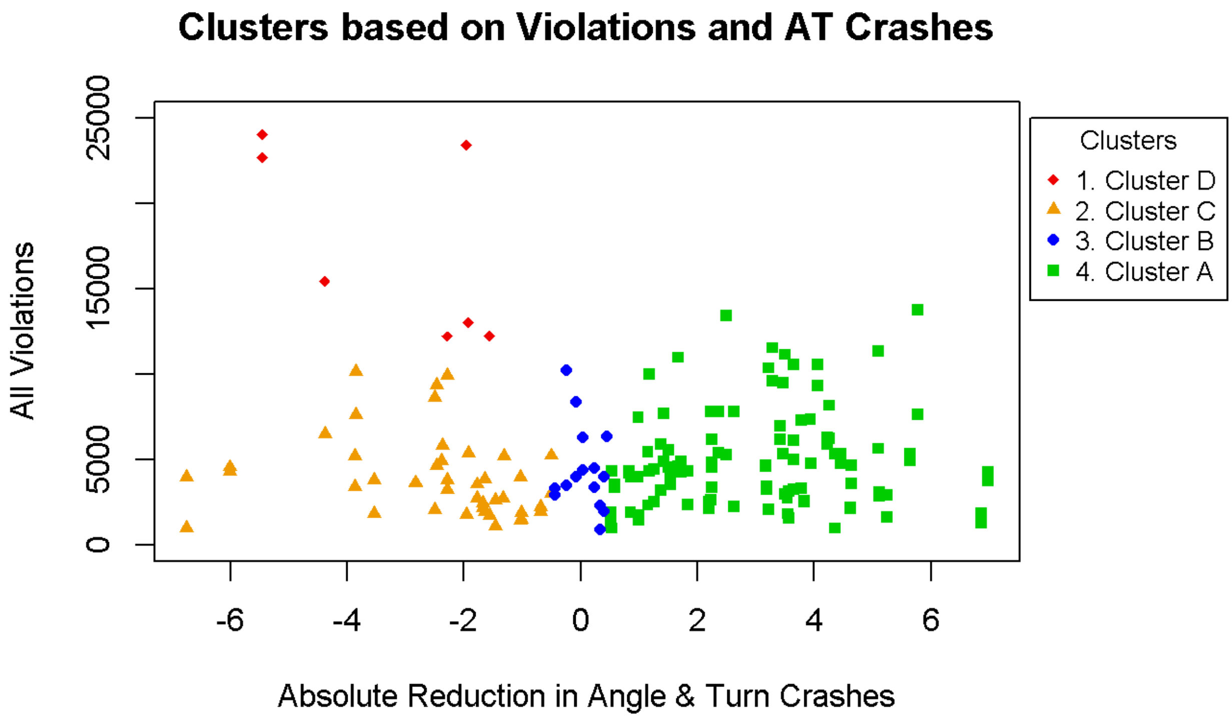


FIGURE 4.1.1 Clusters based on all violations and reductions in angle and turn crashes.

The intersections in Clusters C and D have an increase in the number of angle and turn crashes. There are 43 cameras in Cluster C with a relatively low number of violations, whereas there are seven cameras in Cluster D with a very high number of violations. Those seven cameras and their corresponding intersections call for a closer examination.

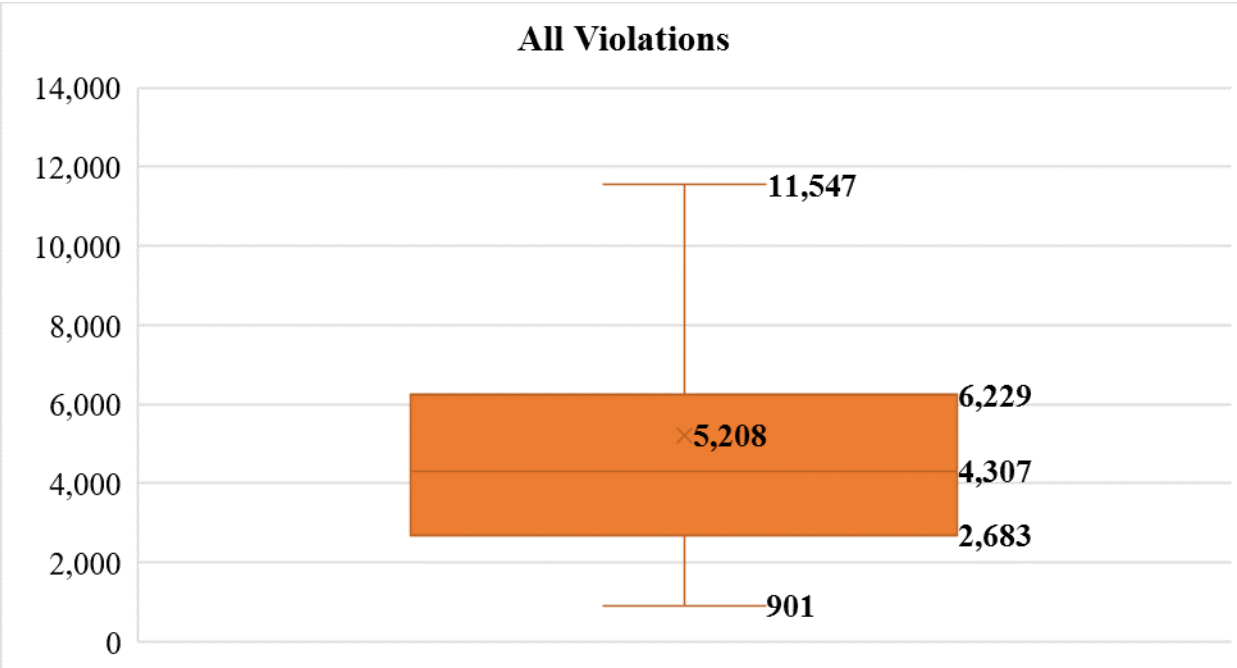


FIGURE 4.1.2 Summary statistics for all violations (2010-2012).

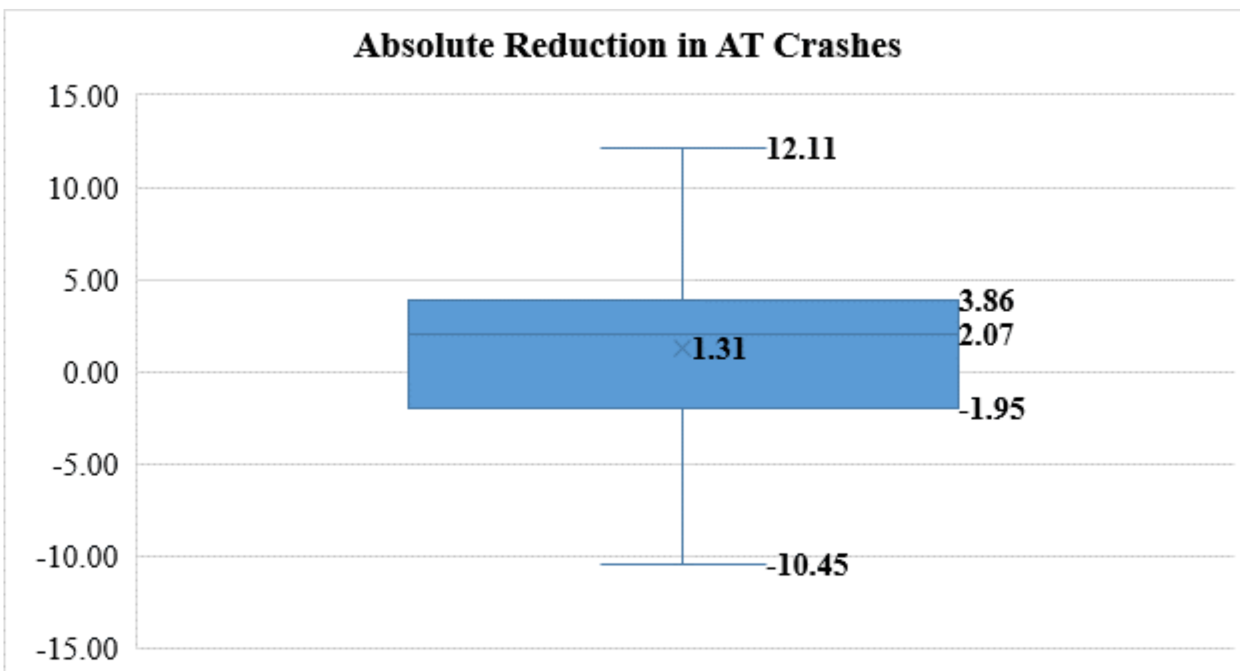


FIGURE 4.1.3 Summary statistics for the absolute reduction in AT crashes (2005-2007 to 2010-2012).

TABLE 4.1.2 Cameras in Cluster D

Camera Name	Intersection	Approach	Cluster	Com. Date	Decom. Date	Number of Violations	Abs. Red. in AT Crashes
CG-95SI-01	95th and Stony Island	EB	1	10/29/2009	Still Active	24,082	-5.46
CG-95SI-02	95th and Stony Island	WB	1	10/29/2009	Still Active	22,713	-5.46
CG-GROP-02	Grand and Oak Park	WB	1	12/15/2009	Still Active	15,457	-4.39
CG-IPKE-02	Irving Park and Kedzie	EB	1	8/26/2008	Still Active	12,222	-2.28
CG-PEPU-01	Peterson and Pulaski	EB	1	10/30/2008	Still Active	23,445	-1.96
CG-WE71-01	Western and 71st	SB	1	12/29/2009	Still Active	12,241	-1.56
CG-WEPR-01	Western and Pershing	SB	1	5/15/2008	Still Active	13,039	-1.93

TABLE 4.1.3 Cameras in Cluster C

Camera Name	Intersection	Approach	Cluster	Com. Date	Decom. Date	Number of Violations	Abs. Red. in AT Crashes
CG-79RA-01	79th and Racine	WB	2	10/31/2009	1/31/2014	5,193	-1.32
CG-RA79-01	Racine and 79th	SB	2	10/31/2009	1/31/2014	2,702	-1.32
CG-MOPU-01	Montrose and Pulaski	WB	2	2/27/2009	3/6/2015	1,477	-1.02
CG-PUMO-01	Pulaski and Montrose	SB	2	2/27/2009	3/6/2015	1,868	-1.02
CG-115HA-01	115th and Halsted	EB	2	5/29/2008	Still Active	2,048	-2.50
CG-71WE-01	71st and Western	WB	2	12/29/2009	Still Active	1,723	-1.56
CG-79HA-01	79th and Halsted	EB	2	4/30/2008	Still Active	3,644	-2.83
CG-CADE-01	California and Devon	NB	2	7/31/2008	Still Active	3,535	-1.78
CG-CARO-01	Canal and Roosevelt	NB	2	11/30/2008	Still Active	7,636	-3.85
CG-CIPE-01	Cicero and Peterson	SB	2	8/26/2008	Still Active	2,620	-1.46
CG-DA63-01	Damen and 63rd	SB	2	5/31/2008	Still Active	3,406	-3.87
CG-DA63-02	Damen and 63rd	NB	2	5/31/2008	Still Active	5,203	-3.87
CG-DECA-01	Devon and California	EB	2	7/31/2008	Still Active	2,735	-1.78
CG-DVPU-01	Diversey and Pulaski	EB	2	5/15/2009	Still Active	1,803	-3.54
CG-FOSH-01	Foster and Sheridan	WB	2	1/26/2008	Still Active	1,954	-0.69
CG-FULA-01	Fullerton and Laramie	WB	2	6/28/2008	Still Active	3,946	-6.76
CG-FUNA-01	Fullerton and Narragansett	EB	2	11/14/2008	Still Active	4,302	-6.02
CG-FUNA-02	Fullerton and Narragansett	WB	2	11/14/2008	Still Active	4,552	-6.02
CG-GROP-01	Grand and Oak Park	EB	2	12/15/2009	Still Active	6,497	-4.39
CG-HA115-01	Halsted and 115th	SB	2	5/29/2008	Still Active	8,609	-2.50
CG-HA79-01	Halsted and 79th	NB	2	4/30/2008	Still Active	3,649	-2.83
CG-IPKE-01	Irving Park and Kedzie	WB	2	8/26/2008	Still Active	9,940	-2.28
CG-KOOG-01	Kostner and Ogden	SB	2	5/23/2008	Still Active	4,639	-2.47
CG-LAFU-01	Laramie and Fullerton	NB	2	6/28/2008	Still Active	994	-6.76

CG-LAWE-01	Lawrence and Western	EB	2	7/31/2008	Still Active	5,229	-0.50
CG-MOWE-01	Montrose and Western	WB	2	8/26/2008	Still Active	1,424	-1.04
CG-NOPU-01	North and Pulaski	WB	2	11/30/2008	Still Active	3,869	-1.64
CG-OGKO-01	Ogden and Kostner	EB	2	5/23/2008	Still Active	9,348	-2.47
CG-PECI-01	Peterson and Cicero	WB	2	8/26/2008	Still Active	1,108	-1.46
CG-PRWE-01	Pershing and Western	WB	2	5/15/2008	Still Active	5,385	-1.93
CG-PUDI-01	Pulaski and Division	SB	2	7/22/2009	Still Active	3,208	-2.29
CG-PUDI-02	Pulaski and Division	NB	2	7/22/2009	Still Active	3,780	-2.29
CG-PUDV-01	Pulaski and Diversey	SB	2	5/15/2009	Still Active	3,796	-3.54
CG-PUNO-01	Pulaski and North	SB	2	11/30/2008	Still Active	1,951	-1.64
CG-PUPE-01	Pulaski and Peterson	SB	2	10/30/2008	Still Active	1,788	-1.96
CG-PURO-01	Pulaski and Roosevelt	NB	2	7/17/2009	Still Active	4,935	-2.38
CG-ROCA-01	Roosevelt and Canal	WB	2	11/30/2008	Still Active	10,129	-3.85
CG-ROPU-01	Roosevelt and Pulaski	WB	2	7/17/2009	Still Active	5,831	-2.38
CG-SHFO-01	Sheridan and Foster	SB	2	1/26/2008	Still Active	2,235	-0.69
CG-WELA-01	Western and Lawrence	SB	2	7/31/2008	Still Active	3,004	-0.50
CG-WEMO-01	Western and Montrose	NB	2	8/26/2008	Still Active	3,980	-1.04
CG-WETO-01	Western and Touhy	SB	2	10/21/2008	Still Active	2,171	-1.67
CG-WETO-02	Western and Touhy	NB	2	10/21/2008	Still Active	2,426	-1.67

