**NOVEL METHODOLOGY FOR SAFETY AND ECONOMIC
EVALUATION OF RED-LIGHT CAMERAS AT SIGNALIZED
INTERSECTIONS**

by

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Abstract

Red-light running is a phenomenon that has led to frequent collisions causing fatalities, injuries, and property damage. Red-light cameras (RLCs) have been used in an attempt to reduce the frequency of these collisions. The main objectives achieved in this thesis are: (1) The site-selection bias of traditional methodologies were corrected by using a novel methodology (propensity score matching); (2) The fixed and random-effect panel regressions were utilized to account for the spatial and temporal correlations in the data; (3) The identification of how RLC effectiveness varies by site characteristics through the use of interaction terms; (4) The determination of spillover distances and times resulting from the presence of RLCs; (5) The benefit-cost methodology supported by economic analysis and sensitivity analysis using the novel methodology; and (6) The establishment of guidelines for effective implementation of the RLC treatment.

The research used field data from the City of Ottawa (Canada) involving 34 RLC intersections and 14 control intersections observed for the period 1999-2012. The results from this thesis indicate a consistent significant reduction in angle and turning movement collisions of 19% and 21%, respectively, and an increase in rear-end and sideswipe collisions of 12% and 6.7%, respectively. The magnitude and the direction of these effects are comparable to results of previous studies in the literature. The benefit-cost analysis, based on social costs of collisions avoided, the spillover effects and fine revenue, yielded an overall annual cost savings to the community of over \$4.4 million CAD across the 34 RLC intersections; with a benefit-cost ratio of 4.50. An extended cost sensitivity analysis was incorporated to quantify the robustness of the base-case conclusions.

RLC implementation decisions represent a major policy action, with serious repercussions for public safety. This thesis enhances such decisions by establishing effective implementation guidelines using rigorous, novel statistical analysis methods aiming to assist in this key policy effort. Furthermore, this thesis contributes to quantifying the RLC spillover effects as well as identifying critical road factors that the RLC treatment is likely to affect and benefit from. These contributions are all critical components of the traffic safety management process.

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List of Symbols

β_i = Coefficients quantifying the relationship between X and λ
 ε = Random error term
 λ = Expected number of collisions per year on a roadway segment
 τ = Impact of treatment
 Γ = Gamma
 ω = Intercept
AADT = Average annual daily traffic
ATE = Average treatment effect
ATT = Average treatment effect on the treated
BCR = Benefit-cost ratio
 D = Indicator of exposure to treatment
 $E(y_i)$ = Expected collision frequency at location i
EB = Empirical Bayes
FE = Fixed-effects
FENB = Fixed-effects negative binomial
GIS = Geographic information system
IPWRA = Inverse-probability-weighted regression adjustment
 L_i = A nominal (dummy) variable
MTO = Ministry of Transportation Ontario
NB = Negative binomial
NPV = Net present value
ZINB = Zero-inflated negative binomial
 $\hat{p}$ = Propensity score
PSM = Propensity score matching
RE = Random-effects
RENB = Random-effects negative binomial
RLC = Red-light camera
RLR = Red-light running
RTM = Regression to mean
SPF = Safety performance function
 x_i = Explanatory variable
 Y_{1i} = Potential outcome in case of treatment
 Y_{0i} = The potential outcome in absence of treatment
ZINB = Zero-inflated negative binomial
ZIP = Zero-inflated Poisson

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1. Introduction

1.1 Background

Traffic signals are intended to promote safe and efficient traffic flow at busy intersections. However, the level of safety achieved largely depends on drivers' compliance with the traffic signals. Red-light running (RLR) is a behavioural phenomenon that occurs when a motorist enters an intersection after the traffic signal light has turned red (FHWA, 2009). Research shows that many drivers routinely violate the red-light signals, placing themselves and other road users at risk for serious collisions (Retting *et al.*, 2007). In 2009, RLR caused 30% of the fatalities and 40% of the serious injuries at signalized intersections across Canada (Transport Canada, 2011). The problem of RLR is not limited to Canada, it is a worldwide phenomenon. In the United States, RLR resulted in 714 fatalities and an estimated 144,000 injuries in 2011 (IIHS, 2013a,b).

The social costs caused by traffic collisions are massive, and include property damage, insurance claims, hospital and health care costs, first responder costs (i.e. police, fire, and ambulance services) and traffic delays. The social cost of motor vehicle collisions in Canada in 2004 was estimated to be \$63 billion (Vodden *et al.*, 2007). According to the Ministry of Transportation Ontario (2007), fatal collisions account for less than 1% of reportable collisions in Ontario in 2004, but they account for 64% (\$11 billion) of the total social cost.

Implementing an effective safety countermeasure is critical in the overall safety management process. Several factors are considered when selecting a countermeasure, including the cost and its effectiveness in reducing specific collision types (e.g. rear-end, angle, night time, etc.) or severities. One of the key enforcement initiatives which has

been used increasingly over the past decade to assist and facilitate enforcement against RLR is red-light cameras (RLCs). A RLC is a type of traffic enforcement camera that captures an image of a vehicle which has entered an intersection in spite of a red-signal phase. Camera enforcement is intended to modify driver behaviour through both general deterrence and punishment of individual violators. Determining the effectiveness of a countermeasure is based on an accurate assessment of the cause-effect relationship between the countermeasure and the outcome. Therefore, it is important to: (1) utilize appropriate statistical methods, (2) identify factors that contribute to the collision occurrence and (3) assess the effectiveness of the countermeasure in preventing collisions.

1.2 Problem Definition

Important data and methodological issues have been identified in the literature regarding countermeasure effectiveness assessment. Studies have utilized different methodologies, different populations and different data sources which may lead to flawed collision frequency predictions and incorrect inferences relating to the factors that determine the frequency of collisions. Conducting a simple before-after study to assess effectiveness has an underlying limitation in that it is not possible to distinguish the regional effects from the intervention. Another limitation is failure to account for regression to the mean (RTM). RTM occurs when the extreme cases chosen in one period are likely to experience lower collision frequencies in the next period, and vice versa, because of random variation (FHWA, 2011). The presence of RTM can exaggerate the positive effects of a countermeasure. Issues of selecting control groups, which can be used to

address the RTM phenomena, and how the treatment and control groups are matched are not clearly outlined in the literature.

At the present time, there is a lack of clear guidelines to use when evaluating the decision to install RLCs at specific intersections. A series of issues related to RLCs addressed in this research have not been investigated in depth before, such as how effectiveness varies by site characteristics and under what conditions RLCs perform most effectively. The absence of important interactions of control variables can affect the accuracy and interpretations of estimations. In addition, ignoring possible spillover effects from the RLC to intersections without the countermeasure can lead to an underestimation of the true benefits. A comparison of results from the different statistical safety evaluation methods is needed in order to establish accurate estimations for assessing and evaluating the regional conditions necessary to make proper decisions on using RLCs as a safety countermeasure.

There is a need to analyze how the intersection characteristics influence the effects of RLCs, and identify the locations which have the most benefit from treatment. Most previous studies on RLCs usually report an average treatment effect, which neglects the fact that the effects of RLCs may differ systematically by intersection characteristics. It is desirable that the treatment is implemented in a way that maximises effectiveness. By revealing patterns of the RLC treatment effect, policy makers can assign RLC treatments to intersections most likely to benefit from the treatment, so as to improve the cost-effectiveness of intervention.

In light of these limitations, this thesis contributes to the field by developing a reliable assessment methodology using novel statistical methods to estimate the treatment

effect of RLCs at signalized intersections on road safety to help set guidelines for practical implementation.

1.3 Objectives

The main objectives of this thesis are: (1) to correct for the site-selection bias of traditional methodologies by using a novel methodology (propensity score matching); (2) to use the fixed-effect and random-effect panel regressions to account for the spatial and temporal correlations in the data; (3) to identify how RLC effectiveness varies by site characteristics by using interaction terms; (4) to measure spillover distances and times resulting from the presence of RLCs; (5) to apply benefit-cost methodology supported by economic analysis and sensitivity analysis using these new estimation methods; and (6) to establish guidelines for effective implementation of the RLC treatment.

RLC implementation decisions represent a major policy action, with serious repercussions for public safety. This thesis enhances such decisions by using rigorous statistical analysis to assist in this key policy effort. This thesis will contribute to more accurate estimation of the direct effectiveness of RLCs, quantifying their spillover effects, and identifying critical road factors which the RLC treatment is likely to have the largest effect on and would benefit the most. These contributions are all critical components of the traffic safety management process.

1.4 Scope of Work

The framework developed in this thesis addresses evaluation of safety and economic aspects of RLCs. To support this evaluation, collision data were collected from the City of Ottawa in Ontario, Canada for 34 signalized intersections as part of the RLC treatment group and for 14 non-RLC signalized intersections as part of the control group. The study

duration involved collision data from 1999 to 2013. Examining site selection criteria and its effects on safety was beyond the scope of this thesis. This thesis analyzes vehicle collisions only, pedestrian and cyclist collisions are beyond the scope of this research. The effectiveness of the RLCs were analysed in terms of reduction in the frequency of reported collisions by impact type and their associated collision costs by classification (severity). This thesis will not provide information on evaluating the effect of RLCs on RLR violation reduction due to the lack of detailed violations data from City of Ottawa localities.

1.5 Evaluation Framework

An evaluation framework was developed to guide the work towards achieving the objectives of this thesis. Figure 1.1 illustrates the different tasks of the framework. The first step was to conduct a comprehensive literature review to study safety at signalized intersections and the different evaluation methods conducted in assessing the effectiveness of the RLC programs. Based on the inconsistencies and deficiencies found in the literature review, the motivation and objectives of this thesis were established. Subsequently, data and information have been collected to develop a statistically based framework consisting of two streams: traffic safety and economic assessment.

As part of the analytical evaluation of the traffic safety assessment, data for control variables were obtained from different sources and aggregated at the same level to explore the various factors affecting the collisions and the RLC intervention. Some of the various factors collected included: a collision database, traffic characteristics, geometric characteristics, and cost data.

Figure 1.1 – Evaluation Framework

Next, observational analytical methods were utilized to examine the causal relationship between traffic interventions and traffic collisions. The three statistical observational methods applied were: cross-sectional studies, observational before-and-after studies, and case-control studies.