TABLE 4.1.4 Cameras in Cluster B

Camera Name	Intersection	Approach	Cluster	Com. Date	Decom. Date	Number of Violations	Abs. Red. In AT Crashes
CG-79JE-01	79th and Jeffery	EB	3	10/22/2009	3/6/2015	3,386	0.23
CG-CEMA-01	Central and Madison	NB	3	8/31/2009	3/6/2015	6,291	0.03
CG-JE79-01	Jeffery and 79th	SB	3	10/22/2009	3/6/2015	4,462	0.23
CG-MACE-01	Madison and Central	WB	3	8/31/2009	3/6/2015	4,362	0.03
CG-47CI-01	47th and Cicero	WB	3	3/31/2008	Still Active	3,952	0.40
CG-95AS-01	95th and Ashland	EB	3	6/26/2009	Still Active	6,347	0.45
CG-AS95-01	Ashland and 95th	SB	3	6/26/2009	Still Active	6,359	0.45
CG-BECE-01	Belmont and Central	WB	3	2/5/2009	Still Active	2,293	0.34
CG-CEBE-01	Central and Belmont	SB	3	2/5/2009	Still Active	901	0.34
CG-CEDI-01	Central and Diversey	SB	3	8/18/2009	Still Active	2,914	-0.45
CG-CEWE-01	Cermak and Western	EB	3	12/29/2009	Still Active	3,450	-0.25
CG-CI47-01	Cicero and 47th	SB	3	3/31/2008	Still Active	1,933	0.40
CG-DICE-01	Diversey and Central	WB	3	8/18/2009	Still Active	3,301	-0.45
CG-HMMA-01	Hamlin and Madison	NB	3	4/29/2009	Still Active	3,988	-0.09
CG-MAHM-01	Madison and Hamlin	EB	3	4/29/2009	Still Active	8,358	-0.09
CG-WECE-01	Western and Cermak	SB	3	12/29/2009	Still Active	10,205	-0.25

TABLE 4.1.5 Cameras in Cluster A

Camera Name	Intersection	Approach	Cluster	Com. Date	Decom. Date	Number of Violations	Abs. Red. In AT Crashes
CG-47CA-01	47th and California	WB	4	11/30/2008	1/31/2014	4,802	2.24
CG-69WE-01	69th and Wentworth	EB	4	10/20/2009	1/31/2014	11,362	5.10
CG-69WE-02	69th and Wentworth	WB	4	10/20/2009	1/31/2014	5,639	5.10
CG-BLHA-01	Belmont and Halsted	WB	4	4/4/2008	1/31/2014	3,608	4.63
CG-CA35-01	California and 35th	NB	4	5/15/2008	1/31/2014	3,775	6.98
CG-CA35-02	California and 35th	SB	4	5/15/2008	1/31/2014	4,270	6.98
CG-CA47-01	California and 47th	SB	4	11/30/2008	1/31/2014	3,372	2.24
CG-DEKE-01	Devon and Kedzie	EB	4	6/30/2009	1/31/2014	8,168	4.26
CG-DEKE-02	Devon and Kedzie	WB	4	6/30/2009	1/31/2014	6,208	4.26
CG-HABL-01	Halsted and Belmont	NB	4	4/4/2008	1/31/2014	4,646	4.63
CG-NOCA-01	North and California	EB	4	10/31/2009	1/31/2014	7,301	3.78
CG-NOCA-02	North and California	WB	4	10/31/2009	1/31/2014	3,291	3.78
CG-NOWL-01	North and Wells	EB	4	6/21/2009	1/31/2014	6,181	3.41
CG-NOWL-02	North and Wells	WB	4	6/21/2009	1/31/2014	6,972	3.41
CG-PU71-01	Pulaski and 71st	NB	4	9/17/2009	1/31/2014	4,863	1.42
CG-PU71-02	Pulaski and 71st	SB	4	9/17/2009	1/31/2014	7,667	1.42
CG-95CG-01	95th and Cottage Grove	EB	4	8/29/2009	3/6/2015	7,801	2.36
CG-ASDY-01	Ashland and Diversey	NB	4	12/15/2009	3/6/2015	10,550	3.64
CG-BIDA-02	Blue Island and Damen	EB	4	10/31/2008	3/6/2015	6,295	4.23
CG-CG95-01	Cottage Grove and 95th	SB	4	8/29/2009	3/6/2015	5,390	2.36
CG-DABI-02	Damen and Blue Island	NB	4	10/31/2008	3/6/2015	5,913	4.23
CG-DYAS-01	Diversey and Ashland	EB	4	12/15/2009	3/6/2015	4,993	3.64
CG-ELFO-01	Elston and Foster	SB	4	7/31/2008	3/6/2015	1,556	3.56
CG-FOEL-01	Foster and Elston	EB	4	7/31/2008	3/6/2015	3,139	3.56
CG-KILI-01	Kimball and McCormick	NB	4	7/31/2008	3/6/2015	1,722	0.99
CG-LIMC-01	Lincoln and McCormick	WB	4	7/31/2008	3/6/2015	1,459	0.99
CG-WEAR-01	Western and Armitage	SB	4	6/30/2008	3/6/2015	2,600	3.83
CG-WEAR-02	Western and Armitage	NB	4	6/30/2008	3/6/2015	2,514	3.83
CG-WEPT-01	Western and Pratt	SB	4	11/19/2009	3/6/2015	5,283	2.49
CG-WEPT-02	Western and Pratt	NB	4	11/19/2009	3/6/2015	13,431	2.49
CG-103HA-01	103rd and Halsted	EB	4	11/30/2008	Still Active	2,236	2.62
CG-31KE-01	31st and Kedzie	WB	4	5/23/2008	Still Active	2,344	1.83
CG-47KE-01	47th and Kedzie	WB	4	3/30/2008	Still Active	3,529	0.58
CG-55KE-01	55th and Kedzie	EB	4	10/20/2009	Still Active	3,265	3.18
CG-71KE-01	71st and Kedzie	WB	4	9/17/2009	Still Active	4,274	1.72
CG-ADAU-01	Addison and Austin	EB	4	6/28/2008	Still Active	1,841	6.86

CG-ADHA-01	Addison and Harlem	EB	4	6/21/2009	Still Active	2,318	1.15
CG-ADWE-01	Addison and Western	EB	4	6/8/2009	Still Active	3,971	0.98
CG-AMCI-01	Armitage and Cicero	EB	4	11/14/2008	Still Active	972	0.53
CG-ARKE-01	Armitage and Kedzie	WB	4	1/23/2009	Still Active	2,106	4.62
CG-ARPL-01	Armitage and Pulaski	EB	4	5/31/2008	Still Active	4,404	1.25
CG-ARPL-02	Armitage and Pulaski	WB	4	5/31/2008	Still Active	2,503	1.25
CG-ASFU-01	Ashland and Fullerton	SB	4	6/8/2009	Still Active	10,565	4.06
CG-ASFU-02	Ashland and Fullerton	NB	4	6/8/2009	Still Active	9,302	4.06
CG-ASIP-01	Ashland and Irving Park	NB	4	8/26/2008	Still Active	3,055	5.12
CG-AUAD-01	Austin and Addison	NB	4	6/28/2008	Still Active	1,277	6.86
CG-AUIP-01	Austin and Irving Park	NB	4	6/30/2008	Still Active	4,338	0.83
CG-CAPE-01	California and Peterson	NB	4	6/29/2009	Still Active	966	4.36
CG-CEIP-01	Central and Irving Park	SB	4	6/30/2008	Still Active	1,906	0.85
CG-CELA-01	Central and Lake	SB	4	7/17/2009	Still Active	9,466	3.46
CG-CHSC-01	Chicago and Sacramento	WB	4	9/18/2009	Still Active	4,783	4.46
CG-CIAD-01	Cicero and Addison	NB	4	11/30/2008	Still Active	4,639	3.17
CG-CIAD-02	Cicero and Addison	SB	4	11/30/2008	Still Active	4,610	3.17
CG-CIAM-01	Cicero and Armitage	NB	4	11/14/2008	Still Active	4,329	0.53
CG-CIWA-01	Cicero and Washington	SB	4	6/14/2008	Still Active	7,615	5.77
CG-CIWA-02	Cicero and Washington	NB	4	6/14/2008	Still Active	13,750	5.77
CG-CLRI-01	Clark and Ridge	NB	4	7/23/2008	Still Active	2,126	2.19
CG-CLRI-02	Clark and Ridge	SB	4	7/23/2008	Still Active	2,512	2.19
CG-DEMI-01	Devon and Milwaukee	WB	4	2/28/2009	Still Active	5,544	1.51
CG-DIAU-01	Diversey and Austin	EB	4	6/28/2008	Still Active	1,811	3.54
CG-DIAU-02	Diversey and Austin	WB	4	6/28/2008	Still Active	2,713	3.54
CG-DVDA-01	Division and Damen	EB	4	12/29/2009	Still Active	4,325	1.17
CG-DVDA-02	Division and Damen	WB	4	12/29/2009	Still Active	10,020	1.17
CG-ELLA-01	Elston and Lawrence	SB	4	6/8/2009	Still Active	3,179	1.37
CG-HA103-01	Halsted and 103rd	SB	4	11/30/2008	Still Active	7,817	2.62
CG-HA95-01	Halsted and 95th	NB	4	4/30/2008	Still Active	2,900	5.25
CG-HA95-02	Halsted and 95th	SB	4	4/30/2008	Still Active	1,595	5.25
CG-HAAD-01	Harlem and Addison	NB	4	6/21/2009	Still Active	5,421	1.15
CG-HALA-01	Hamlin and Lake	SB	4	5/31/2008	Still Active	6,139	3.64
CG-HALA-02	Hamlin and Lake	NB	4	5/31/2008	Still Active	3,260	3.64
CG-HAMA-01	Halsted and Madison	SB	4	6/14/2008	Still Active	7,820	2.24
CG-HAMA-02	Halsted and Madison	NB	4	6/14/2008	Still Active	6,152	2.24
CG-HANT-01	Halsted and North	NB	4	6/29/2009	Still Active	4,513	2.24
CG-IPAS-01	Irving Park and Ashland	EB	4	8/26/2008	Still Active	2,846	5.12
CG-IPAU-01	Irving Park and Austin	EB	4	6/30/2008	Still Active	4,221	0.83
CG-IPCA-01	Irving Park and California	EB	4	8/26/2008	Still Active	9,586	3.29
CG-IPCA-02	Irving Park and California	WB	4	8/26/2008	Still Active	11,547	3.29

CG-IPCE-01	Irving Park and Central	EB	4	6/30/2008	Still Active	3,971	0.85
CG-IPPU-01	Irving Park and Pulaski	WB	4	5/19/2009	Still Active	10,978	1.67
CG-KE31-01	Kedzie and 31st	SB	4	5/23/2008	Still Active	4,312	1.83
CG-KE47-01	Kedzie and 47th	NB	4	3/30/2008	Still Active	3,373	0.58
CG-KE55-01	Kedzie and 55th	SB	4	10/20/2009	Still Active	3,424	3.18
CG-KE71-01	Kedzie and 71st	SB	4	9/17/2009	Still Active	4,882	1.72
CG-KEAR-01	Kedzie and Armitage	SB	4	1/23/2009	Still Active	2,202	4.62
CG-LACE-01	Lake and Central	EB	4	7/17/2009	Still Active	5,346	3.46
CG-LAEL-01	Lawrence and Elston	WB	4	6/8/2009	Still Active	5,872	1.37
CG-LAPU-01	Lawrence and Pulaski	EB	4	7/31/2008	Still Active	1,923	0.51
CG-MIDE-01	Milwaukee and Devon	SB	4	2/28/2009	Still Active	4,552	1.51
CG-MQWE-01	Marquette and Western	WB	4	11/30/2008	Still Active	2,074	3.22
CG-NOCE-01	North and Cicero	EB	4	5/31/2008	Still Active	7,343	3.94
CG-NOCE-02	North and Cicero	WB	4	5/31/2008	Still Active	4,770	3.94
CG-NTHA-01	North and Halsted	WB	4	6/29/2009	Still Active	2,627	2.24
CG-PECA-01	Peterson and California	EB	4	6/29/2009	Still Active	5,334	4.36
CG-PUIP-01	Pulaski and Irving Park	SB	4	5/19/2009	Still Active	4,627	1.67
CG-PULA-01	Pulaski and Lawrence	SB	4	7/31/2008	Still Active	1,331	0.51
CG-SALA-01	Sacramento and Lake	SB	4	10/20/2009	Still Active	4,957	5.64
CG-SALA-02	Sacramento and Lake	NB	4	10/20/2009	Still Active	5,313	5.64
CG-SCCH-01	Sacramento and Chicago	NB	4	9/18/2009	Still Active	5,322	4.46
CG-WEAD-01	Western and Addison	NB	4	6/8/2009	Still Active	7,447	0.98
CG-WEDE-01	Western and Devon	SB	4	7/31/2008	Still Active	4,165	1.53
CG-WEDE-02	Western and Devon	NB	4	7/31/2008	Still Active	3,543	1.53
CG-WEFU-01	Western and Fullerton	SB	4	6/29/2009	Still Active	2,942	3.50
CG-WEFU-02	Western and Fullerton	NB	4	6/29/2009	Still Active	11,152	3.50
CG-WEMQ-01	Western and Marquette	SB	4	11/30/2008	Still Active	10,360	3.22

FIGURE 4.1.4 presents the number of all violations plotted against the reduction in all crashes. As one can see, some of the cameras in Cluster A have experienced an increase in all crashes. The reason for that can be explained by examining FIGURE 4.1.5: The number of rear-end crashes tends to increase with the installation of cameras.

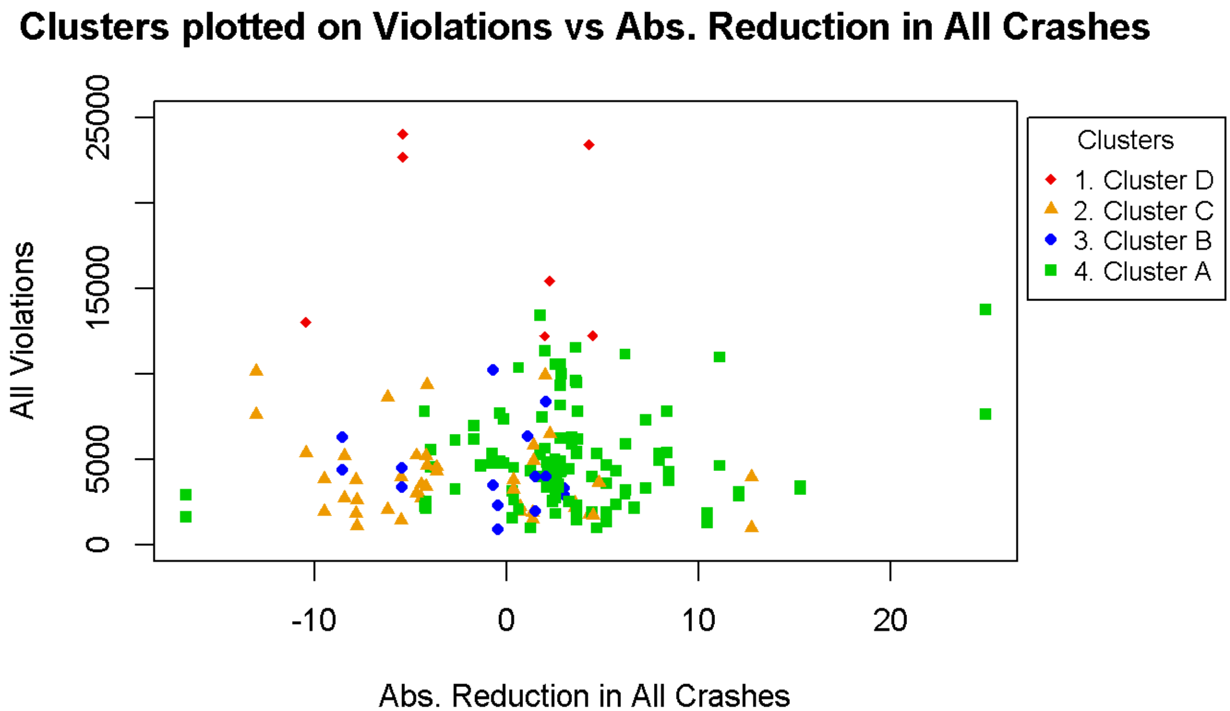


FIGURE 4.1.4 Clusters plotted on all violations vs. absolute reduction in all crashes.