Results of the different evaluation methods were compared in order to evaluate the difference in the results when assessing the effectiveness of the RLC intervention. This comparison is done by quantifying the expected number of collisions has the intervention not been applied and comparing these results to the observed number of collisions in the post-intervention period. The number of collisions avoided were used in the economic evaluation.

The economic evaluation involved collecting data and information relevant to RLCs costs and social costs of collisions to assess the costs and performance of the RLC treatment. A monetary value was assigned to the cost of a collision based on its classification and a comparison between the expected number of collisions had the treatment not been implemented (i.e. derived from the statistical methods). The observed number of collisions that actually occurred with the treatment implemented provided the basis for the benefit-cost analysis of safety effectiveness. The purpose of the benefit-cost analysis was to determine the net societal benefits of the RLC intervention through an assessment of all benefits and costs associated with the operation of RLCs.

The ultimate goal was to provide a better understanding of the causal effects of the RLC intervention on road safety by utilizing appropriate evaluation methods. This led to developing guidelines for policy-makers when evaluating the safety outcomes of RLCs and hence improving the prevention of RLR collisions.

2. Literature Review

A comprehensive literature review was carried out to study research work performed in the field of RLC assessment related to the objectives of this thesis. The studies reviewed in this chapter covered safety at signalized intersections, enforcement against RLR, the impact of RLC programs, collision prediction modeling techniques, and economic effects of RLCs. The primary sources of literature reviewed were Accident Analysis and Prevention publications, Transport Canada reports, Traffic Injury Prevention publications, Institute of Transportation Engineers' publications, conference proceedings of the Transportation Research Board, the National Center for Biotechnology Information and City of Ottawa reports. This chapter is intended to highlight the latest available statistical methods used in treatment assessment and to identify the gaps and limitations in the literature related to the RLC safety assessment.

2.1 Safety at Signalized Intersections

Traffic signals are used to assign the right-of-way to vehicles passing through intersections so conflicting movements do not occur. There are 32 conflict points on a 4-legged intersection, as shown in Figure 2.1. Conflict points are locations in the mid-block or on the approaches to an intersection where vehicle paths merge, diverge, or cross and can lead to collisions.

While installing traffic signals at intersections can often improve safety and traffic flow, such intersections are often studied because they are the scenes of many devastating collisions. Some drivers run red-lights at intersections knowing that there is an all-red light phase before the new green light appears, and other drivers jump the green light or complete a left-turn on the yellow light, resulting in an intersection collision, often at

Figure 2.1– Intersection conflict points

high speed (Transport Canada, 2011). Figure 2.2 displays a visualization of some of the more commonly discussed collision impact types at signalized intersections due to their repeated occurrences and severities; angle collisions, turning movement collisions, rear-end collisions and sideswipe collisions.

Figure 2.2 – Common collision types at signalized intersections

Angle collisions at signalized intersections are seen as most relevant to RLR. They involve two vehicles traveling in perpendicular directions (two adjacent approaches) that collide with each other. Since traffic signals are intended to separate

conflicting movements, one of the vehicles involved in the collision would have had to have proceeded through on a red-signal. The frequency of angle collisions is therefore an indicator of a RLR problem occurring at an intersection. In 2014, there were 655 reported angle collisions at signalized intersections in Ottawa (City of Ottawa, 2016).

A turning movement collision occurs when a left-turning vehicle collides with an on-coming vehicle from the opposite direction; either vehicle may be the red-light violator. A RLR related collision may also occur when a left-turning vehicle strikes a vehicle proceeding through the intersection on an adjacent approach.

Rear-end collisions occur when a vehicle following the vehicle ahead collides into the back of the vehicle. Rear-end collisions are not the direct result of RLR but rather the result of vehicles stopping for a red-signal at an intersection while others behind them do not. By taking action to avoid a rear-end collision, a vehicle may sideswipe a second, adjacent vehicle.

Many sideswipe collisions happen when a driver overreacts to a road hazard. The initial sideswiping contact is normally just the beginning of a more serious vehicle collision. Most people assume that a sideswipe collision usually results in a minor collision involving minor damages to the vehicles and little to no physical injuries. However, they can lead to loss of vehicle control leading to a rollover or other potentially tragic results including severe physical injuries and even death. Seeing the different nature of collision impact types, it is more valuable to focus on target collisions than simply examining the total collisions when conducting causal analysis.

A report published by City of Ottawa (2012), identified that the peak times for angle, turning movement and rear-end collisions are all generally during daylight.

Another important finding is that the peak collisions for these three collision impact types all happen during clear weather conditions. Therefore, bad weather conditions and night time does not seem to be critical factors triggering collisions.

As for collision classifications, a study conducted by the Ministry of Transportation Ontario (2011) found that 19% of fatal collisions and 28% of personal injury collisions occur at intersections. Disobeying the traffic signal is involved in 41% of the fatal collisions and 28% of the injury collisions. This means that approximately 36 fatal collisions and 3,500 injury collisions occur in Ontario each year because of drivers running red-lights.

According to a comparable study in Quebec, RLR caused slightly more than 25% of traffic injuries at signalized intersections (Brault *et al.*, 2007). Another study in Alberta indicates that intersections on urban streets, where the speed limit is 60 km/hr or less, are particularly dangerous; accounting for 47% of all fatalities and 57% of those seriously injured (Alberta Justice and Solicitor General, 2014).

Legislation in Ontario requires that a traffic collision, which results in death, injury, or property damage to an apparent extent of \$1,000 or more, be reported immediately to the Registrar of Motor Vehicles as required under the Highway Traffic Act (Ontario Regulation 596) (Ontario's Regulatory Registry, 2015). An officer completes a standardized collision report form which provides information on various aspects of the traffic collision. This report is based on the data collected from these report forms and summarized by City of Ottawa staff. The collision database includes information regarding the date, time, type, classification, road surface condition, vehicle

type, vehicle maneuver, apparent driver action, road alignment and initial direction of travel date of each incident.

2.2 RLC Enforcement Against RLR

The purpose of the RLC is to increase safety at signalized intersections by reducing red-light violations and the resultant collisions attributable to RLR. When selecting a site for a potential RLC treatment, consideration is usually given to the potential of collision reduction (especially fatal and injury collisions), the geographic distribution, and consideration of alternative engineering countermeasures. Staff at the City of Ottawa has identified a set of site selection criteria, listed in Table 2.1, to be used in the selection of additional locations for the RLC program (Leclair, 2004). The City's first objective is to place RLCs at intersections where high numbers of angle collisions are taking place, since they result in severe type of collisions.

Once a site gets selected, the RLCs are connected to the traffic signal and to sensors that are installed in the pavement to detect vehicles. The sensors are designed to be activated only when the red-light signal is displayed for traffic proceeding in that direction. By having the loop detectors used only for the automated enforcement system, interference and conflicts with other detectors used for the traffic control system are avoided.

When the system is activated by a vehicle running a red light, two pictures are taken by the camera. The first picture shows that the front of the vehicle has just entered the intersection when the traffic signal is red. This picture must show the pavement marking defining the intersection (usually the stop bar or crosswalk), the traffic signal displaying a red-light, and the license plate of the vehicle in question (FHWA, 2009). The

Table 2.1 – Ottawa's RLC site selection criteria and process (Adapted from Table 2 of Leclair, 2004)

Step 1.	a) Review collision data for signalized intersections. b) List signalized intersections with highest frequency of serious angle type collisions. c) List signalized intersections with highest frequency of serious turn type collisions. d) Identify signalized intersections with highest frequency of collisions involving pedestrians and cyclists. e) List signalized intersections with highest frequency of rear-end type collisions.
Step 2.	Consult with Ottawa Police Services to determine intersections with highest issuance of Red-light running infractions and highest number of requests from public for Police Enforcement.
Step 3.	Review short-listed locations for possible alternate solutions involving intersection geometry, signal operation, signage prior to installing Red-light Cameras.
Step 4.	Review short listed intersections for physical suitability of Red-light Camera installation (presence of above and below ground plant in addition to driveways can preclude installation).
Step 5.	Review short listed intersections not deemed suitable for Red-light Camera enforcement for possible additional Police Enforcement.
Step 6.	Conduct ‘before’ Red Light running studies at short-listed intersections.
Step 7.	Select final locations for Red Light enforcement based on highest potential for collision reduction while attempting to achieve even distribution across the City of Ottawa.

second picture then shows the vehicle in the intersection a short time later (0.5 to 1.5 seconds). To be counted as a red-light violation, a vehicle's rear tires must have been positioned behind the crosswalk or stop line prior to entering on red (Retting *et al.*, 2007). Vehicles already in the intersection when the signal changes to red (i.e. when waiting to turn) are not counted as red-light violators. From the pictures taken, the license plate gets magnified to allow for identification. Therefore, the placement of the sensors is critical to the integrity of the RLC system and the citations developed from the photographic data.

At each camera location, only one of the typical four approaches to an intersection is usually monitored. Analysis is usually undertaken to determine the best intersection approach for RLC installation by using collision data supplemented with overall traffic volume data (Auckland Transport, 2011). If the numbers of collisions on each approach of an individual intersection are equal, then the RLC approach site is chosen based on the highest traffic volume during peak traffic times. Studies have found that collision risk

increases on high traffic volume roads as a result of fewer gaps where subsequently drivers take more risks (Auckland Transport, 2011).

Automated RLC enforcement has the advantage of being active 24/7 and therefore has a much greater deterrent effect than the occasional presence of a police officer. Manual enforcement methods are resource intensive and high risk, whereas RLCs can operate 24 hours a day and do not involve high-speed pursuits. However, one downside to automated enforcement is that a manned officer is often able to identify other serious violations at the scene of the collision, such as driving with a suspended license or drug/alcohol impairment.

RLCs are used extensively in many countries around the world including Australia, Austria, Belgium, Canada, Germany, Kuwait, New Zealand, the Netherlands, Singapore, South Africa, Switzerland, United Kingdom and the United States. In Canada, cameras are used in the Provinces of Alberta, British Columbia, Manitoba, Ontario, Quebec, and Saskatchewan (Shimizu and Desrochers, 2015).

Seven Ontario municipalities (including Ottawa) have an existing joint contract with the vendor Traffipax for the installation, operation and maintenance of every RLC in the province. The last contract expired at the end of 2016 but through a recent procurement process, Traffipax was again chosen as the successful vendor for the next contract that began on January 1, 2017. This new contract is for a 5 year-period with an optional extension to 10 years (Keech, 2016).

2.2.1 Impact of RLC Programs from Previous Research

The success of an RLC program in a district is measured by the reduction in the number of fatalities and serious injury related collisions. Since it is not economically feasible nor

technically necessary to install RLCs at all signalized intersections, careful consideration must be taken when assessing the effectiveness of the installed RLCs and their effect on surrounding non-RLC intersections.

Numerous evaluations have been conducted to examine the various effects of RLCs on traffic safety. There is a large debate over whether RLCs actually make the roads safer, and whether the methods used to analyze their safety are suitable. Synectics Transportation Consultants (2003) evaluated the RLC enforcement program along with stepped-up police enforcement in Ontario, Canada. Forty-eight sites distributed throughout six municipalities were selected for the safety evaluation and benefit-cost analysis. An additional set of 12 local control intersections were selected. Collision data at the 48 sites were reviewed for a five-year period prior to the implementation of the RLCs and compared to collisions occurring during the first two years of the pilot project, using the empirical Bayes (EB) method. The study indicated that the two RLC countermeasures were effective at reducing angle collisions at the expense of rear-end collisions. Fatal and injury angle collisions decreased 25.3% while property damage only angle collisions decreased 17.9%. However, there was an increase in rear-end collisions. Fatal and injury rear-end collisions increased 4.9% while property damage only rear-end collisions increased 49.9%. Despite the increase in rear-end collisions, it was felt that as a whole the pilot project had been a success. It was estimated that a total of 47 fatal and injury collisions had been avoided as a result of the pilot project among the study sites.

However, one limitation is that this evaluation study cannot make any claim to the effectiveness of the RLCs on their own. This study involved an evaluation of the effectiveness of two treatments combined (RLCs and stepped-up police enforcement), as

well as a publicity campaign. It is not possible to isolate the effect of the RLCs from the stepped-up police enforcement deployments and the publicity campaign. All the results presented in this study represented the combined effect of the treatments.

More recent statistics from several cities across Canada present results indicating that the number of collisions caused by RLR has been on the decline after installation of RLCs. Toronto has 77 active RLCs and the number of angle collisions causing fatalities, personal injuries, or property damage has reduced more than 60% (City of Toronto, 2017). The Region of Waterloo has 16 active RLCs and the numbers of angle collisions and turning movement collisions caused by disobeying traffic signals have decreased by 27% and 60%, respectively (Region of Waterloo, 2010). However, the Region of Waterloo also saw a 23% increase in rear-end collisions. Saskatoon has four active RLCs in the city and there has been a 9% reduction in injury and fatality rates at intersections with cameras, as well as a 12% decrease in right-angle collisions (City of Saskatoon, 2014). Calgary has nearly 40 intersection safety cameras (which track both RLR and a driver's speed at green lights). Between 2000 and 2013, total collisions at camera intersections decreased by 7% and fatal collisions decreased by 100% (Calgary Police Service, 2013).

Two meta-analysis reviews of before-after implementation of RLC studies have been conducted for intersections from around the USA (Aeron-Thomas & Hess, 2005; Erke, 2009). Both reviews highlighted the failure of most studies to control for RTM and spillover effects, which are likely to overestimate and underestimate the collision reduction effects of RLCs respectively (Erke, 2009). Erke concluded that *“RLCs may reduce collisions under some conditions, but on the whole RLCs do not seem to be a*

successful safety measure” and suggests longer yellow phases should be investigated. Aeron-Thomas & Hess (2005) concluded that the RLCs are effective in reducing total casualty collisions at signalised intersections.

Erke (2009) found that RLCs do not seem to be a successful safety measure. This study found that the installation of RLCs had non-significant effects on the number of collisions by conducting a meta-analysis of 21 studies from mostly the USA and Australia over the period of 1996 to 2007. Results of the analysis found that overall collisions increased by 15%, rear-end collisions increased by about 40% and right angle collisions reduced by about 10%. It concluded that poor handling of RTM and spill-over effects was a key bias present in each previous study where collision reductions associated with the RLCs were identified.

Obeng and Burkley (2008) considered only rear-end collisions in a study and found that changes in driver behaviour when drivers see RLCs indeed offsets the advantages of RLCs by increasing rear-end collisions. Rear-end collisions result from non-uniform changes in driver behavior. Authors caution that limitations of the study design fail to account for changes in other types of collisions (notably decreases in right angle collisions) and that the generalization of these results to other cities may not be appropriate. Also, this study did not investigate whether such offsetting behaviour is time dependent and dissolves as time goes by and drivers become accustomed to the presence of RLCs.

In Queensland, Australia, a study of combined speed and RLC enforcement at intersections stated that there was an overall statistically significant collision reduction of 42% (Newstead & Cameron, 2012). In contrast, changes in rear-end collisions and all

other collision types were not statistically significant. Another study of combined speed and RLC enforcement by Budd *et al.* (2011) studied the effect of RLCs at 77 intersections in Victoria, Australia and quantified their effect on specific intersection approaches. The results showed that the estimated collision reduction was 47% when only the collisions involving vehicles travelling from the approach intersection leg where the camera was placed are considered. When collisions involving vehicles from all approaches are compared, the estimated collision reduction was 26%. A distinction according to the collision type resulted in a significant decrease of 44% in angle and turning movement collisions and a 37% reduction in severe injury/fatal collisions of all types was estimated. There was no statistically significant estimated change in rear-end collisions suggesting the addition of speed enforcement to the RLR enforcement could be responsible for the lack of observed increase in rear-end collisions.

A study by Garber *et al.* (2007) specifically analyzed collisions caused by RLR, where most of the other studies used the broader category of all angle collisions, regardless of the cause. Using EB analysis, Garber *et al.* found no significant change in RLR collisions at RLC sites. A possible explanation is that the majority of RLR collisions result from unintentional, rather than intentional, RLR. For example, when intentional RLR occurs immediately after the signal changing to red, cross traffic has not been released and the likelihood of a collision is low. In contrast, unintentional RLR is hazardous because cross traffic can be in the intersection when the infraction occurs. The failure of RLCs to reduce RLR collisions is consistent with collisions occurring from unintentional RLR. Further, the Garber *et al.* (2007) study reveals that angle collisions

are not a good proxy for RLR collisions since they found that RLR collisions did not significantly change at RLC sites, whereas angle collisions increased.

Estimates of the safety effect of RLCs varied considerably according to the research design and study methodology. A summary of further relevant study findings is provided in Table 2.2. The bulk of the results supports a conclusion that RLCs reduce angle collisions and could increase rear-end collisions; however, most studies are tainted by methodological difficulties that raise questions about any conclusions obtained.

Failure to account for RTM can exaggerate the positive effects, while ignoring possible spillover effects at intersections without RLC will lead to an underestimation of RLC benefits, even more so if sites with these effects are used as a comparison group. The spillover effect is the expected effect of RLCs on intersections other than the ones actually treated, resulting from jurisdiction-wide publicity and the general public's lack of knowledge of where RLCs are installed (AECOM, 2014). Almost all studies had one or the other of these flaws and many had both, in addition to other flaws such as not accounting for changes in traffic volume.

Table 2.2 – Effectiveness of RLCs from previous studies

No.	Author & year	Location of study	Data	Methods	Main Findings
1	Retting & Kyrychenko (2002)	California, USA	11 RLC sites 29 months before and 29 months after Years: 1995 to 1999	Generalized linear regression model	7% reduction in total collisions 32% reduction in total right angle collisions 3% increase in total rear-end collisions 29% reduction in injury collisions 68% reduction in injury right angle collisions
2	Synectics (2003)	Ontario, Canada	19 red light camera sites 17 stepped-up police enforcement sites 12 local comparison sites. Years: 2000 to 2002	Empirical Bayes	6.8% decrease in total injury and fatal collisions 18.5% increase in total PDO collisions 25.3% decrease in fatal and injury angle collisions 4.9% increase in injury and fatality RE collisions 49.9% increase PDO RE collisions
3	Burkey & Obeng (2004)	USA	303 intersections 57-month period	Poisson and NB regression models	40% increase in total collisions 40 to 50% increase in PDO and injury collisions
4	Council <i>et al.</i> (2005)	USA	132 sites (7 jurisdictions) Years: 3 before and 1.5 after	Empirical Bayes	25% reduction in angle collisions 15% increase in rear-end collisions
5	Garber <i>et al.</i> (2007)	Virginia, USA	28 intersections with cameras and 44 without Several jurisdictions. Years: 1998 to 2004	The paired t-test, ANOVA, GLM, Empirical Bayes method	8% to 42% reduction in red light running collisions 27% to 42% increase in rear-end collisions
6	Sayed & de Leur (2007),	Alberta, Canada	25 intersections Before Period: 3 years After Years: 2-3 years	Empirical Bayes	11% reduction in total collisions 17% reduction in angle collisions 12% reduction in rear end collisions 6% reduction in severe collisions 14% reduction in PDO collisions
7	Shin & Washington (2007)	Arizona, USA	24 RLC intersections	Empirical Bayes	20%-42% reduction in angle collisions 10%-45% reduction in left turn collisions 41%-51% increase in rear-end collisions

8	Guerin (2010)	New Mexico, USA	20 RLC intersections Years: 2004 to 2010	Before and after with comparison group and EB method	3.1% increase in total collisions 5.1% reduction in injury collisions 8.3% increase in PDO collisions
9	Auckland Transport (2011)	New Zealand	20 RLC intersections Years: less than 1 year	Before- and after study	69% reduction in total RLR collisions 43% reduction in RLR collisions 32% reduction in rear-end collisions 93% reduction in the social cost of collisions
10	Budd <i>et al.</i> (2011)	Victoria, Australia	87 RLCs 10,245 collisions on 1189 intersections Years: 2000 to 2009	Before-after and Poisson regression	47% reduction in total collisions RLC approach 26% reduction in total collisions all approaches 37% reduction in severe injury/fatal collisions 44% reduction in angle collisions
11	De Leur (2011)	BC, Canada	120 RLC intersections Years: 3 years after	Regression & Empirical Bayes	14% reduction in injury collisions 18 months after program 6.4% reduction in injury collisions 36 months after program
12	Hu <i>et al.</i> (2011)	USA	14 RLC intersections Years: 1992 to 2008	Before and after with comparison group	24% reduction in fatality collisions
13	Solomon (2011)	Hamilton, Ontario	12 RLCs at 15 intersections Years: 2000 to 2010	Before and after study	41% reduction in angle collisions 10% increase in rear-end collisions
14	Vanlaar <i>et al.</i> (2011)	Winnipeg, Manitoba	48 RLC intersections Years: 2010	Multivariate logistic regression	46% reduction in angle collisions 42% increase in rear-end collisions
15	Newstead & Cameron (2012)	Queensland, Australia	142 RLC intersections Years: 2008	Poisson, NB & Empirical Bayes models	23% reduction in all collisions 24% reduction in fatal and hospitalisation
16	Høye (2013)	USA	28 studies	Various (meta-analysis)	33% reduction in angle collisions 19% increase in rear-end injury collisions 39% increase in rear-end collisions
17	Ko <i>et al.</i> (2013)	Texas, USA	245 intersections	Empirical Bayes	20% reduction in total collisions 24% reduction in angle collisions 37% increase in rear-end collisions