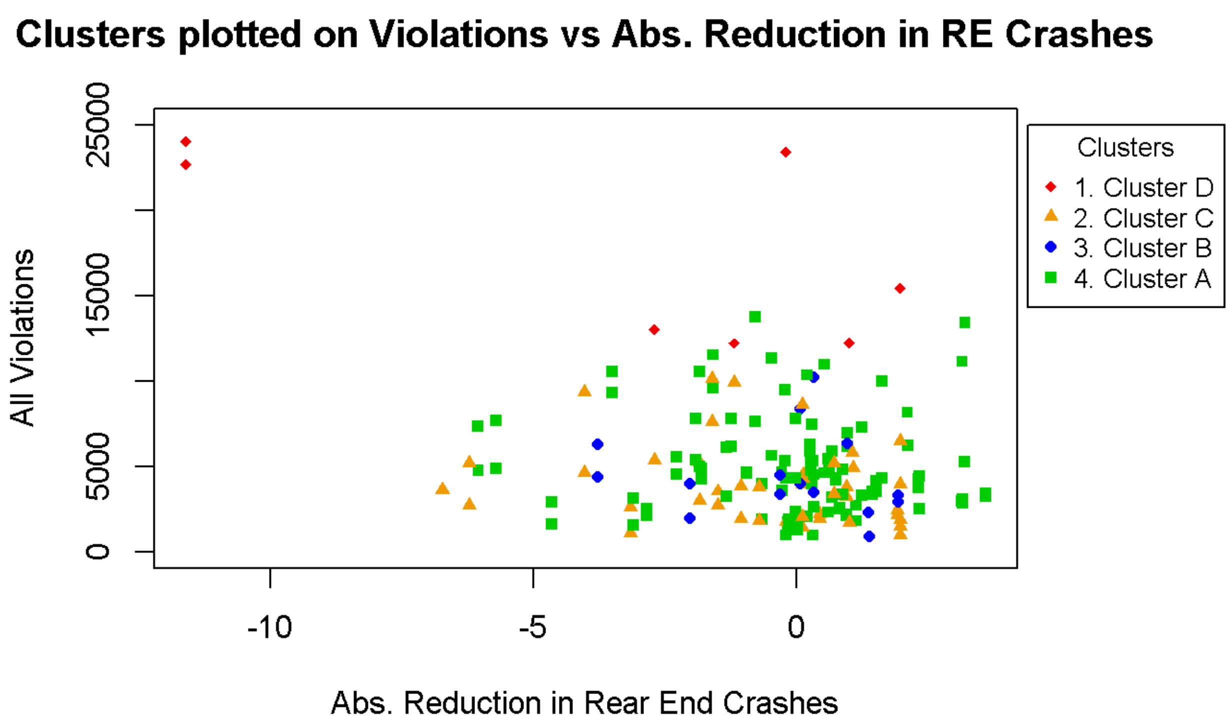


FIGURE 4.1.5 Clusters plotted on all violations vs. absolute reduction in rear-end crashes.

FIGURE 4.1.6 presents the number of violations after one-sec-into-red against the absolute reduction in angle and turn crashes. As can be seen, the cameras in Cluster D move down towards Cluster C. This means that most of the cameras in Cluster D have a high number of violations under one second into red. As discussed in the previous chapter, many of these violations correspond to dilemma zone situations that are not responsive to RLC enforcement.

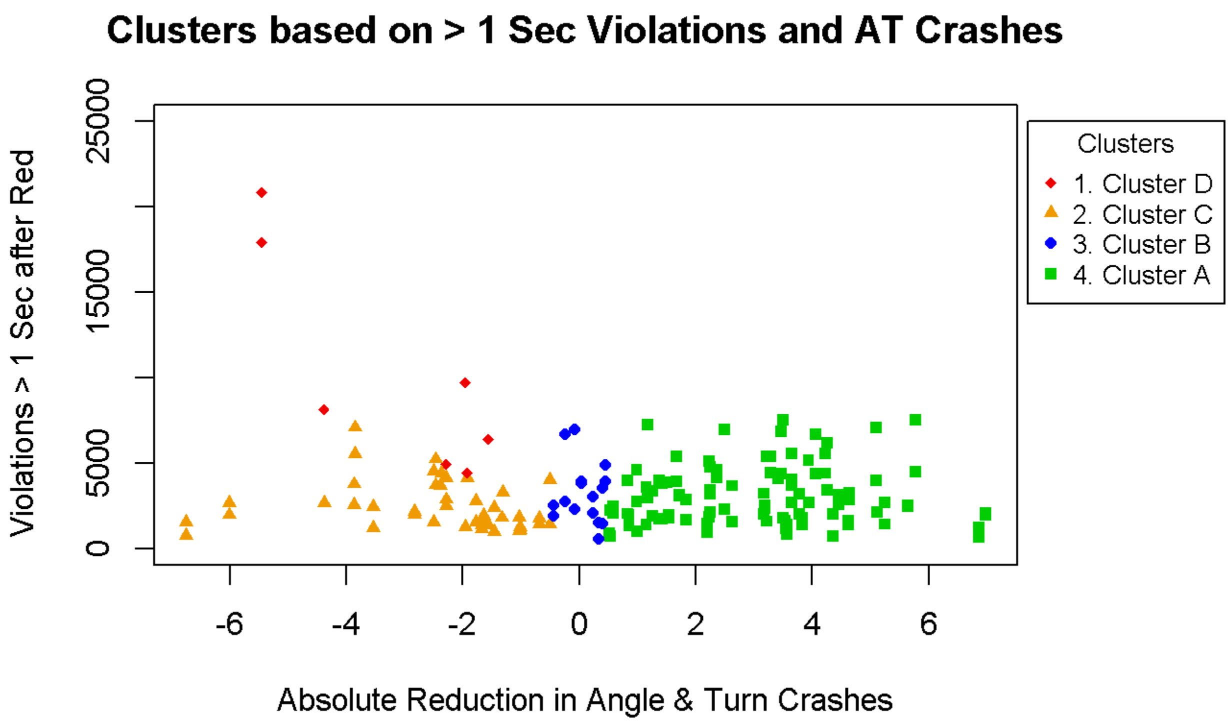


FIGURE 4.1.6 Clusters plotted on violations after one-second-into-red vs. absolute reduction in rear-end crashes.

4.2 Scoring System

As seen in FIGURE 4.2.1, there is no spatial correlation within the clusters. In this section, an analysis is presented that identifies the factors that are associated with an *intersection, approach* pair falling into a certain cluster.

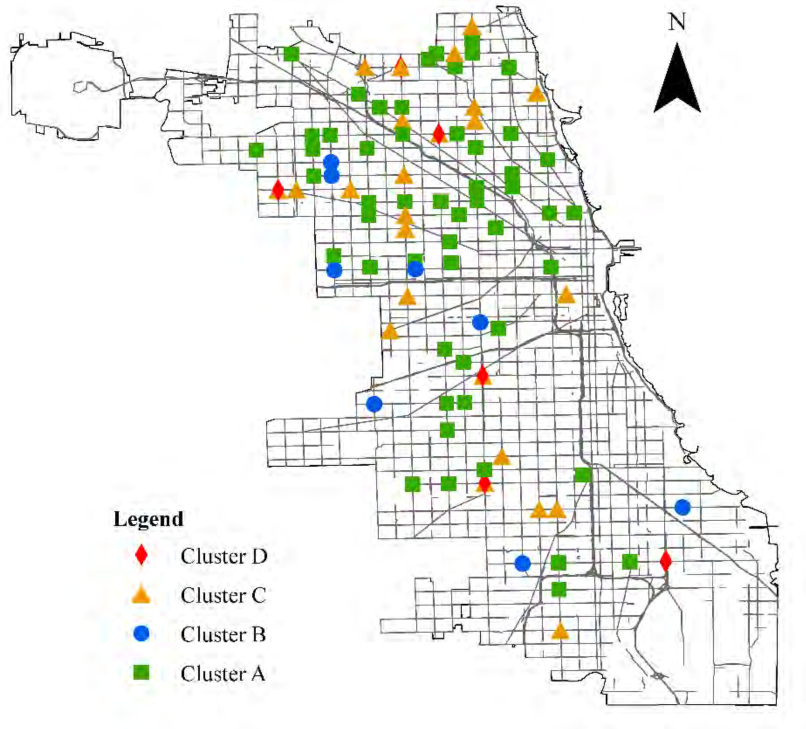


FIGURE 4.2.1 Spatial distribution of clusters.

An ordered probit model is appropriate for estimating the propensity of a camera to fall into one of the clusters (*25*). The analysis can be useful to answer two important questions:

- What are the factors contributing to the treatment's (camera commissioning) success, or the lack thereof?
- How likely would installing a camera at a certain intersection (including one where no RLC presently exists) result in a desired outcome, which is reduction in crashes without too high a number of violations?

This sub-section presents a linearized, easy-to-use scoring system that was determined using the results of the ordered probit model. Please refer to Appendix 8.4.2 for the detailed model results of the ordered probit model. TABLE 4.2.1 presents the multipliers for the scoring. The scoring is performed as shown in Equation (4.2.1):

$$Score = m_1X_1 + m_2X_2 \ldots + m_7X_7 + C \quad (4.2.1)$$

Each criterion value (e.g. angle and turn crashes per million AADT, total number of lanes etc.) is multiplied by its corresponding multiplier. These seven products are added. Then a constant of 35.36 is added to produce the final score. The scores are grouped into 4 categories:

- Score D <45
- Score C: 45-80
- Score B: 80-90
- Score A: >90

The results suggest the installation of cameras at the intersections with high number of angle and turn crashes per AADT. Conversely, according to the model results, it is not recommended to install cameras at locations with an already high number of rear-end crashes. This outcome agrees with the safety analysis, since cameras tend to increase the number of rear-end crashes. Moreover, locations with long cycle lengths or high number of lanes are more likely to succeed. On the other hand, places with a high crossing traffic, 2 sec. all-red duration (as opposed to 1 sec.) or with left turn bays would not be highly recommended, as these places tend to be safer in the first place.

TABLE 4.2.1 Multipliers for Scoring

Explanatory Variable	Coefficient
1. AT Crashes per M AADT	0.06060
2. RE Crashes per M AADT	-0.26782
3. AADT Crossing	-0.00057
4. Total Number of Lanes	2.68372
5. All Red Crossing – 2 sec – (1: 2 sec, 0: otherwsie)	-21.04347
6. Cycle Length	0.48362
7. Left Turn Bay – Left Approach – Dummy – (1: There is a bay, 0: otherwise)	-16.06733
Constant	35.36019

TABLE 4.2.2 presents the cluster of a camera as the result of the clustering analysis, and its score as the result of the scoring system. As one can see, the cameras with the low score are in Clusters C and D, and the cameras with high score are in Cluster A.

TABLE 4.2.2 Predictive Capability Example

Camera Name	Approach	Cluster	Score	Camera Name	Approach	Cluster	Score
CG-95SI-01	EB	D	20.65	CG-IPAU-01	EB	A	70.23
CG-95SI-02	WB	D	20.65	CG-HA103-01	SB	A	71.33
CG-WE71-01	SB	D	20.91	CG-KEAR-01	SB	A	71.49
CG-IPKE-02	EB	D	25.91	CG-ARKE-01	WB	A	72.82
CG-GROP-02	WB	D	28.03	CG-CIWA-02	NB	A	75.60
CG-PEPU-01	EB	D	34.02	CG-CIWA-01	SB	A	75.60
CG-WEPR-01	SB	D	63.06	CG-LACE-01	EB	A	75.61
CG-LAWE-01	EB	C	12.94	CG-IPCA-01	EB	A	77.99
CG-WELA-01	SB	C	18.71	CG-IPCA-02	WB	A	77.99
CG-RA79-01	SB	C	23.02	CG-CELA-01	SB	A	82.63
CG-PUPE-01	SB	C	24.17	CG-CA35-01	NB	A	87.46
CG-FULA-01	WB	C	24.67	CG-CA35-02	SB	A	87.46
CG-IPKE-01	WB	C	25.91	CG-NOWL-01	EB	A	91.50
CG-DVPU-01	EB	C	26.21	CG-NOWL-02	WB	A	91.50
CG-PUDV-01	SB	C	26.87	CG-CHSC-01	WB	A	92.43
CG-79RA-01	WB	C	27.29	CG-SCCH-01	NB	A	95.71
CG-GROP-01	EB	C	28.03	CG-SALA-02	NB	A	96.47
CG-FUNA-01	EB	C	29.35	CG-SALA-01	SB	A	96.47
CG-FUNA-02	WB	C	29.35	CG-HALA-02	NB	A	100.00
CG-71WE-01	WB	C	32.30	CG-HALA-01	SB	A	100.00

4.3 Sample Recommendation

The model results of the scoring system presented in the previous sub-section are applied to the reference (*intersection, approach)* pairs. In this example, crash and AADT values of the period 2010-2012 are used.

TABLE 4.3.1 presents the intersection, approach pairs that are very likely to fall into Cluster A, where a high reduction in angle and turn crashes would be expected along with a relatively low number of violations. It must be noted that these recommendations are not conclusive in the sense that each intersection must be examined closely before reaching a final decision. Furthermore, intersections where RLC enforcement is deemed not especially effective, alternative means of improving safety should be examined. FIGURE 4.3.1 depicts the location of these intersections.