18	AECOM (2014)	Alberta, Canada	76 RLC intersections 141 non-RLC signalized intersections 37 un-signalized sites	Empirical Bayes	8.4% reduction in total collisions 37.7% reduction in right-angle collision 32.4% reduction in severe collisions 7.7% increase in rear-end collisions 1.4% increase in PDO collisions
19	Boudreaux (2014)	Florida, USA	Years: 2010 to 2011	Poisson and NB regression	1.3% reduction in total collisions 46% decrease in fatal collision
20	De Pauw <i>et al.</i> (2014)	Belgium	Combined speed and red light cameras at 253 intersections Years: 2002 to 2007	Before- and after study with control for the trend	5% increase in injury collisions 14% reduction in severe collisions 6% reduction in side collisions 44% increase in rear-end collisions 12% reduction in right-angle collision
21	Lord & Geedipally (2014)	Chicago, USA	90 RLC intersections 56 non-RLC intersections Years: 3 yrs before 3 yrs after	Empirical Bayes	5% increase in total injury collisions 15% reduction in angle and turning injury collisions 22% increase in rear-end injury collisions
22	Currie & Basak (2015)	Toronto, Ontario	77 RLC intersections Years: 2007 to 2014	Before- and after study	40% reduction in angle (fatal) collisions 27% increase in rear-end (PDO) collisions 14% reduction in rear-end (injury) collisions 19% reduction in PDO collisions 37% reduction in injury collisions
23	Keech (2016)	Kingston, Ontario	10 RLC intersections Years: 2016	Before- and after study	25% reduction in angle collisions 15% increase in rear-end collisions
24	Cohan (2017)	Delaware, USA	30 RLCs intersections Years: 3 yrs before 10 yrs after	Before- and after study	6% increase in total collisions 47% reduction in angle collisions 9% increase in rear-end collisions 24% decrease in red-light running collisions
25	Mahmassani <i>et al.</i> (2017)	Chicago, USA	151 RLC intersections Years: 2008 to 2009	Empirical Bayes	10% reduction in total collisions 19% reduction in angle collisions 14% increase in rear-end collisions

2.2.2 Spillover Effect and Collision Migration

It is important to find out whether RLCs affect the safety performance only at the specific intersections at which RLCs are installed, or if their presence influences the behaviour of drivers in general. RLCs can improve safety at other signalized intersections, not equipped with RLCs, by creating a general deterrence of signal violation leading to collision reductions (Christie *et al.*, 2003). Figure 2.3 illustrates this type of behavioural influence, where drivers carry over their careful behaviour from RLC intersections to non-RLC intersections, referred to as spillover or halo effect.

Figure 2.3 – Spillover effect

On the other hand, RLCs implemented at a particular location may be followed by a migration of collisions to adjacent intersections. Crash migration is the phenomenon that the collision frequency or collision severity apparently rises at the untreated sites adjacent to treated sites as a result of the treatment (Shen & Gan, 2003). There are two mechanisms speculated by which collisions might increase at other locations due to site-specific RLC enforcement: (1) If the enforcement zone is widely known, motorists may

decrease speeds near the intersection sites, perhaps abruptly, and increase their speeds before or after the treated intersections to make up for lost time. (2) Drivers may choose alternate routes to avoid treated intersections, and therefore, collision frequencies at treated sites may decline and move to the surrounding intersections. Safety assessments should be performed to individual intersections within a roadwork to help avoid missing potential system-wide effects.

Therefore, the examination of collisions at surrounding intersections can help determine the true effect of RLCs. The spillover effect does not happen immediately, as the connection to the public consciousness through violation notices, signage at RLC sites, word-of-mouth and through formal and informal media takes a significant period of time (Solomon, 2011) . Wilson *et al.* (2006) defines a time-halo as the length of time an effect of enforcement is present after detection devices have been installed. The distance-halo is the distance from the point of enforcement that the decrease in RLR continues. Time and distance-halos should be computed to investigate the local and widespread effects of an enforcement.

Studies reporting halo effects varied in terms of location, duration of intervention, data collection and measurement. The distance halo of stationary policing appears to be in the range of 1.5 miles (2.4 km) to 5 miles (8 km) from the enforcement site (Elliott and Broughton, 2005).

Distance-halos of speed cameras have been reviewed in the literature, yet no research has been conducted related to RLCs. Studies indicate that 500 m is about the maximum distance halo of a speed camera (Elliott and Broughton, 2005; Champness and Folkman, 2005). Mountain and Fawaz (1992) used 500 m as a limit for selecting the sites

surrounding automated speed cameras and concluded that crash migration did occur because of treatment and that the area of influence varied with time and distance from the treated site. However, there was no explanation in the report as to why the distance of 500 m was chosen. Keenan (2002) also looked at 500 m before automated speed cameras and 500 m after. The study found that by 500 m after passing a speed camera mean speeds increased to the same levels they were 500 m before the camera. At these points, around 80% of drivers were exceeding the speed limit. This finding is consistent with previous research by Nilsson (1992) who also found that the distance halo effect due to speed cameras was 500 m. However, no published studies evaluating distance halos for RLCs were found.

A study by Malone *et al.* (2010) found that the possible spillover effects of the RLC program in Alberta, Canada demonstrated a moderate, yet significant, effect on angle collisions based on trend analysis. Collisions at non-RLC equipped signalized intersections were found to significantly decrease by 8.6% in the after-period, representing a reduction of 25 right angle incidents. Another study in Alberta, Canada (AECOM, 2014) separated the spillover effect of RLCs and determined that the effect was significant across the entire series of jurisdictions studied. That is, there was a significant safety impact on intersections without RLCs. However, no specific spillover distances were mentioned in the report.

Studies on the effectiveness of speed camera enforcement in Fairfax, Virginia, Oxnard California, Scottsdale, Arizona, and Cambridgeshire, UK also found evidence of spillover effects (Retting & Kyrychenko 2002; Shin & Washington 2007; Hess 2004; Erke, 2009). Although there is some evidence of a spillover effect, some studies indicate

no such effect was found (Hillier *et al.*, 1993, Garber *et al.*, 2007). Specific time and distance-halos resulting from the RLC treatment have not been discussed in the literature and need further investigation.

2.3 Statistical Modeling of Safety Performance

Accurate estimation of countermeasure effectiveness is critical in transportation safety. Analytic methods are usually utilized to attempt to quantify the effect of an intervention on an outcome. This thesis focuses on observational methods, since there was no involvement from the researcher on the use or change of the RLC intervention. Three commonly used observational methods to determine the effectiveness of traffic safety countermeasure are cross-sectional regression studies (e.g. negative binomial (NB)), observational before-after studies (i.e. EB), and case-control studies (i.e. propensity score matching) (Sasidharan & Donnell, 2013).

Traditional cross-sectional studies are known as prevalence studies and do not have an inherent temporal dimension. These studies evaluate subjects at one point in time. Observational before-after are usually retrospective studies where they look back in time to examine causal associations. Case-control study designs are also retrospective and assess the history of the subject for the presence or absence of an exposure. It is important to recognize the strengths and limitations associated with the various methods to help identify a suitable method given the constraints of each specific evaluation. Table 2.3 summarizes the strengths and limitations of each method used to analyze observational data in traffic safety. The application of these methods will be discussed further in the next chapter.

Table 2.3 – Methods used to analyze observational data in traffic safety

Analytic approach	About the method	Strengths	Limitations
Cross-sectional	Is a type of regression in which the explained and explanatory variables are associated with one point in time.	<ol style="list-style-type: none"> 1. Produces specific coefficients for each individual confounder which allows examination of these specific effects on the outcome. 2. Useful when the before period data are not available; data exhibits over-dispersion; or, the countermeasure installation date is unknown. 	<ol style="list-style-type: none"> 1. Not useful for rare events because in a one-time snapshot (rare outcomes or rare exposures may not be captured) . 2. Does not permit distinction between cause and effect.
EB	Uses a control group to estimate a safety performance function (SPF). A SPF is used in combination with observed “before” collisions at the treated sites to predict the number of collisions that would have been expected in the after period for the treated entities had the treatment not been implemented. This prediction is then compared to the expected number of collisions in the after period with the treatment.	<ol style="list-style-type: none"> 1. Mitigates regression-to-the-mean (RTM) bias. 2. Accounts for differences in traffic volume and collision trends between the before and after periods at the treatment sites. 	<ol style="list-style-type: none"> 1. Large sample sizes and long follow-up periods (years of data) are necessary. 2. No guidelines exist concerning how to most effectively select the group of reference sites for developing SPFs. 3. The statistical significance of observed changes cannot be evaluated.
Case-control	Match an untreated group to the treated group such that the matched group is comparable to the treated group in all aspects of characteristics except the treatment. The observed outcome for the matched group can then be used as the counterfactual, and the treatment effect is estimated simply as the difference between the average outcomes of the two groups.	<ol style="list-style-type: none"> 1. Feasible method for studying rare outcomes or those with long lag between exposure and outcome. 2. Identify possible predictors of outcome and are useful for studying rare outcomes. 	<ol style="list-style-type: none"> 1. Only adjusts for measured confounders. 2. Balancing all the variables across strata can be hard to achieve.

With traditional cross-sectional data not much can be inferred about intra-individual change over time. When all variables are measured at the same time point, it is frequently not possible to establish whether causal influence occurs. In addition to the various statistical models and estimation tools available for count data, such as Poisson estimation and NB regressions, further advancements have been made to improve the statistical models by using panel count data (Yaacoub *et al.*, 2011).

When dealing with panel type data of traffic collision counts, for example, both collision frequency and severity often have observations that are in close spatial or temporal proximity (data from the same geographic region or data collected from the same observational unit over successive time periods). All data are likely to have unobserved factors that may influence the frequency and/or severity of collisions and, because these unobserved factors are likely to be correlated over space and time (Mannering and Bhat, 2014). Ignoring the spatial and temporal correlation of data will most likely result in inefficient and possibly inconsistent parameter estimates. Examples of such unobserved factors could be pavement irregularities that may not be observed but may extend over time or space, climate effects that may result in reduced pavement friction over time and space, local sight-distance restrictions that again may extend over time and space.

To account for these spatial and temporal correlations, random-effects (RE) and fixed-effects (FE) regression models can be considered. These models were first examined by Hausman *et al.* (1984). Random-effect models are used where the common unobserved effects are assumed to be distributed over the spatial/temporal units according to some distribution and the shared unobserved effects are assumed to be uncorrelated with explanatory variables. With count data, a suitable model distribution may be a random-effects negative binomial (RENB) regression.

Fixed-effect models are used where common unobserved effects are accounted for by indicator variables and the shared unobserved effects are assumed to be correlated with independent variables. A FE model examines if intercepts vary across group or time

period, whereas a RE model explores differences in error variance components across individual or time period (Park, 2011).

These modeling approaches have several advantages over cross-sectional models, particularly, for their ability to account for heterogeneity in the data (Yaacoub *et al.*, 2011). It is important to determine whether there are genuine differences underlying the results of the studies (heterogeneity), or whether the variation in findings is due to random error or chance alone (homogeneity) (Higgins *et al.*, 2003).

Previous work on panel count models in traffic collision analysis applied both FE and RE models, as suggested by Hausman *et al.* (1984). Fixed-effect models have been studied by a number of researchers including Eisenberg (2004) who examined the relationship between precipitation and traffic collisions in 48 contiguous states in the US using a FENB model for the period of 1975 to 2000. Karlaftis and Tarko (1998) employed FE Poisson and FENB to develop a collision model based on 6-year collision data set for urban and suburban arterials of 92 counties in Indiana. Noland (2003) also used the FENB models to study the impacts of roadway infrastructure improvements on fatal and injury collision frequencies based on the aggregate state-wide and county-level data.

Shankar *et al.* (1998) first developed a random-effects negative binomial (RENB) model to investigate the impacts of geometric and traffic factors on median crossover collision frequency in Washington State. Random-effects models have also been studied by a number of other researchers including Johansson (1996) who studied the effect of a lowered speed limit on the number of crashes on roadways in Sweden. Miaou *et al.* (2003) used RE in the development of collision-risk maps in Texas. However, no

research has been conducted utilizing the FE and RE models to assess the treatment effects of RLCs on the different traffic collision impact types.

Many studies that aim to estimate the effect of a treatment using the basic NB method and the EB method suffer from selection bias, where the units who receive the treatment may have different characteristics from those in the control group. These pre-existing differences between the groups must be controlled to obtain approximately unbiased estimates of the effects of interest. It is crucial to try to separate out the causal effect of the treatment from the effect of these pre-existing differences between the treated and control groups. However, in previous research, not only is there insufficient justification of the selection of control groups, how the treatment and control groups are matched is also unclear.

Given the limitations associated with the EB and cross-sectional methods, alternative evaluation methods are needed to estimate the safety effectiveness of the RLCs. The propensity score matching (PSM) method has become a popular approach to estimate causal treatment effects by modeling the relationship between the covariates and the treatment assignment. The PSM approach is used to tackle the critical issue of choosing an appropriate control group to evaluate the effect of RLCs on the reduction of road collisions. What makes the PSM method attractive is that it gives a clear criterion, the propensity score, by which to select the control group. The PSM method has been widely used in the multiple fields, such as medicine (Stone *et al.* 1995; Gum *et al.* 2001; and Akematsu *et al.* 2012), communications (Kincaid 2009), economics (Lechner 2002), and policy evaluation (Harknett 2006).

PSM is a relatively new method that has had few applications in traffic safety. One of first applications of propensity scores in traffic safety research (Davis, 2000) argued that the selection mechanism for the treatment should be included as a part of a traffic safety evaluation. It suggested that, when this does not occur, both EB and cross-sectional analysis methods become inconsistent with the true outcome. Other applications of propensity scores in traffic safety include estimating child safety restraint effectiveness (Elliott *et al.*, 2009), estimation of design exception safety impacts (Wood & Porter, 2013), safety effects of intersection lighting (Sasidharan & Donnell, 2013) and assessing the impacts of speed cameras on safety (Li *et al.*, 2013). Though widely implemented in diverse disciplines and in many contexts, to the best of the authors' knowledge, it remains untried in RLC safety research by traffic management scholars. It should be considered as an additional tool available to investigators when estimating treatment effects in studies where potential bias may exist.

The overall objective of the PSM method is to replicate a randomized experiment in two ways: (1) by comparing treated and control units that look as if they could have been randomly assigned to treatment or control groups; and (2) by forming the comparison groups without the use of the outcome, thus preventing intentional or unintentional bias in selecting a particular sample to achieve a desired result.

The primary objective of a treatment evaluation is to confirm and quantify the treatment effect. Although important, the final result is usually a conclusion with respect to the average treatment effect on the entire study population. However, treated units may not be different from the untreated units when examining the overall study population, but treatment may still be better for a subset of the population. Identifying the treatment

and covariate interactions may provide valuable information for determining this subgroup of the population. In the traffic studies reviewed in the literature review, interaction terms were not explored related to the RLC effectiveness. Therefore, adding interaction terms to the statistical models can greatly expand understanding of the relationships among the treatment and road factors. Interaction terms are used to test how a dependent variable changes when an independent variable changes conditional on the presence or magnitude of another independent variable (Drichoutis, 2011).

2.4 Economic Effect of RLC

The annual operating financial cost of the RLCs in Ottawa is estimated at around \$30,000 to \$35,000 per camera (Foote, 2016). This cost includes monthly payments to the vendor (Traffipax) for the installation, operation and maintenance of the cameras, and payments to the City of Toronto processing centre (once per year) and the Ministry of Transportation Ontario (four times per year) for vehicle ownership information.

No current benefit-cost reports were published assessing the effectiveness of RLCs in Ottawa. The only public report found analyzing Ottawa's RLC program was from 2003 (Synectics, 2003), which estimated a benefit-cost ratio of 1.57, where the net benefits in collision reductions exceeded the operating costs. This study, however, cannot make any claim to the effectiveness of the RLCs on their own as this evaluation study involved an evaluation of the effectiveness of RLCs with stepped-up police enforcement as well as this was a combined result from other cities from around Ontario.

A review was conducted of the economic effects of RLCs from other cities in Canada with a similar RLC programs to Ottawa. The RLC program in the city of Toronto also started in 2000 and currently comprises 77 RLC intersections. Since 2007, angle

collisions resulting in fatality/injury and property-damage have decreased between 19% and 40%. Net revenues generated through the program are approximately \$11,500,000 and associated societal cost savings have been estimated at over \$58 million (City of Toronto, 2015).

Several other studies have shown a reduction in both the injury severity and cost of collisions when comparing the results of the before and after installation periods for RLCs. A study of 132 RLC intersections from across seven jurisdictions in the USA showed a total reduction in right angle collisions of 24.6%, a reduction in right angle injury collisions of 15.7%, a total increase in rear-end collisions of 14.9%, an increase in rear-end injury collisions of 24.0%, and a total crash cost savings of \$38,000 per RLC intersection per year (Council *et al.*, 2005). The jurisdictions chosen for this study were El Cajon, San Diego, and San Francisco, CA; Howard County, Montgomery County, and Baltimore, MD; and Charlotte, NC.

A study in Phoenix, AZ by Washington and Shin (2005) found the installation of RLCs effectively reduced the total amount of angle collisions by 14% and increased the rear-end collisions by 20% at 10 RLC intersections. The total number of collisions was essentially unchanged as a result of the RLCs. The expected safety net benefit was calculated at \$4,504 per year (for the 10 target approaches). There was a relatively large variability in the benefit from RLCs across Phoenix intersections, with several intersections that revealed a negative expected benefit.

The Washington and Shin (2005) report also studied the effectiveness of RLCs in Scottsdale, AZ which showed a reduction in angle collisions by 20% and increased the rear-end collisions by 41% with RLCs for 14 sites. The total number of collisions were

slightly reduced by about 11%. The expected net safety benefit at the 14 target approaches was estimated at \$684,134 per year where the RLCs in Scottsdale contributed more to decreasing fatal and injury angle and left-turn crashes than to decreasing the PDO crashes of those crash types.

The implementation of RLCs in Missouri, USA reduced overall angle collisions by 11.6%, whereas rear-end crashes increased by 16.5%. The net economic collision cost benefit of the implementation of RLCs was \$35,269 per site per year in 2001 dollars (approximately \$47,000 in 2016 dollars). Thus, RLCs produced a sizable net positive safety benefit that is consistent with previous statistical studies (Boris & Carlos, 2016).

An evaluation of RLC enforcement in Fairfax County, Virginia conducted by Ruby (2001) concluded that the reduction of collisions saved \$12.8 million over the eight-year life cycle of the system.

A report by Chen *et al.* (2012) presents results of an evaluation of RLCs conducted between July 7 and August 8, 2010 in the Perth, Western Australia. The results found that the RLCs significantly reduced all reported collisions; angle, turning movement, rear-end and serious injury collisions by 19%, 41%, 20% and 72%, respectively. After accounting for the initial project costs of \$1.65 million (\$150,000 per site) and operating and maintenance costs, the net cost savings to the community were estimated as \$2.29 million. This is the equivalent of a benefit-cost ratio of 1.8.

In addition to collision reductions, other possible benefits or costs of implementing safety programs are changes in delays at intersections, resulting in effective increases or reductions in road capacity. These changes affect travel times for

roadway users and should be counted properly in benefit-cost ratios. Other benefits include reduced fuel use as well as reduced pollution from vehicle emissions.

2.5 Limitations Identified in the Literature

The methodologies used to assess the effectiveness of RLC programs have varied, as have the conclusions drawn from the different reviewed studies. Many safety-related factors such as traffic volumes and approach speeds are uncontrolled during the periods of observation. It is important to identify the geometric and operational characteristics of intersections that could adversely affect the safety impacts of RLCs. The existence of a causal link between the RLC enforcement and road collisions remains unclear.