TABLE 4.3.1 Potential Candidates for Successful Implementation

Intersection No	Approach	Location	Score
20236	WB	E PERSHING RD-S STATE ST-W PERSHING RD	124.2
14704	EB	E JACKSON BLVD-E JACKSON DR-S MICHIGAN AVE	110.28
14704	WB	E JACKSON BLVD-E JACKSON DR-S MICHIGAN AVE	110.28
20236	SB	E PERSHING RD-S STATE ST-W PERSHING RD	106.04
3672	EB	N CENTRAL AVE-W FOSTER AVE	96.14
3672	WB	N CENTRAL AVE-W FOSTER AVE	96.14
53	EB	N SHERIDAN RD-W HOWARD ST	95.49
53	WB	N SHERIDAN RD-W HOWARD ST	95.49
33439	WB	E 111TH ST-S DR MARTIN LUTHER KING JR DR	93.89
14691	NB	E JACKSON DR-S COLUMBUS DR	87.37
2743	NB	N CENTRAL AVE-W BRYN MAWR AVE	86.81
2743	SB	N CENTRAL AVE-W BRYN MAWR AVE	86.81
172	NB	N CLARK ST-N ROGERS AVE	86.11
172	SB	N CLARK ST-N ROGERS AVE	86.11
13029	NB	N ELIZABETH ST-N OGDEN AVE-W GRAND AVE	84.88
30831	SB	E 95TH ST-S STATE ST-W 95TH ST	83.52
2743	EB	N CENTRAL AVE-W BRYN MAWR AVE	82.82
2743	WB	N CENTRAL AVE-W BRYN MAWR AVE	82.82
32137	EB	S WENTWORTH AVE-W 103RD ST	82.8
32137	WB	S WENTWORTH AVE-W 103RD ST	82.8

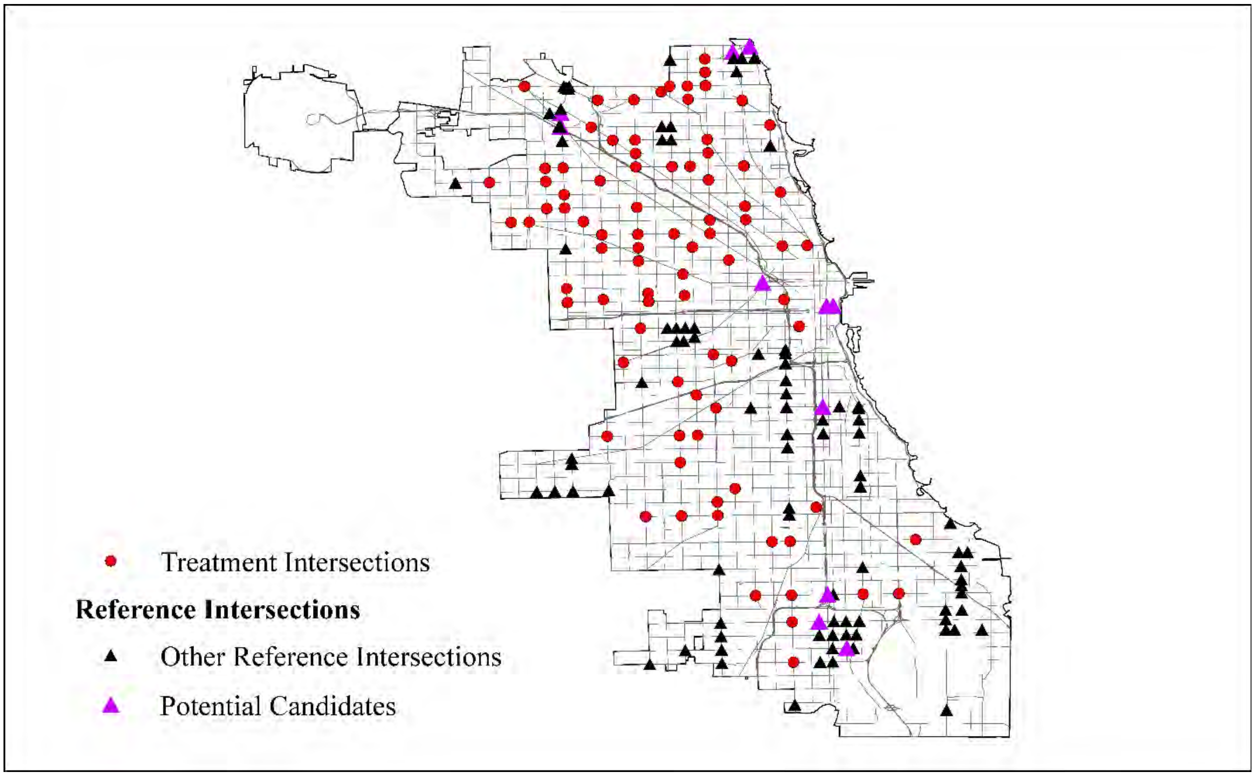


FIGURE 4.3.1 Spatial distribution of potential candidates.

4.4 Conclusion

This chapter presented a clustering analysis with respect to the absolute reduction in angle and turn crashes at the intersection level, and the number of all violations at the intersection, approach (camera) level. According to the analysis, seven cameras require closer attention as these have a very high number of violations, but there is a reduction in safety at these locations. On the other hand, most of the cameras have resulted in an increase in safety. At 104 locations, the angle and turn crashes have reduced significantly, at the cost of a relatively low number of violations, reflecting effective deterrence through use of the RLCs.

After the clustering analysis, a scoring system is presented which determines the factors contributing to the propensity of success, which is intended to serve as a recipe for identifying the intersections where RLC enforcement is likely to be effective, and should as such be considered as possible candidates for camera addition.

However, as noted previously, the methodology is intended primarily as a screening technique; individual intersections should be examined and subjected to engineering judgment that considers special factors-- such as sight distance, heavy turning movement patterns at certain times of the day, frequent parking maneuvers in the vicinity, and presence of pedestrians and bicycles-- before reaching a final decision.

5 STAKEHOLDER OUTREACH

5.1 Purpose

The purpose of the stakeholder outreach effort was to collect and assess views of key stakeholders of both the current Chicago RLC program and RLC programs in general, and to invite suggestions for evolution of the Chicago RLC program.

5.2 Methodology

Stakeholders were selected in 3 categories:

- **Advocates** – people defined by their support of particular policies and modes: anti-RLC, non-motorized travel, automobile and insurance industry associations.
- **Experts** – on traffic safety, traffic operations, traffic law enforcement, including researchers and practitioners: e.g., traffic engineers, traffic researchers, and law enforcement experts.
- **Community representatives** – spokespersons for several community groups in Chicago, and selected Aldermen, whose strength is their perspective on and commitment to the values of particular Chicago communities.

Interviews were conducted by telephone with one person at time; the interview guide is included in Appendix 8.5. Interviewees were asked to share their independent views, and thus none was provided with a description of the Chicago RLC program or a summary of our quantitative research findings at the time of the interview. The interviews were not discussions. Questions were presented, responses were invited, and these were captured in notes written by the interviewers.

The questions fell into four categories:

- Awareness of the current program;
- Effectiveness of the current program, as well as perceptions of side effects, positive or negative;
- Fairness/transparency of the current program; and
- Suggestions for making the current program better – or eliminating it altogether

We completed 5, 4, and 9 interviews with advocates/opponents, experts, and local stakeholder groups, respectively. In the local stakeholder category, representatives from 7 community groups responded to requests for interviews out of a total of 18 geographically distributed groups that were contacted. These interviews did not necessarily reflect an official policy position of the neighborhood group or area, but were the views of the individual respondent. The communities represented in the interviews were located in and/or represented the following neighborhood areas:

- Austin
- Belmont-Craigin

- Garfield Park
- Humboldt Park
- Kenwood
- Portage Park
- Oakland
- West Loop

Ten other community groups were contacted but failed to respond to interview requests.

The advocacy groups were:

- AAA Chicago
- Active Transportation Alliance
- Citizens to Abolish Red Light Cameras
- Insurance Institute for Highway Safety
- SRAM Cycling Fund (grants private funds to promote cycling)

The experts were from:

- Center for Neighborhood Technology
- National Safety Council
- Sam Schwartz Consulting, traffic and transportation experts
- Alexander Weiss Consulting, state and local public safety experts

5.3 Results

5.3.1 Program Awareness

Community representatives, as well as the experts and advocates – local and national – were aware of the Chicago RLC program. Among the experts and advocates, aside from the anti-RLC advocacy group, there was broad acceptance of RLC programs as a valuable component of a traffic enforcement program. Experts, and advocates, and most of the community representatives, viewed conventional enforcement and enhanced education as other important parts of a comprehensive traffic safety program.

5.3.2 Perceptions of the RLC Program

Perceptions of RLC programs, and Chicago's program in particular, differed among stakeholder groups. The dominant view among community groups was that the Chicago RLC program is primarily for the purpose of revenue generation. However, some community spokespersons expressed the view that the purpose of the Chicago program was traffic safety, i.e., crash reduction. Those who did acknowledge the safety benefits of RLC enforcement indicated that the value of the program is diminished by a perceived emphasis on revenue generation. Among those who expressed this dual view of the RLC program, most suggested that reducing the magnitude of the fines was a way to achieve better balance of the stated purpose – traffic safety – with the image of the program.

None of the community spokespersons viewed red light running or excessive speed as among the top 5 problems in their neighborhoods. Two of the interviewees considered red light running or speeding as among the top 10 neighborhood problems. Rather, some indicated that red light running was concentrated at only a few intersections in their neighborhoods. At the community level, there appears to be a lack of awareness of the magnitude, extent and severity of the traffic safety problem or the consequences of red light running or excessive speeds.

More technically informed interviewees, both subject matter experts and technically inclined community leaders, viewed safety as the primary purpose of the RLC program. However, they also saw shortcomings of the current program and opportunities for its enhancement, and they expressed concerns about the public perception that the program was revenue driven.

5.3.3 Incidence and Equity

Some community group spokespersons expressed strong concerns about the incidence and social equity of the RLC and automated speed enforcement programs. For example, some community respondents viewed the level of the fines as excessive and falling heavily on the poor. Some referred to it as a regressive "tax" or penalty on those communities. These views were often linked with suggestions to reduce fines substantially or to adopt a system of graduated fines which increase with repeated offenses.

Contributing to the negative perception of the incidence of the RLC program were reports of, or experiences with, short yellow phases, leading to a feeling of entrapment by the camera technology. Some individuals perceived camera deployment decisions (location decisions) to be driven by the need to collect fines, rather than by crash experience or a safety risk assessment. That is, community respondents in general did not see the association between camera placement and excessive intersection crash risk.

Even though many saw the RLC program as unfair and biased, interviewees indicated that the RLC ticket penalties do get people's attention, and thus probably affected behaviors favorably. Some suggested that lower fines would be equally effective for getting the attention of drivers and changing their behavior. Some community respondents saw the RLC ticketing process as procedurally fair because video evidence (usually) documented the offense convincingly. Still, some felt trapped by technology and advocated for more human enforcement. Many described the appeals process as biased and one-sided, because too little time is given to file an appeal after receiving a ticket, and successful appeals even in the face of apparently strong evidence were rare.

5.4 Reporting traffic safety program performance

It is important to report to the community and key stakeholders on the performance of the traffic safety program on an annual basis to assure stakeholders of the integrity effectiveness of the program and to build community support for it. Many cities and most states do this in some manner, and while there are precedents to consider in building a reporting process, many of the examples are deficient in some ways.

It is common for communities to report on the performance of their automated enforcement programs (*26*), (*27*), (*28*). These can be useful, but they are narrow, in that automated enforcement is only part of the package of crash countermeasures. More traditional forms of enforcement should play an important role in the traffic safety program, and education and engineering are also key parts of any safety program. Highlighting the RLC program alone risks giving the impression (both inside and outside the transportation agency) that this is all that is being done to assure traffic safety, and because of the confounding of the revenue generation aspect of RLCs with the safety objective, this narrow approach may serve to heighten the controversy.

The typical RLC evaluation report shows before-after RLC crash counts and percentage changes, sometimes broken down by crash type (severity class) and mechanism (rear end, angle, etc.). Commonly there are no statistical analyses (e.g., tests for significant differences, which means recognizing than crashes are rare and random events) or consideration of rival hypotheses and secular trends.

A common deficiency is over-emphasis on program design and inputs – the scale and intensity of enforcement activities. While this information is of interest, stakeholders are likely to care much more about outcomes, the effects on crashes and crash rates, and on the overall costs of traffic accidents. Sometimes this concentration on enforcement inputs is used to substitute for useful data on outcomes and assessment of the enforcement programs. Some of these reports attempt to justify programs through unsupported claims as to their effectiveness.

A broader approach seems desirable, and there are some good examples of this. Because crash data nominally flow to the state level for processing, most states are the source of safety performance reports. A good example is the report issued annually by the California Department of Transportation, (*29*) which highlights crash trends and some causal factors, although it does not address specific safety program outcomes and evaluation, e.g., the RLC program. State level reports for the most part do not provide any detail on what is going on in cities.

Where the focus is a large city like Chicago, a state level report is insufficient. This argues for the City to own its data and produce customized reports to meet local program management needs. Some cities, for example, Los Angeles, produce their own performance reports, but they rely on state data, which can be so aggregate that it is not possible to know what is going on in the neighborhoods. As a city of neighborhoods, Chicago needs to address safety issues and outcomes at a more detailed level to engage local stakeholders, help them understand their own problems and the impacts of safety interventions, and thus garner their support for an appropriate enforcement program.

For example, Washington, D.C. issues a report produced by Howard University (*30*) that contains a useful set of maps showing crash locations by type – good to help neighborhoods understand their own risks – but as a static document, it does not support drilling down to the circumstances of each crash. The Washington report does not address program evaluation, instead it only describes patterns and trends.

Among the more interesting safety performance schemes is New York website (*31*) reporting on its own version of the Vision Zero program, a multinational effort, begun in Sweden two decades ago, to eradicate traffic fatalities. A web-based reporting system has the advantages of being dynamic, highly graphical, and strongly map-based, which supports exploring details of crashes by location. The disadvantage is that not everyone interested in the traffic safety program has ready access to the Internet. The website does provide access to a series of printable annual reports (*32*).

New York City is developing its own electronic data bases to capture and integrate crash and hospital data. FORMS – Finest Online Records Management System, is said to be able to provide city officials with immediate data on crashes, instead of waiting a year for data to come back from the state, and it is designed to provide citizens immediate access to their own crash reports (*32*). New York City DOT collaborates with DataKind (*33*), a non-profit data analysis group, to plan and conduct analyses of crash patterns and evaluation of programs and other interventions. NYC DOT also operates a DDACTS (Data Driven Approaches to Crime and Traffic Safety) program that integrates and derives synergies from jointly addressing these two important challenges.

5.5 Stakeholder Recommendations

A number of specific recommendations for improving the Chicago RLC program came from the stakeholders. Among these were the following:

- Deploy cameras only in high risk locations. This responds to perceptions that location selection is not data driven, but is either random or driven by the desire to maximize revenue collected. To make this recommendation work, it will be necessary to demonstrate that intersections chosen for camera enforcement have crash rates or risks higher than average for the City.
- Reduce fines and adopt graduated fines so that first offenses cost less; some stakeholders felt that a single citation would be enough to assure future compliance.
- Use revenue collected from RLC citations for traffic safety and transportation improvements. Recycling funds back to traffic safety would show the community that safety is indeed the motivation for the RLC program.
- Assure that the yellow signal phase is sufficiently long and consistent. Variations in the yellow phase, and unreasonably short yellows, were perceived as unfair to drivers, an entrapment strategy. Some respondents were aware of the favorable crash reduction effects of a longer yellow phase and suggested increasing it to 4 seconds city-wide.
- Demonstrate the crash reduction effectiveness of the RLC program with empirical data. Annual, data-based outcome reports to the community and key stakeholders would boost objectivity and credibility of the RLC program.
- Monitor accuracy and reliability of the *in situ* RLC equipment and provide public reports that demonstrate reliable performance.
- Respond quickly and objectively to reported and observed performance failures; this includes rebating funds collected from erroneously issued tickets.
- Ensure that the process of adjudicating protested RLC tickets is balanced and fair.

5.5.1 Building a Safety Performance Evaluation Program

While there are some good examples of safety performance evaluation and reporting, there does not seem to be a model system that offers a relevant template for Chicago. A review of these and other examples, and this analysis of the Chicago RLC program, provides a basis for guiding the development of a Chicago safety performance reporting effort.

The report should be issued and updated annually within the first three months of each year, describing activities and outcomes in the previous year. The primary report should be web-based to support interactive graphics, particularly a GIS application that provides map-based crash data at various levels of aggregation, along with some drill-down capability to allow data exploration by the public. A much shorter (5 pages or less) supplementary paper product should also be produced with qualitative summaries of trends, comparisons with other places, and examples of outcomes of enforcement initiatives. A generic outline of the report contents is shown below.

1. Executive summary – Qualitative description and assessment, overall trends, successes and failures, problems to be addressed and future priorities, supported by several graphics.
2. Performance in the reporting period and five-year trends
    a. Performance measures
        i. Snapshot of crash experience for the reporting year, citywide, by community area, and through a GIS application, a dot map by location. This should show absolute numbers and rates where exposure data are available, by severity class (KABC) and crash mechanism (angle, rear end…)
        ii. Five-year trend for same aggregations.
        iii. Five-year comparison with the nation and state, and where data available, peer cities, e.g., Boston, Philadelphia, Houston, Minneapolis.
3. Enforcement program description and performance
    a. Description of safety enforcement program: education and outreach activities, traditional and automated enforcement, scale of resources deployed, stops, citations by mode of capture and violation type, in aggregate and by location at various levels of aggregation (with GIS, community areas, intersections, block faces).
    b. Performance measures for automated enforcement programs - RLCs and speed cameras.
        i. <u>Aggregate crash experience</u> for all RLC sites, all ASE sites. Reporting year, five-year trend, by severity class and mechanism, as well as rates; compare with city-wide data (above).
        ii. <u>Intersection/enforcement site performance</u>. For brevity in main report, target 6-10 key intersections with high crash rates; intersections selected may differ from year to year; include tabular data and charts for all active automated enforcement sites in appendix. Show annual crash statistics for at least three years prior to automated enforcement initiation at site, and up

to five most recent years after. Using tools from this study, estimate changes in crash counts associated with automated enforcement Use graphics and statistics to show trends and distinguish between significant and non-significant differences.

iii. Estimate social cost changes associated with changes in crashes associated with RLC and ASE. These could be derived from estimates of crashes avoided by severity class (type), applied to average costs of crashes by type.

iv. Neutral, qualitative assessment of effectiveness, describing conclusions that are well-supported, avoiding speculation on causation, avoiding optimism bias, and addressing confounding factors (e.g., secular trends, changes in traffic patterns, signalization, infrastructure, local land use, etc.) where these are known or suspected. Identify both successes and failures, problems to be addressed and future priorities. Balance is important to build credibility and community support.

v. Quantitative and qualitative description of quality control/quality assurance program, monitoring activities, problems, resolution and remediation.

An effective traffic safety performance system will be strongly data-driven, requiring timely and detailed data on crashes and contributing factors, gathered and retained over time to support meaningful program evaluation and effective management. Such a measurement system will be a good investment to support informed decision-making, maximize traffic safety, and help assure public understanding and support for the safety enforcement program.

6 CONCLUSION: GOING FORWARD

Results of the stakeholder interviews, as well as findings of the statistical analyses, provide the basis for recommendations for an improved RLC program. A starting point is that quantitative studies do show significant safety benefits of the current program, suggesting that continuation of the program is desirable. This suggestion is also consistent with findings of studies conducted in other U.S. cities. Not surprisingly, the safety benefits are somewhat mixed – there are crash reductions at many intersections, no change in others, and increases in a few places. This is to be expected because of the complexity and variety in the real world process that generates traffic crashes. This process is very much dependent on the behavior of many drivers, whose skills, knowledge, and attitudes differ widely. This process is also subject to considerable randomness.

This study has identified characteristics of intersections where successful outcomes from RLC deployment are more likely. In cases where specific RLCs fail to meet expectations and/or create unacceptable side effects, such deviations should be used as opportunities for detailed investigation and learning to design and deploy more effective automated enforcement programs. An important part of a successful and respected RLC program will be continuous monitoring, evaluation, adaptation, and reporting to the community. Based on the outcomes of the clustering and ordered probit analysis, some potential locations for successful implementation have been identified. A simple formula with readily available intersection data can be used to identify locations with high likelihood of effective RLC performance for future deployment consideration.

Community support is an important element of any enforcement program. Securing that support requires closing the gap in perceptions between opponents and advocates. Educating the community about the scale and scope of the traffic crash problem is an important starting point. Data describing the crash problem should be spatially specific so residents know if, and where, they face serious crash risks.

Demonstrating the effectiveness of automated enforcement programs, in this case the RLC program, is obviously essential to gain community support. That requires the kind of data collected and analyzed in this study. It will also be important to respect the limitations of the data and analyses – accepting a modest level of uncertainty and balancing it with a systematic evaluation and adjustment program.

Deploying RLCs based on demonstrated risks – current and detailed crash statistics and the substantial presence of vulnerable people – will be important for assuring program effectiveness and for gaining support of community members who are skeptical about the distribution of cameras. Winning over the skeptics will require revealing the site selection criteria. For example, CDOT might post, and update, intersection crash data at those risky locations.

Because of concerns about the functioning of the enforcement technologies themselves, a routine, integrated, and visible quality assurance and quality control (QA/QC) program will also be an important part of building community support. This calls for continuously monitoring performance and quickly responding to and remedying detected and reported equipment failures. A useful goal to guide design of a monitoring system is that it should be proactive, detecting and resolving anomalies in camera performance before they reach the public and the media.

An immediate concern lies with violations within a fraction of a second into the red phase. Legitimate dilemma zones at the onset of the yellow do occur, especially at higher speed intersections, and may be difficult to eliminate completely without substantially longer intervals. In addition, the electrical technology behind traffic signal controllers may itself produce slight variations in the actual duration of the yellow interval. Public perceptions of fairness diminish when otherwise well-meaning, law-abiding drivers are effectively caught in the dilemma zone. The effect of the dilemma zone is evidenced by the significant reduction in violations when the yellow interval is 4 sec compared to 3 sec. While dense, high-traffic urban areas generally call for shorter yellow intervals, with 3 sec being a commonly recommended value, this calls for greater tolerance when a driver enters the intersection within a fraction of a second. The detailed analysis conducted in this study suggests that an enforcement threshold of 0.3 or 0.4 sec (instead of the current 0.1 sec) would be appropriate. Applying this threshold to the existing data suggests that no change would occur to the effectiveness clusters identified in the study.

Another element of public support, program transparency, will be periodic – at least annual – reports to the community on program effectiveness, equipment performance, and data driven program adaptations. These reports could come in several forms, such as a formal annual document, a website with a continuously updated performance dashboard, and, as suggested above, short messages about crash experience and RLC performance posted at key intersections. This calls for designing the routine data collection, analysis, and reporting process to minimize future work effort while assuring that assessment reports are completed and issued on a timely basis. The foundation underlying this multi-element reporting process will be accurate and timely data on traffic crashes, volumes, intersection characteristics, etc., as well as a routine statistical analysis process that generates the results. The experience with this study can serve as a basis for structuring a routine analysis and reporting process.

The City of Chicago started in the past couple of years producing an annual report focused on its RLC enforcement program (available at the following url https://www.cityofchicago.org/city/en/depts/cdot/provdrs/automated-enforcement.html). The report contains several of the elements identified in the previous chapter. However its focus is almost exclusively on the RLC program, and not on traffic safety in broader terms, as discussed in the previous chapter. Furthermore, it does not incorporate the elements of quality assurance (e.g. of functioning equipment) recommended in the previous chapter. In addition, recent steps by the City to make violation data available as part of its open data portal are all steps in the right direction.

Finally, it is the broad consensus of professionals in the traffic safety field, supported by community stakeholders contacted in this effort, that an automated enforcement program must be embedded within a more comprehensive and visible traffic safety program that includes education about risks and risky behaviors, communication about goals and programs, and traditional police enforcement. While there are many pressures on police today, there has been a history of successful integration of traffic safety and law enforcement that may bring broad community benefits (*36*).

These program adjustments and enhancements will help build community support for, and compliance with, the Chicago RLC program.

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8 APPENDIX

8.1 Literature Review

This study uses an EB method to model the safety effects of Red Light Cameras capturing the spillover effect. A crucial step in the EB approach is the selection of the reference intersections (*37*), (*38*). These intersections must be similar to the RLC intersections. The Safety Performance Functions (SPF) are estimated using them, and then applied to the RLC intersections to predict the number of crashes had there been no treatment (*3*). However, these intersections are affected by the installment of the Red Light Cameras at other intersections. This 'spillover' effect must be factored in into the analysis (*13; 14*). Council et al. calculate the spillover effect by comparing the EB estimates to the actual observations at the reference intersections in the after period (*15*). To avoid the spillover effect, Persaud et al. used reference intersections consisting of non-signalized intersections to estimate the SPFs (*7*). On the other hand, Washington and Shin (*16; 17*) treat the spillover effect as limited to the RLC intersection itself, where the affected sites are the approaches without the RLC (*16; 17*).

The aforementioned studies (*7; 13-17*) acknowledge the existence of the spillover effect, where some of these calculate it with different assumptions (*7; 15-17*). However, these studies do not factor in the spillover effect into the before-after analyses. This study proposes two methods to factor in the spillover effect into the before-after analysis. Zero-Inflated Negative Binomial (ZINB) models are used to estimate Safety Performance Functions for crashes of different types at the intersection, approach level. There are several models used in the literature to estimate the crash frequencies. For a deeper and broader review of the literature, readers are encouraged to refer to (*3; 39; 40*).

The following paragraphs provide a brief literature review on the Poisson, Negative Binomial (NB) regression models, and their zero-inflated derivatives. For the review of random effect, Conway-Maxwell-Poisson, Poisson-lognormal, Poisson–Weibull, Gamma, Censored regression, generalized additive models etc.; and for phenomena such as unobserved heterogeneity, parsimonious vs. fully specified models, endogeneity, and spatial and temporal correlations, please refer to previous studies (*12; 39-41*).

8.1.1 Crash Frequency Models

Since crashes are rare events with non-integer frequencies, application of ordinary least-squares regression (OLS) techniques, where the dependent variable is assumed to be continuous, is not appropriate for estimating crash frequencies (*39*). As a starting point, Poisson regression models have been used in crash estimations, an approach dating back to 1976 (*42-44*). Miaou and Lam compared an additive linear (normal), a multiplicative linear (log-normal), and three Poisson regression models with different functional forms (*45*). In another study, Miaou compared three models: Poisson regression, Zero-Inflated Poisson regression (ZIP), and Negative Binomial (NB) regression (*46*). The author recommended the NB models due to their ability of addressing overdispersion (*46*).

Hauer et al. described the underlying assumptions behind the NB models: The number of accidents at a given site is Poisson distributed, where the mean itself is Gamma distributed over different entities (*3; 47*). Shankar et al. proposed an NB model where they interact geometric and weather-related variables (*48*). Poch and Mannering proposed an NB model where they estimate the crash frequencies at individual approaches of an intersection and thereby capture various movement related effects (*49*). Karlaftis and Tarko used a clustering technique to disaggregate the observations into homogenous clusters and estimated separate NB models and compared it with a joint model (*50*). Ben-Akiva et al. used an Empirical Bayes approach to calculate the safety effectiveness of several treatments in Massachusetts, where the crash frequencies are estimated using an NB model (*5*). Miaou and Lord challenged several assumptions used in the literature for estimating crashes at intersections (*51*). These included the fixed vs. variable dispersion parameter, the widely used functional forms, and the Empirical Bayes (EB) vs fully Bayes methods (*51*). Persaud et al. proposed another EB method, where they also attempted to capture spillover effects (*7*).

Given that the accidents are rare events, intersections or road sections with zero accidents carry significant information that are not captured by the Poisson or NB models (*39*). As a result, zero-inflated (i.e. dual-state or zero-altered) models have been developed (*39*). In these models, the probability of having no accidents, is estimated using a logit or a probit model (*39*). The number of accidents in the non-zero state can then be estimated using Poisson or NB models (*39*). After Miaou in 1994 (*46*), Shankar et al. used zero-inflated models and highlight that some of the covariates has the same sign for the non-zero state (if positive, increasing accidents) and the zero-state (if positive, increases the probability of having no accident) (*52*). Using a Zero-Inflated Negative Binomial (ZINB) model , Carson and Mannering showed that the ice-warning signs in Washington state do not significantly reduce crash frequencies (*53*). Other implementations of ZINB models included run-off-roadway accidents (*54*), and signalized tee intersections (*55*). Implementations of ZIP models included crashes involving pedestrians and motorized traffic (*56*), and two-lane highway segments (*57*). Several studies in the literature including (*52-56; 58; 59*) refer to the statistical test introduced by Vuong (*60*). The larger the Vuong statistic, the more significantly a zero-inflated model (Poisson or NB) is different from the corresponding conventional model (*60*).

8.1.2 Modeling Driver Behavior at RLC intersections

There is an abundance of literature on RLC-related studies focusing on the safety aspect, as previously mentioned, mostly in the form of “before-after” analyses where the researchers analyzed the effect of RLC deployment on the number of intersection-related crashes. [See works by Lord (*6*) , Walden (*61*), Washington and Shin (*12)*, Hu et al. (*62*), and Retting et al. (*63*), (*64*)]. However, less focus has been given by researchers towards the impact of RLCs on violation behavior.

In their analysis of RLC programs in the US, McFadden and McGee found that automated enforcement of RLC can result in a 20 to 60 percent reduction in traffic violations (*65*). There had been studies which, conversely, reached more pessimistic findings. Some showed counterproductive results demonstrating an increase in the number of accidents at less accident prone sites following RLC deployment (*66*), (*67*) or stating no change in angle accidents and large increases in rear-end crashes and many other types of crashes relative to other intersections (*68*). Therefore, RLC deployment has been and still is the focus of substantial controversy as indicated by public opinion (*69*).