The lack of formal causal models makes it difficult fully to address issues such as confounding effects and RTM bias. RTM is a statistical phenomenon that may occur when the extreme cases chosen in one period are very likely to experience lower collision frequencies in the next period, and vice versa, because of random variation (FHWA, 2010). Simply stated; the highest get lower and the lowest get higher. Two key factors that together may allow this to occur are that the initial data set must be small, and that the data within this sample must be unrepresentative of the population by chance (Auckland Transport, 2011).

While the EB method has been used to account for the RTM effect, the validity of the EB approach relies heavily on the availability of an appropriate reference group. There is insufficient justification of the selection criterion and how the treatment and control groups are matched in the literature, thereby making the estimator inconsistent (Davis, 2000). Also, the EB approach requires a large sample size of data pertaining to all

types of intersections for developing SPFs required for the EB-adjusted collision frequency estimation.

Traditional cross-sectional data and methods applied in the literature ignore the spatial and temporal correlation of data which can result in inefficient and possibly inconsistent parameter estimates when assessing the RLC effectiveness. This thesis is an attempt to overcome these limitations by setting up spatial panel data and applying statistical methods to accommodate the nature of the data.

Another limitation in the literature is that most studies that have assessed the effectiveness of RLCs have conducted their analysis for an after period which is usually fairly close to installation of the cameras. It is not well understood if the cameras have the same impact over time. In some cases, countermeasures become less effective over a long period time because drivers become accustomed to the treatment. On the other hand, enforcement may be more effective over time. Drivers who speed or run red-lights may change their behavior when they or someone they know receives a ticket. Therefore, the evaluation of traffic safety interventions often requires the collection of time series data so that a meaningful change in the series will likely be detected.

Furthermore, the existing literature is vague about the existence of spillover effects, as it fails to provide a range of magnitudes regarding distance and time-halos to help determine the local and widespread effects of the RLC enforcement. More research is needed to shed light on spillover effects of RLC programs.

Another limitation observed in most studies was that evaluations were performed city wide, hence it is not possible to evaluate or comment on the effectiveness of

treatments at specific intersections. There is a need to more clearly evaluate the program on an individual RLC site basis.

As part of the economic analysis assessments, due to the wide variety of the collision costing methods, data accuracy, availability and the interests of the agency examining collision costs, there is a wide range in the values that have been generated for collision costs. Values can vary from a low of approximately \$1 million to a high of nearly \$20 million for a fatal collision (De Leur, 2010). Estimated collision social costs have not been challenged in the economics literature. Conducting sensitivity analysis will present the effect of varying the assumptions relating to the calculated collision reduction frequencies and the estimated social costs from previous studies.

Many researchers and journals place a strong emphasis on the sign and statistical significance of effects, but often there is very little emphasis on the substantive and practical significance of the findings. It should be recognized that no two intersections will be the same in terms of all road environment factors. Therefore, the introduction of interaction terms with the RLC presence is valuable and not found in the literature. It is important to identify the subgroups of intersections which the RLC treatment is likely to have the largest effect on and would benefit the most. It is also very important to identify those intersections for which treatment may be harmful and refrain from treating such intersections.

3. Methodology

One of the most important elements of any evaluation process is the methodology that will be followed. It consists of the study design and the type of statistical analysis employed. The evaluation methodology is selected in this section is based on the available data and the resources available to conduct the evaluation. Section 3.1 discusses the collision prediction methodologies, Section 3.2 reviews the spillover effect methodology and Section 3.3 discusses the economic analysis methodology.

3.1 Collision Prediction Methods

A collision prediction model (CPM) is a mathematical formula describing the relationship between the safety level of existing roads or intersections and various traffic and geometric variables that explain this level (Sayed & de Leur, 2008). The aim is to build a reliable model that fits the data well, simple enough to be interpretable and useful in practice. As with all statistical methods, the reliability of the model is partially a function of how well the model fits the original data and partially a function of how well the model has been calibrated to local data (HSM, 2010). Figure 3.1 presents a flow chart of the traffic safety modeling techniques that will be examined in this thesis to estimate the RLC effectiveness, where the results obtained will be compared.

3.1.1 Cross-Sectional Methods

Generalized linear models (GLMs), such as Poisson and NB regression models, have become a popular approach in investigating the relationship between collision frequency and various covariates in cross-sectional studies. The GLMs accommodates for non-negative discrete data. The Poisson model assumes that the conditional variance

Figure 3.1 – Traffic safety statistical modeling techniques

of the dependent variable is equal to the conditional mean. In most count data sets, however, the conditional variance is greater than the conditional mean, a phenomenon known as over-dispersion (Lord and Mannering, 2010). Therefore, the Poisson regression model often fits count data poorly, as indicated by a deviance or Pearson χ^2 test. The NB regression model can be used to overcome problems associated with over-dispersed data by adding an extra term to the variance that accommodates over-dispersion. The negative binomial regression model is assumed to take the general form presented in eq. 3.1 adapted from (Donnell *et al.*, 2009):

$$\lambda = \exp (\omega + \sum X_i \beta_i + \sum L_i \theta_i + \varepsilon_i) \quad (\text{eq. 3.1})$$

where λ = expected number of collisions on a roadway segment/intersection; ω = intercept; X_i = variables influencing λ (e.g., traffic, road geometry, etc.); β_i = coefficients quantifying the relationship between X and λ ; L_i = a binary (dummy) variable indicating the presence of the treatment; θ_i = coefficient quantifying the relationship between L and λ ; ε_i = is a random error that is assumed to be uncorrelated with x and L . The dependent variable, λ , considered in the model is the frequency of traffic collisions. The regression coefficients (i.e. β_i and θ_i) are estimated using the method of maximum likelihood.

When the dependent variable is a count variable of a rare event and is over-dispersed, the use of the NB distribution is a good way of answering the question of how often does the event occur. By itself, however, it does not answer the question of what predicts whether the event occurs at all or not. Using the ZINB regression will address this issue.

The idea is that there are two ways to think of the dependent variables: (1) that one set of variables predicts whether an event occurs at all or does not, and (2) another set of variables predicts how often the behavior occurs. In other words, what predicts what intersections will have more collisions rather than less may be different from what predicts what intersections will have collisions at all or not at all. Therefore, it is imperative to test whether using the zero-inflated model is necessary. This can be achieved by conducting the Vuong test (Vuong 1989).

Zero-inflated models operate on the principle that the excess zero density that cannot be accommodated by a traditional count structure is accounted for by a splitting regime that models a collision-free versus a collision prone propensity of an intersection (Lord and Mannering, 2010). Such models assume that the data are a mixture of two separate data generation processes: one is governed by a binary distribution that generates only zeros, and the other is either a Poisson or a NB data-generating process that generates counts, some of which may be zero (Allison, 2012 & Lord and Mannering, 2010). The two model components of the zero-inflated Poisson (ZIP) model are described as follows (Lord *et al.*, 2005):

$$P(y_j = 0) = \alpha + (1-\alpha) e^{-\lambda}; n = 0 \quad (\text{eq. 3.2})$$

$$P(y_j = n_i) = (1-\alpha) \frac{e^{-\lambda} \lambda^n}{n!}; n \geq 0 \quad (\text{eq. 3.3})$$

where the outcome variable y_j has any non-negative integer value, λ_i is the expected Poisson count for the i th individual; α is the probability of extra zeros. The first part of the equation has a mean of zero and the second part of the equation has a mean that depends on the covariates. The Vuong statistic (Vuong, 1989) is used to measure whether the ZIP or ZINB is appropriate for fitting the datasets. A likelihood ratio test is conducted

to compare the NB model and ZINB model fits (by taking twice the positive difference in the log-likelihoods) (Allison, 2012).

Traditional cross-sectional collision frequency models with large temporal scales and aggregated variables are not sufficient to capture the time-varying nature of some of the road factors, causing significant loss of critical information on collision frequency modeling (Chen *et al.*, 2016). Therefore, FE and RE models will be also examined as an extension of the NB method. The functional forms of FE and RE models are (Torres-Reyna, 2007):

$$\text{Fixed-effect model: } \lambda_{it} = \exp (\omega + \sum X_{it}\beta_{it} + \sum L_{it}\theta_{it} + u_{it}) \quad (\text{eq. 3.4})$$

$$\text{Random-effect model: } \lambda_{it} = \exp (\omega + \sum X_{it}\beta_{it} + \sum L_{it}\theta_{it} + u_{it} + \varepsilon_{it}) \quad (\text{eq. 3.5})$$

where i = entity, t = time, u_{it} = the between-entity error term specific to individual (group) or time period that is not included in the regression and the ε_{it} = the within-entity error term. Fixed-effects regression model is used to control for omitted variables that differ between cases but are constant over time. They accomplish this by introducing an additional parameter (u_{it}) for each individual in the sample. Since an individual specific effect is time invariant and considered a part of the intercept, u_{it} is allowed to be correlated with other regressors (Park, 2011). The idea is that whatever effects the omitted variables have on the subject at one time, they will also have the same effect at a later time; hence their effects will be constant, or “fixed.” The omitted variables must have time-invariant values with time-invariant effects, meaning that the value of the variable does not change across time (Williams, 2016). Gender, race and the educational level of the respondent’s father are some examples in social studies.

If some omitted variables are constant over time but vary between cases, and others are fixed between cases but vary over time, then both types can be included by using RE. If it is believed that the omitted variables are uncorrelated with the explanatory variables that are in the model then a RE model is probably best (Williams, 2016). Random-effects models can potentially capture unobserved heterogeneity by allowing parameters to vary across observations (Torres-Reyna, 2007).

The generally accepted way of choosing between a FE and a RE model is running a Hausman's test for each set of models where the null hypothesis is that the preferred model is RE vs. the FE (Green, 2008). It basically tests whether the unique errors u_{it} are correlated with the regressors, the null hypothesis is they are not. In the presence of such correlation, the RE slope estimator is inconsistent; consequently, the FE model should be chosen over the RE model. If there is no correlation, then both the FE and RE estimators are unbiased, but the RE estimator is preferred because it is more efficient.

Since traditional cross-section data ignore the dynamics of the changes and the heterogeneity of spatial units, this thesis is an attempt to overcome these limitations by using a spatial panel method. FE and RE regressions constitute an analytically powerful instrument to do so, which, to the authors' knowledge, has not yet been implemented in estimating the effect of RLCs on traffic collisions.