Attempting to understand the reasons for RLC violations has proven to be challenging since it involves a combination of various behavioral, demographic and intersection characteristics. In general, RLC violations and crashes are negatively associated with amber light duration and width of the intersection while positively associated with approaching flow rates and speeds (*70*). In some instances, all-red (clearance) intervals and amber phase extensions are supplementary to RLC enforcement in reducing red light violations. This practice has shown promising results according to a number of studies (*63*), (*64*), (*71*). Bonneson and Zimmerman (*71*) found that an additional 0.5 to 1.5 seconds of the amber indication interval (as long as the total time did not exceed 5.5 seconds) decreased RLC violations by 50%. Different models have been introduced in literature to predict the frequency of RLC violations.

Bonneson et al. (*72*) developed a prediction model of RLC violations based on the probability distribution relative to driver's stop or go decision which combined "exposure and contributory" factors. The model accounted for the differences among drivers due to these factors. The exposure variables were approach flow rate, number of signal cycles, and phase termination by max-out, while the contributory ones were probability of stopping and amber interval duration. The assumption was that each driver decides to go (or stop) independently of any other driver.

Hill and Lindly (*73*) tested various statistical models (linear, curvilinear, and multiple linear) to predict RLC violation frequency. Average daily traffic (ADT), number of approach lanes and speed limit were identified as the most relevant explanatory variables. However, the signal control and timing element was excluded from the analysis. Lum and Wong (*74*) applied a generalized linear model relating three independent categorical—variables, approach, lane, and time of day—to the after-red times (time-into-red), which acted as the dependent variable for the before-and-after study. Around a 40% decrease in the number of violations was observed for camera approaches; non-camera ones experienced an increase. The aggregated net reduction for all approaches was around 7%. The presence or absence of RLC significantly influenced the violation onset times (i.e. time into red) and lower mean times into red were observed for camera approaches.

Bonneson and Zimmerman (*75*), building on their previous research, examined the relationship between violation frequency and amber interval duration, indicating a trend toward more violations with shorter amber times. The authors observed the number of violations decreased with an increase in cycle length, amber indication duration, volume-to-capacity (V/C) ratio, intersection width, speed etc. Most interestingly, the authors found the lowest number of violations were associated with V/C ratios in the range of 0.6 to 0.7, regardless of any other significant factor value.

Yang and Wassim (*76*) built a logistic regression model in order to understand the relation between red light violations and various driver, intersection, and environmental factors. They reported that approximately 56 % of the violators traveled at or below the posted speed limit. Additionally, violations occurred 94 % of the time within 2 seconds after the onset of the red light. The authors' findings confirmed older drivers were more likely to run a red light than younger drivers when the elapsed time since the onset of red light was more than 2 seconds.

The most recent approaches, in RLC violation prediction studies, involves using observational data supplemented with driving simulator data. Jahangiri et al. (*77*) adopted a random forest (RF) machine-learning technique to develop RLC violation prediction models.

The majority of the previous research efforts, however, recognized the limitations of the models suggested. This was predominately related to the types of models and variables used and "local" prediction model calibration issues (that is, models not robust enough to be transferable to other areas and/or geometry configurations).

8.2 Appendix – Modeling the Safety Effects of Red-Light Camera Enforcement with Spillover Effects

This section gives a math oriented reader an in-depth insight to the math that goes into the calculations for the methodology adopted for the study.

8.2.1 Methodology

8.2.1.1 Notation

The following notation is used in this section:

I: Set of treatment sites; $i \in$ I,

J: Set of reference sites; $j \in$ J,

C: Set of crash types; $c \in$ C,

K_{ic}: Number of observed crashes of type $c \in$ C at a treatment site $i \in$ I in the before period,

κ_{ic}: Estimated number of crashes of type $c \in$ C at a treatment site $i \in$ I in the before period,

L_{ic}: Number of observed crashes of type $c \in$ C at a treatment site $i \in$ I in the after period,

λ_{ic}: Estimated number of crashes of type $c \in$ C at a treatment site $i \in$ I in the after period,

π_{ic}: Estimated number of crashes of type $c \in$ C at a treatment site $i \in$ I in the after period had there been no treatment,

π'_{ic}: Estimated number of crashes of type $c \in$ C at a treatment site $i \in$ I in the after period had there been no treatment considering an uncontrolled spillover effect,

π''_{ic}: Estimated number of crashes of type $c \in$ C at a treatment site $i \in$ I in the after period had there been no treatment considering a controlled spillover effect,

M_{jc}: Number of observed crashes of type $c \in$ C at a reference site $j \in$ J in the before period ",

μ_{jc}: Estimated number of crashes of type $c \in$ C at a reference site $j \in$ J in the before period,

N_{jc}:	Number of observed crashes of type $c \in \mathrm{C}$ at a reference site $j \in \mathrm{J}$ in the after period,
ν_{jc}:	Estimated number of crashes of type $c \in \mathrm{C}$ at a reference site $j \in \mathrm{J}$ in the after period,
β:	Rate parameter of a Gamma distribution,
α:	Shape parameter of a Gamma distribution,
$\Gamma(b)$:	Gamma function evaluated at $\Gamma(b)$,
δ_{ic}:	Reduction in number of crashes of type $c \in \mathrm{C}$ at a treatment site $i \in \mathrm{I}$,
θ_{ic}:	Index of Safety Effectiveness of type $c \in \mathrm{C}$ at a treatment site $i \in \mathrm{I}$,
$\vec{X}_i^b$:	Vector of covariates at a treatment site $i \in \mathrm{I}$ in the before period,
$\vec{X}_i^a$:	Vector of covariates at a treatment site $i \in \mathrm{I}$ in the after period,
$\vec{X}_j^b$:	Vector of covariates at a treatment site $j \in \mathrm{J}$ in the before period,
$\vec{X}_j^a$:	Vector of covariates at a treatment site $j \in \mathrm{J}$ in the after period,
$SPF_c^b(\vec{X})$:	Safety Performance Function for crash type $c \in \mathrm{C}$ in the before period,
$SPF_c^a(\vec{X})$:	Safety Performance Function for crash type $c \in \mathrm{C}$ in the after period,
w_{ic}:	Weight used for the Empirical-Bayesian estimation at a treatment site $i \in \mathrm{I}$ in the before period,
w_{jc}^b:	Weight used for the Empirical-Bayesian estimation at a treatment site $j \in \mathrm{J}$ in the before period,
w_{jc}^a:	Weight used for the Empirical-Bayesian estimation at a treatment site $j \in \mathrm{J}$ in the after period,
ϕ:	Inverse of the dispersion parameter of a Negative Binomial (NB) or a Zero-Inflated Negative Binomial (ZINB) regression model,
ρ_{uc}:	Uncontrolled spillover effect for crash type $c \in \mathrm{C}$,
ρ_{rc}:	Controlled spillover effect for crash type $c \in \mathrm{C}$,
ψ_{nc}:	Observed percentage reduction in crashes in neighboring areas for crash type $c \in \mathrm{C}$,
ψ_{sc}:	Observed percentage reduction in crashes at reference sites for crash type $c \in \mathrm{C}$.

8.2.1.2 Assumptions

In this sub-section, site and crash type indices are dropped for simplicity. Based on the commonly used assumptions in the literature (*3*), crashes at a site are Poisson distributed:

$$P(M) = \frac{\mu^M e^{-\mu}}{M!} \tag{8.2.1}$$

The expected value and the variance of the Poisson distribution are (*3*):

$$E(M) = \mathrm{Var}(M) = \mu \tag{8.2.2}$$

On the other hand, the expected value μ in a reference population is Gamma distributed (*3*):

$$g(\mu) = \frac{\beta^\alpha \mu^{\alpha-1} e^{-\beta\mu}}{\Gamma(\alpha)} \tag{8.2.3}$$

The expected value and the variance are (*3*):

$$E(\mu) = \frac{\alpha}{\beta} \tag{8.2.4}$$

$$\mathrm{Var}(\mu) = \frac{\alpha}{\beta^2} \tag{8.2.5}$$

8.2.1.3 Calculation of Safety Metrics

There are two main safety metrics used in the literature (*3*): reduction in the expected number of crashes δ_{ic}, and the Index of Safety Effectiveness θ_{ic}.

$$\delta_{ic} = \pi_{ic} - \lambda_{ic} \tag{8.2.6}$$

$$\theta_{ic} = \frac{\lambda_{ic}/\pi_{ic}}{1 + \mathrm{Var}(\pi_{ic})/{\pi_{ic}}^2} \tag{8.2.7}$$

It can be seen from Equation (8.2.7) that δ_{ic} is the difference between the predicted number of crashes in the after period had there been no treatment (π_{ic}) and the expected number of crashes in the after period with treatment (λ_{ic}) at i. A positive value indicates a reduction in crashes. The Index of Safety Effectiveness is the ratio of the expected number of crashes in the after period with treatment (λ_{ic}) to the predicted number of crashes in the after period had there been no treatment (π_{ic}): λ_{ic}/π_{ic}. A smaller value indicates a higher effectiveness. The term $(1+\mathrm{Var}(\pi_{ic})/\pi_{ic}{}^2)$ in the denominator is used to correct for the small sample size bias (*3*).

8.2.1.4 Empirical-Bayes (EB) Formulation

Agencies tend to install RLCs where the number of crashes are high. Since crashes are random events, comparing the sheer number of crashes before and after treatment would suffer from the 'regression-to-the-mean' bias (*3*). If an agency selects a site $i \in \mathrm{I}$ with a high number of K_{ic}, then it is possible to observe a significantly lower number of crashes L_{ic} in the after period. However, this reduction should not be solely attributed to the treatment itself because the number of crashes would reduce towards the mean anyway. As a result, an unbiased estimation of π_{ic} is needed.

Below is the step-by-step description of how to use the EB method to estimate the two safety metrics δ_c and λ_c:

Step 1. Estimate the functions $SPF_c^b(\vec{X}_j^b)$ and $SPF_c^a(\vec{X}_j^a)$ using a selected regression model (here ZINB) for the before and after periods. The dependent variables are the observed number of crashes at the reference sites $j \in \mathrm{J}$ in the before (M_{jc}) and after (N_{jc}) periods respectively, and the independent variables are in the vectors $\vec{X}_j^b$ and $\vec{X}_j^a$:

$$M_{jc} \cong SPF_c^b(\vec{X}_j^b) = \mu_{jc} \tag{8.2.8}$$

$$N_{jc} \cong SPF_c^a(\vec{X}_j^a) = \nu_{jc} \tag{8.2.9}$$

Step 2. Plug in the covariates $\vec{X}_i^b$ and $\vec{X}_i^a$ into the Safety Performance Functions SPF_c^b and SPF_c^a respectively to predict the expected number of crashes at the treatment sites:

$$\mathrm{E}(\kappa_{ic}) = SPF_c^b(\vec{X}_i^b) \tag{8.2.10}$$

$$\mathrm{E}(\lambda_{ic}) = SPF_c^a\left(\vec{X}_j^a\right) \tag{8.2.11}$$

Step 3. Calculate the Empirical-Bayesian estimate of crashes in the before period, which is a weighted sum of the expected number of crashes $\mathrm{E}(\kappa_{ic})$ and the observed number of crashes K_{ic}:

$$\mathrm{E}(\kappa_{ic}|K_{ic}) = w_{ic}\mathrm{E}(\kappa_{ic}) + (1 - w_{ic})K_{ic} \tag{8.2.12}$$

The weight w_{ic} can be calculated as:

$$w_{ic} = \frac{1}{1 + \frac{\mathrm{E}(\kappa_i)}{\emptyset}} \tag{8.2.13}$$

Step 4. Predict the number of crashes π_{ic} for type $c \in \mathrm{C}$ had there been no treatment at site $i \in \mathrm{I}$, and its variance:

$$\pi_{ic} \equiv \mathrm{E}(\pi_{ic}) = \frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})}\mathrm{E}(\kappa_{ic}|K_{ic}) = \frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})}[w_{ic}\mathrm{E}(\kappa_{ic}) + (1 - w_{ic})K_{ic}] \tag{8.2.14}$$

$$\mathrm{Var}(\pi_{ic}) = \left(\frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})}\right)^2 (1 - w_{ic})\mathrm{E}(\kappa_{ic}|K_{ic}) \tag{8.2.15}$$

Step 5. Calculate the number of crashes λ_{ic} for type $c \in \mathrm{C}$ at site $i \in \mathrm{I}$ in the after period, and its variance:

$$\lambda_{ic} = \mathrm{L_{ic}} \tag{8.2.16}$$

$$\mathrm{Var}(\lambda_{ic}) = \lambda_{ic} = L_{ic} \tag{8.2.17}$$

The following steps are performed to evaluate the overall effectiveness of treatment by aggregating the values over the treatment sites $i \in \mathrm{I}$. The aggregation is called the 'composite' site.

Step 6. Calculate the composite number of crashes π_c for type $c \in \mathrm{C}$ had there been no treatment, and its variance:

$$\pi_c = \sum_{i \in \mathrm{I}} \pi_{ic} \tag{8.2.18}$$

$$\mathrm{Var}(\pi_c) = \sum_{i \in \mathrm{I}} \mathrm{Var}(\pi_{ic}) \tag{8.2.19}$$

Step 7. Calculate the composite number of crashes λ_c for type $c \in \mathrm{C}$ in the after period, and its variance:

$$\lambda_c = \sum_{i \in \mathrm{I}} \lambda_{ic} \tag{8.2.20}$$

$$\mathrm{Var}(\lambda_c) = \sum_{i \in \mathrm{I}} \mathrm{Var}(\lambda_{ic}) \tag{8.2.21}$$

Step 8. Calculate the composite reduction in crashes δ_c for type $c \in \mathrm{C}$, and its variance:

$$\delta_c = \pi_c - \lambda_c \tag{8.2.22}$$

$$\mathrm{Var}(\delta_c) = \mathrm{Var}(\pi_c) + \mathrm{Var}(\lambda_c) \tag{8.2.23}$$

Step 9. Calculate the composite Index of Safety Effectiveness θ_c for type $c \in \mathrm{C}$, and its variance:

$$\theta_c = \frac{\lambda_c/\pi_c}{1 + \mathrm{Var}(\pi_c)/\pi_c{}^2} \tag{8.2.24}$$

$$\mathrm{Var}(\theta_c) = \theta_c{}^2 \frac{\mathrm{Var}(\lambda_c)/\lambda_c{}^2 + \mathrm{Var}(\pi_c)/\pi_c{}^2}{(1 + \mathrm{Var}(\pi_c)/\pi_c{}^2)^2} \tag{8.2.25}$$

8.2.1.5 Spillover Effect

8.2.1.5.1 Uncontrolled Spillover Effect

Since the significant variables, as well as the coefficient values are potentially different for the safety performance functions in the before (SPF_c^b) and after periods (SPF_c^a), one can plug in the variables of the reference sites $j \in \mathrm{J}$ in the after period $\vec{X}_j^a$ into both functions. If nothing else had changed, the two models would be statistically the same resulting in the same expected crash values. If these values are different then the ratio ρ_{uc} in Equation (8.2.26) captures the reduction in crashes at the reference intersections due to the unobserved factors:

$$\rho_{uc} = \frac{w_{jc}^a \times SPF_c^a\left(\vec{X}_j^a\right) + \left(1 - w_{jc}^a\right) \times N_{jc}}{w_{jc}^b \times SPF_c^b\left(\vec{X}_j^a\right) + \left(1 - w_{jc}^b\right) \times N_{jc}} \tag{8.2.26}$$

If one assumes that this whole reduction is due to the spillover, ρ_{uc} would yield the spillover effect, which can be seen as an upper bound to the actual spillover effect. This modifies the predicted number of crashes π_{ic}, which is shown below. The Steps (5-9) follow the same calculations and are not repeated here.