3.1.2 Empirical Bayes Method

The EB method is a statistical method that combines the observed collision frequency with the predicted collision frequency using safety performance functions (SPFs) to calculate the expected collision frequency for a site of interest. SPFs are regression equations that are calibrated using data from a sample of intersections, called comparison

sites, with characteristics similar to the characteristics of the treated intersections. These characteristics typically include traffic volume and may include other variables such as traffic control and geometric characteristics. These comparable sites are used to develop an estimate of the collision frequency before the cameras were installed, which in turn is used in the calculation of the expected collision frequency (AECOM, 2014).

The number of collisions predicted from the SPF model serves as a baseline in the local environment. In the model, the predicted yearly average number of collisions is the dependent variable, while traffic volume is the independent variable. The model takes the form as specified by Hauer (1997):

$$E(\kappa) = \beta_0 \times V^{\beta_1} \quad (\text{eq. 3.6})$$

where $E(\kappa)$ = mean annual expected collision frequency for the prior distribution; V =annual average daily traffic (AADT); β_0, β_1 = model parameters. The regression parameters of the SPFs are determined by assuming that collision frequencies follow a NB distribution.

SPFs are constructed by plotting the collision and exposure data and then fitting a curve through the data using the negative binomial regression formula. The resulting curve (or equation) is the SPF. The EB method is portrayed in Figure 3.2 which illustrates how the observed collision frequency is combined with the predicted collision frequency based on the SPF model. The EB method is applied to calculate an expected collision frequency or corrected value, which lies somewhere between the observed value and the predicted value from the SPF.

The EB analysis requires AADT and collision data for the treatment site for both before and after the treatment was implemented to calculate a site's expected collision frequency, N_{expected} . The SPF is incorporated into the EB analysis, $N_{\text{predicted}}$, to determine the average collision frequency at similar sites. The sites expected collision frequency can be calculated as follows (AASHTO, 2010):

$$N_{\text{expected}} = w \times N_{\text{predicted}} + (1 - w) \times N_{\text{observed}} \quad (\text{eq. 3.7})$$

where

$$w = \frac{1}{1 + k \times \left(\sum_{\text{all study years}} N_{\text{predicted}} \right)} \quad (\text{eq. 3.8})$$

where N_{expected} is an estimate of expected average collisions frequency for the study period. The $N_{\text{predicted}}$ is a predictive model estimate of average collision frequency predicted for the study period under the given conditions. The N_{observed} is the observed collision frequency at the site over the study period. The w is the weighted adjustment to be placed on the predictive model estimate. The k is the over-dispersion parameter of the associated SPF used to estimate $N_{\text{predicted}}$. The over-dispersion parameter is used to determine the value of a weight factor for use in the EB method. The weight factor is applied to reflect the model's statistical reliability.

In summary, the EB method uses a reference group to estimate a SPF. The SPF is then used in combination with observed collisions pre-treatment at the treated sites to predict the number of collisions that would have been expected in the after period for the treated entities had the treatment not been implemented. This prediction is then compared to the expected number of collisions in the after period with the treatment.

3.1.3 Case-Control Method

Most studies in the literature review simply compared regression models to the observed results, and they stopped there. This thesis will go further into matching, which is an analytical method widely implemented in social science fields when evaluating the impact of a program. The PSM is a technique by Rosenbaum and Ruben (1983; 1985; 2002) that allows researchers to reconstruct counterfactuals using observational data by adjusting covariates between the treated and control groups. Regression analysis cannot tell researchers the distribution overlap between two samples, which is a major source of bias. Therefore, the PSM method should be used as a robust test to justify the findings estimated.

A key objective is to include variables in the models that are likely to affect both the participation and the outcome of interest so that, conditional on these measured variables, there are no unmeasured factors affecting either participation or the relevant nonparticipation outcome. These covariates are used to estimate a propensity score with a probit or logit model.

Treated units are matched to similar untreated units based on the proximity of their propensity scores. At this point, a matching algorithm has to be chosen among the

different alternatives (e.g. nearest neighbor, radius, kernel, etc.) considering data issues (such as sample sizes) and the bias/efficiency trade-off.

Once each treated unit has been matched with one or more untreated units, the impact of the program is estimated as a weighted average of the difference in outcomes between treated and untreated. These results need to be complemented with evidence of covariate balancing between groups.

The impact of a treatment for an individual i , noted τ_i , is defined as the difference between the potential outcome in case of treatment and the potential outcome in absence of treatment (Caliendo & Kopeinig, 2005 & Heinrich *et al.*, 2010):

$$\tau_i = Y_{1i} - Y_{0i} \quad (\text{eq. 3.9})$$

The fundamental evaluation problem arises because only one of the potential outcomes is observed for each individual i . The unobserved outcome is called the counterfactual outcome. Hence, estimating the individual treatment effects, τ_i , is not possible. An evaluation seeks to estimate the mean impact of the treatment by measuring the impact of the treatment on the population and on those individuals who participated. These two parameters are known as Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATT), respectively.

The ATE can be defined as the average effect that would be observed if everyone in the treated and the control groups received treatment, compared with if no one in both groups received treatment (Harder *et al.*, 2010). In contrast to the ATE, the ATT refers to the average difference that would be found if everyone in the treated group received treatment compared with if none of these individuals in the treated group received treatment.

The parameter that will be discussed here is the Average Treatment Effect on the Treated (ATT), which is defined as (Caliendo & Kopeinig, 2005 & Heinrich *et al.*, 2010):

$$\tau_{ATT} = E[Y_1 | D = 1] - E[Y_0 | D = 1] \quad (\text{eq. 3.10})$$

where E represents the expected value and D is the indicator of exposure to treatment. The second term, $E(Y_0 | D=1)$, is the average outcome that the treated individuals would have obtained in absence of treatment, which is not observed. On the other hand, the term $E[Y_0 | D=0]$, the value of Y_0 for the untreated individuals, is observed. However, using the mean outcome of untreated individuals $E[Y_0 | D = 0]$ in non-experimental studies is usually not a good idea, because it is most likely that components which determine the treatment decision also determine the outcome variable of interest. Thus, the outcomes of individuals from treatment and comparison group would differ even in the absence of treatment leading to a selection bias. The selection bias is the difference between the counterfactual for treated individuals and the observed outcome for the untreated individuals. For ATT it can be noted as (Caliendo & Kopeinig, 2005):

$$E[Y_1 | D = 1] - E[Y_0 | D = 0] = \tau_{ATT} + \overbrace{E[Y_0 | D = 1] - E[Y_0 | D = 0]}^{\text{selection bias}} \quad (\text{eq. 3.11})$$

The difference between the left hand side of equation (3.5) and τ_{ATT} is the selection bias. If this term is equal to 0, then the τ_{ATT} can be estimated by the difference between the mean observed outcomes for treated and untreated (Heinrich *et al.*, 2010):

$$\tau_{ATT} = E(Y | D=1) - E(Y | D=0) \quad (\text{eq. 3.12})$$

The conditional probability of an entity receiving treatment is given by the covariates (X) and outcomes (Y). When the treatment assignment mechanism is

unconfounded, the propensity score ($\hat{p}$) is represented as shown in the following equation (Sasidharan & Donnell, 2013):

$$\hat{p} = E(D = 1|X) \quad (\text{eq. 3.13})$$

where D = treatment status ($D = 1$, treated and $D = 0$, untreated); X = covariates influencing treatment selection. The $\hat{p}$ is unknown in observational studies and must be estimated from the sample based on important covariates influencing the treatment selection. The $\hat{p}$ is commonly estimated using logistic regression. The propensity scores help to balance the covariates in the treated and untreated groups when the data are non-randomized. Given a population of units denoted by i , if the propensity score $\hat{p}_i$ is known, then the ATT can be estimated as follows (Sasidharan & Donnell, 2013):

$$ATT = E [E(Y_{1i}|D_i = 1, \hat{p}_i) - E(Y_{0i}|D_i = 0, \hat{p}_i)] \quad (\text{eq. 3.14})$$

where the outer expectation is over the distribution of $(\hat{p}_i|D_i = 1)$ and Y_{1i} and Y_{0i} are the potential outcomes in the two counterfactual situations of treatment and no treatment. The ATT is the effect of the treatment on the outcome among those who received the treatment. The treatment effect on the outcome is estimated using the propensity score matching command `teffects` in StataSE software.

The treatment-effects estimator that will be used in this thesis is the inverse-probability-weighted regression adjustment (IPWRA). IPWRA estimator models both the outcome and the treatment to account for the non-random treatment assignment. The covariates in the outcome model and the treatment model do not have to be the same, and they often are not because the variables that influence a subject's selection of treatment group are often different from the variables associated with the outcome. IPWRA estimators use weighted regression coefficients to compute averages of treatment-level

predicted outcomes, where the weights are the estimated inverse probabilities of treatment (Huber, 2015).

In the first step, the probability of treatment is estimated, and in the second step regression methods are used, with weights provided by the inverse of the probability of treatment (Wooldridge, 2010). The IPWRA is called double-robust estimator as it allows for potential misspecifications in either the propensity model or the regression model predicting the two potential outcomes (Wooldridge, 2007, 2010). If one of the two models is specified incorrectly, the IPWRA estimator still produces a consistent estimate of the treatment effect (Bördös *et al.*, 2015).

An essential aim of the analysis phases of this method is to prevent, reduce, and assess bias, confounding, and chance by matching so that a causal unbiased association between exposure and outcome is estimated (Jespen *et al.*, 2004).

3.1.4 Incorporating Interaction Terms

The way interaction terms work is by running a regression analysis first, including both independent variables (an independent variable and moderator) and their interaction (product) term (Dawson, 2015). The product term should be significant in the regression equation in order for the interaction to be interpretable. The interpretation of an interaction is the change in the slope of one variable as the other variable itself changes. Using the general functional form of Eq.3.1, the conditional expected value of y is a general function of the linear index function (Karaca-Mandic *et al.*, 2012):

$$E[y|x_1x_2] = \exp (\beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_{12}(x_1 x_2)) \quad (\text{eq. 3.15})$$

where y is an outcome (dependent) variable, x_1 and x_2 are explanatory variable, and β_x are parameters to be estimated. The interaction term is the product of x_1 and x_2 . The effect of

a one-unit change on the dependent variable is the marginal effect of the explanatory variable on the dependent variable. The marginal effect of an independent variable is the derivative (slope) of a given function of the covariates and coefficients of the preceding estimation (Data Analysis and Statistical Software, 2015). The derivative is evaluated at the values of the independent variables specified; if no values are specified, it is evaluated at the default values, which are the means of the independent variables.