Modified Step 4'. Predict the number of crashes π_{ic}' for type $c \in \mathrm{C}$ had there been no treatment at site $i \in \mathrm{I}$ with considering an 'uncontrolled' spillover effect, and its variance:

$$\pi_{ic}' \equiv \mathrm{E}(\pi_{ic}') = \frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})} \frac{1}{\rho_{uc}} \mathrm{E}(\kappa_{ic} | K_{ic}) = \frac{1}{\rho_{uc}} \pi_{ic} \tag{8.2.27}$$

$$\mathrm{Var}(\pi'_{ic}) = \left(\frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})}\frac{1}{\rho_{uc}}\right)^2 (1 - w_{ic})\mathrm{E}(\kappa_{ic}|K_{ic}) = \frac{1}{{\rho_{uc}}^2}\mathrm{Var}(\pi_{ic}) \tag{8.2.28}$$

8.2.1.5.2 Controlled Spillover Effect

Acknowledging that ρ_{uc} overestimates the spillover effect, a correction factor is proposed. Since the reference intersections are subject to a potential spillover, one can look at the changes in crashes at locations that are far enough from the RLC intersections but still close enough to the general area. The underlying assumption is that the same drivers are driving in those areas but they are far enough to behave no more that carefully. If the percentage reduction in crashes for crash type $c \in \mathrm{C}$ is ψ_s in the study area, and ψ_n in the neighboring area, then $\psi_s - \psi_n$ can be seen as the 'pure' reduction due to spillover. As a result, the proposed controlled spillover effect ρ_{rc} is given in Equation (8.2.29)

$$\rho_{rc} = \frac{\psi_{sc} - \psi_{nc}}{\psi_{sc}} \times \rho_{uc} \tag{8.2.29}$$

Modified Step 4". Predict the number of crashes π''_{ic} for type $c \in \mathrm{C}$ had there been no treatment at site $i \in \mathrm{I}$, and its variance:

$$\pi''_{ic} \equiv \mathrm{E}(\pi''_{ic}) = \frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})}\frac{1}{\rho_{rc}}\mathrm{E}(\kappa_{ic}|K_{ic}) = \frac{1}{\rho_{rc}}\pi_{ic} \tag{8.2.30}$$

$$\mathrm{Var}(\pi''_{ic}) = \left(\frac{\mathrm{E}(\lambda_{ic})}{\mathrm{E}(\kappa_{ic})}\frac{1}{\rho_{ur}}\right)^2 (1 - w_{ic})\mathrm{E}(\kappa_{ic}|K_{ic}) = \frac{1}{{\rho_{rc}}^2}\mathrm{Var}(\pi_{ic}) \tag{8.2.31}$$

8.2.2 Results

TABLE 8.2.1 through TABLE 8.2.5 present the ZINB model results for all KABC, angle & turn KABC, and rear-end KABC crashes. TABLE 8.2.6 presents the before-after study results with statistical details.

TABLE 8.2.1 Estimates of ZINB Model for All KABC Crashes in the Before Period

Variable	Coefficient	Std. Err.	z
Negative Binomial State			
ln(AADT) - Self and Opposite	0.4312	0.1185	3.64
Protective Left Turn Arrow - Left Approach	-1.5317	0.6037	-2.54
Right on Red Prohibition - Self	-0.1964	0.1276	-1.54
Intercept	-2.3963	1.0431	-2.30
Zero-State			
ln(AADT) - Self and Opposite	0.8375	0.7648	1.10
Left Turn Allowed - Opposite Approach	-1.7393	1.2785	-1.36
Right Turn Allowed - Opposite Approach	-2.6014	1.7847	-1.46
Median - Opposite Approach	-2.0040	1.7028	-1.18
Cycle Length (sec)	0.0439	0.0310	1.42
Intercept	-9.7423	6.0099	-1.62
Dispersion Parameter	0.5152	0.0958	
Likelihood Ratio χ^2 Test of the Full Model	16.23		
$Pr > \chi^2$	0.001		
Likelihood Ratio of Dispersion Parameter = 0	128.60		
$Pr \geq \overline{\chi}^2$	0.0000		
Vuong Test of Zero-Inflated NB vs Standard NB	1.26		
$Pr > z$	0.1039		

TABLE 8.2.2 Estimates of ZINB Model for All KABC Crashes in the After Period

Variable	Coefficient	Std. Err.	z
Negative Binomial State			
ln(AADT) - All Aproaches	0.7876	0.1957	4.02
Protective Left Turn Arrow - Self	-1.6257	0.8477	-1.92
Protective Left Turn Arrow - Opposite Approach	2.1719	1.0497	2.07
Protective Left Turn Arrow - Right Approach	-1.2767	0.8792	-1.45
All Red - Self and Opposite (2 sec)	-0.5181	0.2100	-2.47
All Red - Crossing Approaches (2 sec)	0.5538	0.2078	2.66
Cycle Length (sec)	-0.0126	0.0049	-2.57
Intercept	-5.3197	1.8417	-2.89
Zero-State			
Permissive Left Turn Arrow - Self	-0.3990	0.3087	-1.29
Right on Red Prohibition - Self	-0.6688	0.5195	-1.29
Right on Red Prohibition - Left Approach	0.6555	0.5180	1.27
Yellow - Self and Opposite (4 sec)	0.7868	0.7339	1.07
Intercept	0.1933	0.1964	0.98
Dispersion Parameter	0.2687	0.0757	
Likelihood Ratio χ^2 Test of the Full Model	25.36		
$Pr > \chi^2$	0.0007		
Likelihood Ratio of Dispersion Parameter = 0	49.93		
$Pr \geq \bar{\chi}^2$	0.0000		
Vuong Test of Zero-Inflated NB vs Standard NB	4.13		
$Pr > z$	0.0000		

TABLE 8.2.3 Estimates of ZINB Model for KABC Angle & Turn Crashes in Both Periods

Variable	Coefficient	Std. Err.	z
Negative Binomial State			
ln(AADT) - Self interacting with 'After' Dummy			
0	0.3847	0.1170	3.29
1	0.3573	0.1207	2.96
Protective Left Turn Arrow - Left Approach	-1.6763	0.6671	-2.51
Right on Red Prohibition - Self	-0.3240	0.1342	-2.42
Intercept	-2.4625	1.0319	-2.39
Zero-State			
ln(AADT/lane) - All Approaches	0.8060	0.5084	1.59
Permissive Left Turn Arrow - Left Approach	-0.7937	0.5477	-1.45
Cycle Length (sec)	0.0128	0.0105	1.23
Intercept	-8.7708	4.5419	-1.93
Dispersion Parameter	0.6711	0.2430	
Likelihood Ratio χ^2 Test of the Full Model	21.98		
$Pr > \chi^2$	0.0002		
Likelihood Ratio of Dispersion Parameter = 0	51.17		
$Pr \geq \bar{\chi}^2$	0.0000		
Vuong Test of Zero-Inflated NB vs Standard NB	1.37		
$Pr > z$	0.0854		

TABLE 8.2.4 Estimates of ZINB Model for KABC Rear End Crashes in the Before Period

Variable	Coefficient	Std. Err.	z
Negative Binomial State			
ln(AADT) - Self and Opposite	0.4006	0.1743	2.30
Permissive Left Turn Arrow - Self	1.0890	0.2763	3.94
Intercept	-4.2222	1.5483	-2.73
Zero-State			
ln(Speed Limit) - Self	-3.9734	2.6887	-1.48
Permissive or Protective Left Turn Arrow - Self	14.0160	9.2925	1.51
Median - Self	-0.9598	0.8286	-1.16
Dispersion Parameter	0.2178	0.2244	
Likelihood Ratio χ^2 Test of the Full Model	20.16		
$Pr > \chi^2$	0.0000		
Likelihood Ratio of Dispersion Parameter = 0	0.88		
$Pr \geq \bar{\chi}^2$	0.1738		
Vuong Test of Zero-Inflated NB vs Standard NB	1.63		
$Pr > z$	0.0515		

TABLE 8.2.5 Estimates of ZINB Model for KABC Rear End Crashes in the After Period

Variable	Coefficient	Std. Err.	z
Negative Binomial State			
ln(AADT) - All Approaches	0.6678	0.2332	2.86
Permissive Left Turn Arrow - Self	0.6657	0.2419	2.75
Intercept	-6.9377	2.3756	-2.92
Zero-State			
Protective Left Turn Arrow - Self	1.2375	1.2121	1.02
Permissive Left Turn Arrow - Left Approach	0.5091	0.3485	1.46
Median - Self	-0.5951	0.5726	-1.04
Dispersion Parameter	0.1528	0.1452	
Likelihood Ratio χ^2 Test of the Full Model	20.54		
$Pr > \chi^2$	0.0000		
Likelihood Ratio of Dispersion Parameter = 0	1.87		
$Pr \geq \bar{\chi}^2$	0.0859		
Vuong Test of Zero-Inflated NB vs Standard NB	1.88		
$Pr > z$	0.0298		

TABLE 8.2.6 Before-After Study Results using ZINB with No, Uncontrolled, and Controlled Spillover Effects

Crash Type	ZINB with No Spillover								
	K_c	L_c	π_c	λ_c	δ_c	θ_c		$z(\delta)$	$z(\theta)$
All KABC	1,229	1,054	1147 (28.7)	1054 (32.5)	93 (43.3)	0.92	(0.0364)	2.15	2.25
KABC Angle & Turn	581	400	461 (14.1)	400 (20)	61 (24.4)	0.87	(0.0508)	2.48	2.61
KABC Rear-End	230	301	267 (6.7)	301 (17.4)	-34 (18.6)	1.13	(0.0708)	-1.83	-1.79
Crash Type	**ZINB with Uncontrolled Spillover**								
	K_c	L_c	π_c	λ_c	δ_c	θ_c		$z(\delta)$	$z(\theta)$
All KABC	1,229	1,054	1248 (31.2)	1054 (32.5)	194 (45)	0.84	(0.0334)	4.32	4.67
KABC Angle & Turn	581	400	587 (17.9)	400 (20)	187 (26.8)	0.68	(0.0398)	6.97	8.02
KABC Rear-End	230	301	263 (6.6)	301 (17.4)	-38 (18.6)	1.14	(0.0719)	-2.05	-2.00
Crash Type	**ZINB with Controlled Spillover**								
	K_c	L_c	π_c	λ_c	δ_c	θ_c		$z(\delta)$	$z(\theta)$
All KABC	1,229	1,054	1165 (29.1)	1054 (32.5)	111 (43.6)	0.90	(0.0358)	2.55	2.68
KABC Angle & Turn	581	400	492 (15)	400 (20)	92 (25)	0.81	(0.0475)	3.69	3.96
KABC Rear-End	230	301	263 (6.6)	301 (17.4)	-38 (18.6)	1.14	(0.0719)	-2.05	-2.00

8.3 Appendix – Determinants of Red-light Camera Violation Behavior

8.3.1 Missing Data

The data set includes 10,944 observations (152 x 72), for 152 red-light cameras (panels) over 72-month period. Due to maintenance and short black-out periods of some cameras, violations were not detected for specific time periods. For a better estimate of the models, the missing values were predicted before using the data to build the regression models (*22*).

As model specifications of spatial and serial correlations require a balanced panel data set where the same number of time periods is available for all panels, a multiple imputations algorithm was implemented to fill in missing observations of RLC violations based on the trends of the known observations. Although missing observations account for only 3.4% percent of the total observations in the data set, using a multiple imputations should reduce the bias that might result from missing observations or using a simple average to fill them (*22*). One concern was that the imputed values were of the dependent variable rather than explanatory variables of which no data was missing. However, as Young, Johnson, and Graham (*78*) (*79*) explain, an imputation model does not capture causal relationships in the data. Rather a tool to "preserve important features of observed information in imputed values" (*78*).

The implemented algorithm, AMELIA (a package in R system), performs multiple imputations for each missing cell in the data set based on observed data to create a complete data set. The multiple imputations capture the uncertainty in the missing data. AMELIA has two main assumptions behind its algorithm: 1) complete data are multivariate normal, 2) data are missing at random (MAR). MAR means that the "pattern of missingness depends on the observed data"(*22*). Thirty imputations were performed for each missing cell, and the average of those 30 imputations was used to fill the missing data. The creators of the algorithm suggest that 5 imputations are enough for most data sets, however, 30 imputations were used to reduce uncertainty. More information on the imputation algorithm can be found in (*22*).

8.3.2 Serially Correlated Panels

The assumption behind serial correlation is that some unobserved factors that affect violation behavior are correlated over time (i.e. has a persistence pattern over time). To capture that, a first-order serial autocorrelation parameter was specified in the error term of a pooled linear regression model (*80*). Individual (fixed) effects model was disregarded since all RLCs are located in Chicago, IL and are setup at comparable signalized intersections. The model specification is as follows:

$$y_{i,t} = x_{i,t}\beta + \nu_{i,t} \tag{8.3.1}$$

$$\nu_{i,t} = \rho_i \nu_{t-1} + e_{i,t} \tag{8.3.2}$$

where i = 1,…,N cameras, t =1,…,T time-periods, $y_{i,t}$ is the frequency of RLC violations for camera i and time-period t, $x_{i,t}$ is a vector of explanatory variables (AADT, road geometry, and signal timing variables) with coefficients β, ν is a vector of first-order serially autoregressive errors (AR1) with ρ_i as the serially autoregressive parameter for camera i.

8.3.3 Testing for Heteroscedasticity and Serial Correlation

Generalized Least Squares (GLS), built in the statistical software STATA, was used to estimate the total RLC violations models. GLS performs better at estimating effects in time-series data when heteroscedasticity and serial correlation are significant (*80*).

The log-likelihood ratio (LR) test was used to test for significance of heteroscedasticity. To do so, two models were estimated: one assuming heteroscedastic panels and another assuming homoscedastic panels. To estimate log-likelihoods of the models, the iterated GLS option was used in STATA where maximum-likelihood estimates are produced. The LR chi-squared value for the test was 10845.33 with p-value equal 0.00 for 151 degrees of freedom at the 0.05% significance level, indicating significant heteroscedasticity in the data.

For testing serial correlation, Wooldridge's test of autocorrelation in panel data was used (*81*). Wooldridge uses the F statistic to test the null hypothesis that no first-order autocorrelation exists in the data. The F statistic value for the total violations model was 484.24 with p-value equal 0.00 for (1,151) degrees of freedom at 0.05% significance level, indicating significant serial correlation.

8.3.4 Model Estimate for all RLC Violations

TABLE 8.3.1 Model Estimate for All Violations Assuming Serial Correlation

Variable	Coefficient	Std. Error	z	P>|z|	[95% Conf.	Interval]
AADT/lane - self	1.72	0.64	2.68	0.01	0.46	2.97
AADT/lane - crossing	-1.71	0.67	-2.57	0.01	-3.02	-0.41
N. lanes - self	26.13	2.13	12.24	0.00	21.94	30.31
N. lanes - crossing	-6.25	2.30	-2.71	0.01	-10.76	-1.73
Speed limit - self	4.04	0.58	7.03	0.00	2.91	5.17
Speed limit - crossing	2.85	0.62	4.63	0.00	1.64	4.06
Traverse Distance - self	-0.63	0.13	-5.00	0.00	-0.87	-0.38
Traverse Distance - crossing	0.95	0.13	7.24	0.00	0.69	1.21
Left-turn bay - self	-24.06	5.88	-4.09	0.00	-35.58	-12.53
Left-turn blocked - self	61.37	12.29	4.99	0.00	37.28	85.46
Left-turn arrow – oppst.	-30.94	3.94	-7.86	0.00	-38.65	-23.22
ROR prohibition - self	-24.51	3.20	-7.66	0.00	-30.78	-18.24
Median - self	-15.91	5.47	-2.91	0.00	-26.63	-5.20
Cycle length	1.26	0.16	8.01	0.00	0.95	1.57
Yellow phase =4	0			(Reference)		
Yellow phase =4	-108.80	7.83	-13.89	0.00	-124.15	-93.45
All-red phase =1	0			(Reference)		
All-red phase =2	10.11	3.97	2.54	0.01	2.32	17.90
Month						
1	0			(Reference)		
2	-0.91	0.86	-1.07	0.29	-2.59	0.76
3	11.44	1.30	8.82	0.00	8.90	13.99
4	13.61	1.51	9.01	0.00	10.65	16.57
5	26.42	1.58	16.76	0.00	23.33	29.51
6	27.98	1.66	16.82	0.00	24.72	31.24
7	29.93	1.72	17.40	0.00	26.56	33.30
8	26.20	1.63	16.06	0.00	23.00	29.40
9	18.41	1.53	12.04	0.00	15.41	21.41
10	12.79	1.50	8.52	0.00	9.85	15.73
11	4.51	1.39	3.25	0.00	1.79	7.23
12	1.03	1.08	0.95	0.34	-1.08	3.14
Year						
2010	0			(Reference)		
2011	-11.96	1.96	-6.09	0.00	-15.81	-8.11
2012	-22.42	2.53	-8.87	0.00	-27.37	-17.47
2013	-28.80	2.84	-10.13	0.00	-34.38	-23.23
2014	-34.25	3.22	-10.62	0.00	-40.57	-27.93
2015	-34.66	3.63	-9.55	0.00	-41.77	-27.55
Intercept	-237.71	33.42	-7.11	0.00	-303.20	-172.21

8.3.5 Model Estimates for Different Classifications of RLC Violations

The following tables summarize the model estimates for the different violation classifications. Starred coefficients (with * next to it) indicates that variable has a significant effect on frequency of violation while not starred variables indicated insignificant effects.

8.3.5.1 Rolling-Right-On-Red Violations Model

TABLE 8.3.2 Rolling-Right-On-Red Models

Variable		Model Estimates	
		RROR	**Non- RROR**
AADT/lane - self		-1.1***	3.7***
AADT/lane - crossing		0.6**	-1.7**
N. lanes - self		3.8***	21.5***
N. lanes - crossing		6.2***	-9.2***
Speed limit - self		1.9***	1.5**
Speed limit - crossing		1.2***	-0.4
Traverse Distance - self		-0.2***	-0.3**
Traverse Distance - crossing		0.1***	0.8***
Left-turn bay - self		-7.7***	-10.1*
Left-turn blocked		18.2*	25.5
Left-turn arrow - oppst		-9.0***	-21.7***
ROR prohibition - self		-4.1***	-14.5***
Right-turn bay - self		13.7***	7
Median - self		-0.02	-19.0***
Cycle length		0.5***	0.6***
Yellow phase =3		0	(Reference)
Yellow phase =4		-21.9***	-78.3***
All-red phase =1		0	(Reference)
All-red phase =2		0.7	9.0**
Month			
	1	0	(Reference)
	2	-0.7*	-0.2
	3	4.1***	4.7***
	4	5.1***	5.4***
	5	9.0***	13.0***
	6	8.4***	15.2***
	7	8.8***	15.7***
	8	6.8***	15.0***
	9	4.8***	10.7***
	10	3.6***	6.5***
	11	2.0***	0.7
	12	0.8*	-0.6
Year			
	2010	0	(Reference)
	2011	-1.7*	-8.1***
	2012	-4.4***	-14.7***
	2013	-5.7***	-21.0***
	2014	-7.9***	-23.9***
	2015	-8.1***	-24.9***
Constant		-112.1***	-68.5*

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

8.3.5.2 High-speed Violations Model

TABLE 8.3.3 High Speed RLC Violations Models

Variable	Model Estimates	
	High-speed	**Non-High-speed**
AADT/lane - self	1.2***	0.1
AADT/lane - crossing	-0.8***	0.2
N. lanes - self	7.9***	17.1***
N. lanes - crossing	-3.9***	0.9
Speed limit - self	0.3	2.8***
Speed limit - crossing	-0.08	1.9***
Traverse Distance - self	-0.1*	-0.3**
Traverse Distance - crossing	0.4***	0.6***
Left-turn bay - self	-2.3	-21.6***
Left-turn blocked	2.2	65.8***
Left-turn arrow - oppst	-3.5*	-23.2***
ROR prohibition - self	-4.4***	-18.5***
Right-turn bay - self	7.3***	10.0*
Median - self	-3.4	-6.3
Cycle length	-0.03	1.1***
Yellow phase =3	0	(Reference)
Yellow phase =4	-24.6***	-72.2***
All-red phase =1	0	(Reference)
All-red phase =2	5.4***	0.6
Month		
1	0	(Reference)
2	-0.7**	-0.2
3	0.5	9.6***
4	0.4	11.8***
5	1.4***	23.2***
6	1.5***	24.4***
7	2.0***	25.2***
8	1.7***	22.0***
9	0.6	16.0***
10	0.04	10.9***
11	-0.8*	3.8***
12	-1.2***	1.2
Year		
2010	0	(Reference)
2011	-1.8***	-11.4***
2012	-4.4***	-20.0***
2013	-7.4***	-24.7***
2014	-10.4***	-26.7***
2015	-12.6***	-24.9***
Constant	-17.2	-174.4***

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

8.3.5.3 One-sec-into-red Violations Model

TABLE 8.3.4 One-Sec-Into-Red Model

Variable	Model Estimates	
	One-into-red	**Non-One-into-red**
AADT/lane - self	3.0***	-0.5
AADT/lane - crossing	-1.1**	-0.3
N. lanes - self	16.5***	11.0***
N. lanes - crossing	-6.6***	1.4
Speed limit - self	1.8***	2.2***
Speed limit - crossing	-0.3	2.2***
Traverse Distance - self	-0.3***	0.02
Traverse Distance - crossing	0.5***	0.2**
Left-turn bay - self	-4.2	-6.2
Left-turn blocked	43.6***	37.1***
Left-turn arrow - oppst	-12.3***	-14.5***
ROR prohibition - self	-8.0***	-12.0***
Right-turn bay - self	11.4**	-3
Median - self	-7.2*	-10.0**
Cycle length	0.4***	0.5***
Yellow phase =3	0	(Reference)
Yellow phase =4	-56.1***	-42.7***
All-red phase =1	0	(Reference)
All-red phase =2	6.6**	-2.8
Month		
1	0	(Reference)
2	-0.3	-0.6
3	3.8***	5.9***
4	4.7***	7.3***
5	10.5***	13.6***
6	11.5***	14.3***
7	12.0***	15.0***
8	11.6***	11.8***
9	9.1***	7.0***
10	6.5***	4.3***
11	7.4***	-5.1***
12	6.4***	-7.0***
Year		
2010	0	(Reference)
2011	0.5	-14.2***
2012	2	-27.4***
2013	7.0***	-40.6***
2014	17.5***	-55.5***
2015	24.1***	-63.9***
Constant	-90.3***	-125.6***

* p<0.05, ** p<0.01, *** p<0.001

8.4 Appendix – Evaluation and Scoring

8.4.1 Methodology 1: Clustering Analysis

In this study, a K-Means clustering algorithm is performed (*24*). Given M observations (cameras) and N variables (performance criteria) for each observation, the objective is to place each observation m into one and only one cluster k so as to minimize the dissimilarities within each cluster:

$$\min \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_m^k \sqrt{\sum_{n}^{N} \left(x_{mn} - \mu_n^k\right)^2} \tag{8.4.1}$$

In Equation (8.4.1), x_{mn} is value of the variable n for the observation m. In our specific example, m is one of the 170 cameras, and n is one of the two criteria. μ_n^k is the average value of the attribute n in cluster k. δ_m^k is a binary variable, which is 1 if camera m belongs to cluster k and 0 otherwise. An additional constraint is needed to guarantee that m belongs to one and only one cluster k:

$$\sum_{k=1}^{K} \delta_m^k = 1, \qquad \forall m \in \{1, \dots, M\} \tag{8.4.2}$$

By changing δ_m^k as the decision variable, the algorithm seeks to minimize the sum of the squared differences of every variable n associated with camera m from the cluster average μ_n^k. This is repeated for every possible camera, cluster pairing (m, k). The cluster average μ_n^k varies as the members of the clusters change:

$$\mu_n^k = \frac{\sum_{m=1}^{M} \delta_m^k x_{mn}}{\sum_{m=1}^{M} \delta_m^k}, \qquad \forall n \in \{1, \dots, N\}, \forall k \in \{1, \dots, K\} \tag{8.4.3}$$

8.4.2 Methodology 2: Ordered Probit Model Results

See TABLE 4.2.1 for model results. The results suggest the installation of cameras at the intersections with high number of angle and turn crashes per AADT. Conversely, according to the model results, it is not recommended to install cameras at locations with already high number of rear-end crashes. This outcome agrees with the safety analysis, since cameras tend to increase the number of rear-end crashes. Moreover, locations with long cycle lengths or high number of lanes are more likely to succeed. On the other hand, places with a high crossing traffic, 2 sec. all-red duration (as opposed to 1 sec.) or with left turn bays would not be highly recommended, as these places tend to be safer in the first place.

TABLE 8.4.1 Ordered Probit Model Results for the Clusters

Variable	Coefficient	Std. Err.	z
Angle and Turn Crashes per 1,000 AADT	2.2220	0.9295	2.39
Rear-End Crashes per 1,000 AADT	-9.8201	2.4747	-3.97
AADT Crossing	-0.0207	0.0141	-1.47
Total Number of Lanes	0.0984	0.0729	1.35
2 Sec. All Red - Crossing Approaches	-0.7716	0.2278	-3.39
Cycle Length (sec)	0.0177	0.0076	2.35
Left Bay - Left Approach	-0.5891	0.3817	-1.54
Breakpoints			
Cut 1	-1.5075	0.6899	
Cut 2	-0.1303	0.6669	
Cut 3	0.1678	0.6689	

8.5 Northwestern University Transportation Center Red Light Camera Stakeholder Interview Guide

1. Your perceptions of current RLC program:
    a. Are you aware of Chicago's program of automated enforcement of red lights – red light cameras?

        [If not, explain: Chicago has deployed about XXX cameras at intersections throughout the city to capture red light violations by motorists, and issue traffic citations to owners of violating vehicles…]

    b. In your view, what are the purposes of the program?
        i. E.g., crash reduction, revenue raising, other
    c. Do you think the program works?
        i. For example, do you think it affects the number of intersection crashes?
        ii. Does it encourage people to obey traffic signals?
        iii. Are there side effects – negative or positive – resulting from the program?
            1. If so, what are they?
    d. Do you think the red light camera program is fair to drivers?
        i. What do you mean by "fair"?
    e. Is the program and process for ticketing transparent? That is, do people understand why it is there and how it works?
    f. For community groups and Aldermen only: Would you rank red light running among the top five most important problems in your community?
        i. If no, among the top 10?
    g. Have you ever gotten a ticket from a red light camera?
2. Your expectations, guidance for future red light camera programs:
    a. Do you think the current program should be continued or terminated?
        i. In either case, why?
    b. If you think it should be stopped, is there some alternative way to enforce red light rules that you would recommend?
        i. If so, why?
    c. If the program is continued, how should it be changed?
        i. No changes necessary
        ii. Change the targets? For example, cameras in different places, or turned on at different times of day
        iii. More or fewer red light cameras?
        iv. Make it more fair?
            1. How could we do this?
        v. Make it more transparent – understandable and understood by people?
            1. How can we do this?
        vi. Should the program make a profit for the City of Chicago?
        vii. Or should it be revenue neutral – just cover its costs?
3. Can you suggest other ways to make the red light camera program better?

4. Sometimes red light cameras reduce the number of the most severe intersection crashes (e.g., "T-bone") but increase the number of minor crashes (e.g., rear end). If the city-wide program eliminates 50 severe crashes per year, would you find it acceptable to have…

50 more minor crashes in a year?	Yes	no	maybe/not sure
How about 25 more minor crashes?	Yes	no	maybe/not sure
How about 75 more minor crashes?	Yes	no	maybe/not sure
How about 100 more minor crashes?	Yes	no	maybe/not sure

Automated speed enforcement is also a part of Chicago's traffic safety program, and we're interested in your views on that, as well.

5. Is excessive vehicle speed a serious problem in your community?
   a. Top 5? Top 10?
6. Are you aware of the speed camera program in Chicago (or elsewhere)?
7. Do you think that automated speed enforcement contributes to traffic safety? (speed reduction? Crash reduction?)
   a. Not at all b. A little c. A lot d. Don't know
8. Is the program fair to drivers?
9. Is the program and ticketing process transparent (understandable to drivers, citizens)?
10. What are your thoughts on the future of automated speed enforcement?
    a. Should it continue in some form?
    b. How should it change?
       i. Grow or shrink
       ii. Focus on high crash locations
       iii. Other changes
11. Are there additional comments you wish to offer?