Results can often be made more tangible by computing predicted or expected values for hypothetical cases. Such predictions are sometimes referred to as margins, predictive margins, or (StataSE's preferred terminology) adjusted predictions (Williams, 2012). StataSE has a number of handy commands such as `margins` and `marginsplot` for making sense of regression results. A margin is a statistic computed from predictions from a model while manipulating the values of the covariates. It is typically used to estimate cell means of an effect (often an interaction), averaged over the other covariates in the population (IDRE, 2017).

These commands estimate and graphically plot predicted probabilities and are potentially more informative than regression tables when examining interaction effects, or any model which returns non-intuitive coefficients. Despite their advantages, these commands are still somewhat underutilized. It may be the case that since margins is only a few years young, many researchers simply don't know about it or don't fully understand how useful it can be at clarifying regression results. Therefore, the margins command will be used in StataSE to calculate the predicted collision counts for models with interaction terms, holding all other variables in the model at their mean values.

In summary, the motivation for including an interaction is to get a better idea of how the RLC treatment effect varies with different intersection elements. Also, one of the motivations for investigating interactions is to identify which subgroups would benefit most from RLC treatment when resources are limited.

3.2 Spillover Effect Method

The distance-halo and a time-halo will be investigated to examine the local and widespread effects of the RLC enforcement. In order to assess the distance-halo, the Geographic Information System (GIS) ArcMAP 10.4.1 software was used to determine the distances of the three closest RLC intersections (referred to as "facilities" in the GIS software) to each of the non-RLC intersections (referred to as "incidents" in the GIS software). This will determine if the proximity of RLCs impact the traffic safety effectiveness; i.e. whether or not when there are two or more RLCs within a specified distance the collisions reductions were higher. The geo-processing tool utilized to accomplish this was the Network Analyst, using the closest facility tool. The closest facility solver finds and displays the shortest routes between incidents and facilities. Figure 3.3 presents an overview of the routes created, with a close up of one of the incidents and the three routes to the closest three facilities.

The Network Analyst can find multiple closest facilities from an incident by setting the "TargetFacilityCount" under the "Load Locations" of the incidents to the number of facilities wanting to search, three in this research. An example is highlighted in cyan in Figure 3.4 where the three closest facilities were ordered based on shortest travel distance to the incidents. The yellow road highlighted in each figure is the selected route which has the travel distance displayed in the table. The three closest RLC

Figure 3.3 – Identifying the three closest facilities to each incident

Figure 3.4 – Example of closest facilities identified

intersections to each RLC intersection were also identified. A summary of the descriptive statistics of the time and distance variables created are discussed further in Chapter 4.

3.3 Economic Analysis Method

The general analysis methodology used to define the economic effects of the RLC program is evaluating the difference between the net economic costs expected without treatment and observed with treatment in the post-treatment period. The objective of a benefit-cost analysis is to estimate the net impact of a policy. The benefit-cost analysis involves the cost of the RLCs in terms capital costs, maintenance, operations, processing, etc. and the cost savings from a reduction in the number of collisions following installation of the RLCs. Two indicators of the economic worth of the RLCs are the net present value (NPV) and the benefit-cost ratio (BCR) (Chen *et al.*, 2012). A summary of the economic analysis work flow is presented in Figure 3.5.

Figure 3.5 – Economical analysis process

When assessing the costs and benefits of a project, it is necessary to take into account the time value of money by converting the costs and benefits that take place in different years into a common year (Chen *et al.*, 2012). This process is known as discounting. Discounting converts future costs and benefits that occur in different years into a value for a common year (present value) in order to make a comparison.

Since the period in which the RLCs have been in effect at various intersections is different, and also for consistency purposes, all cost amounts will be converted into present value and then compared among intersections on an average annual basis (i.e.,

annual net revenue). The future stream of discounted costs is subtracted from the future stream of discounted benefits to estimate the Net Present Value (NPV). The formulas for calculating the NPV is as follows (Chen *et al.*, 2012):

$$NPV = \sum_{i=0}^n \left(\frac{B_i}{(1+r)^i} \right) - \sum_{i=0}^n \left(\frac{C_i}{(1+r)^i} \right) \quad (\text{eq. 3.16})$$

where B_i = benefits in year i resulting from savings in road collision costs, C_i = costs of installing the RLC treatments in year 0 and the operating and maintenance costs in subsequent years r = discount rate (5% used in the analysis, consistent with the discount being used by Ministry of Transportation for Ontario (MTO) to evaluate transit projects (MKI, 2011)) and n = the expected life of the project (5 years will be used for the RLC program in Ottawa). The duration of project life was chosen based on the 5 year contract with the RLC vendor.

The BCR ratio is calculated by dividing the total benefit amount by the total cost amount (both in NPV terms) for the entire study period. The formula for calculating the BCR is as follows (Chen *et al.*, 2012):

$$BCR = \left[\sum_{i=0}^n \left(\frac{B_i}{(1+r)^i} \right) \right] / \left[\sum_{i=0}^n \left(\frac{C_i}{(1+r)^i} \right) \right] \quad (\text{eq. 3.17})$$

The BCR has no units, since it is a ratio of monetary values. A BCR significantly greater than one indicates a project is worthwhile, or if the economic worth of two or more projects are being compared then the project with the highest BCR is the most worthwhile.

4. Data Collection and Processing

4.1 RLC Data

There are 34 intersections equipped with RLC units at intersections in the City of Ottawa.

A list of the RLC intersections along with their installation date and on which approach they are located is found in Table 4.1 A list of the non-RLC locations chosen is located in Appendix A (Table A).

Table 4.1 – RLC intersections in Ottawa

No.	RLC Intersection Name	RLC Approach	Installation Date
1	BRONSON AVE & CARLING AVE	SB	20-Nov-00
2	CARLING AVE & RICHMOND RD	WB	01-Dec-00
3	COVENTRY RD & ST. LAURENT BLVD	NB	01-Feb-01
4	EAGLESON RD & HAZELDEAN RD	SB	01-Apr-01
5	HERON RD & RIVERSIDE DR	EB	01-Jul-01
6	MEADOWLANDS DR & MERIVALE RD	NB	01-Dec-01
7	ALBERT ST & KENT ST (OTTAWA)	NB	01-Dec-01
8	BANK ST & HUNT CLUB RD	EB	13-Jun-08
9	BANK ST & RIVERSIDE DR N	WB	13-Jun-08
10	BASELINE RD & MERIVALE RD	WB	13-Jun-08
11	BELFAST RD & ST. LAURENT BLVD	EB	13-Jun-08
12	BOOTH ST & OTTAWA RIVER PKWY	EB	13-Jun-08
13	CAMPEAU DR & MARCH RD	WB	13-Jun-08
14	CARLING AVE & ISLAND PARK DR	WB	13-Jun-08
15	CATHERINE ST & HWY 417 O'CONN	SB	13-Jun-08
16	CATHERINE ST & KENT ST	NB	13-Jun-08
17	CHARLEMAGNE BLVD N & TENTH LINE RD	SB	13-Jun-08
18	RUSSELL RD & WALKLEY RD	EB	30-Sep-08
19	ALBERT ST & BOOTH ST	WB	07-Sep-10
20	AVIATION PKWY & OGILVIE RD	SB	07-Sep-10
21	BANK ST & HERON RD	EB	07-Sep-10
22	BERRIGAN DR & GREENBANK RD	NB	07-Sep-10
23	BLAIR RD & BLAIR RD RAMP 36	WB	07-Sep-10
24	BRONSON AVE & COMMISSIONER ST	SB	07-Sep-10
25	CONROY RD & LORRY GREENBERG DR	SB	07-Sep-10
26	CYRVILLE RD & INNES RD	SB	07-Sep-10
27	DRIVEWAY (THE) & ISLAND PARK DR	WB	07-Sep-10
28	DUFORD DR & ST. JOSEPH BLVD	EB	07-Sep-10
29	FISHER AVE & MEADOWLANDS DR	SB	07-Sep-10
30	HAWTHORNE AVE & QUEEN ELIZABETH DRWY	EB	07-Sep-10
31	JOCKVALE RD & STRANDHERD DR	SB	07-Sep-10
32	KING EDWARD AVE & ST. ANDREW ST	SB	01-Feb-11
33	KING EDWARD AVE & ST. PATRICK ST	EB	01-Feb-11
34	SAUNDERSON DR & SMYTH RD	NB	01-Feb-11

A map of the locations of the RLC and non-RLC intersections, illustrated in Figure 4.1, was created using the geographic information system (GIS) software ArcMap 10.4.1. The Ontario roads network layer was obtained from the Carleton University Library database GeoPortal Scholars, which included attributes about each road. The majority of the 34 RLC intersections are located in the urban areas, with a few in the suburbs.

Figure 4.1 – Location of the 34 RLC intersections and comparison intersections in Ottawa

Photos of a typical RLC set up in Ottawa, taken at the Meadowlands Drive and Merivale Road intersection, are presented in Figure 4.2. The photos exhibit the camera units and their location relative to the intersection. Figure 4.3 shows a posted warning sign for RLC enforcement, which at this specific intersection was placed approximately 80 m away in the direction of travel from the RLC box and 125 m away from the midblock

Figure 4.2 – A typical RLC set up in Ottawa (photos by: Amal Abdulsalam)

Figure 4.3 – A typical warning sign of an approaching RLC intersection (photo by: Amal Abdulsalam)

of the intersection. The advance distance at which these signs should be located is generally dependent on the speed limit and stopping sight distances.

4.2 Collision Data

The City of Ottawa provided detailed traffic collision data for 34 RLC intersections and 14 non-RLC intersections for a period from January 1, 1999 to December 31, 2012. Data for the year 2013 was provided for RLC intersections installed in 2010 and 2011 to have at least three years of data for the post-treatment period. The 14 non-RLC intersections were chosen from a pool of 82 intersections based on an average total number of collisions of over 10, which is an overall average just under the RLC intersections' average. The chosen intersections have similar total collision frequencies as the RLC intersections. This selection process represents a preliminary attempt to control for selection bias by using data from non-RLC intersections that on one key variable (i.e. average number of annual collisions) are similar to the RLC intersections. Additional supplementary data collected from City of Ottawa's Annual Road Safety Reports on population demographics, number of licensed drivers, and number of vehicle registrations are presented in Appendix A (Table B) for future city-to-city comparison purposes (City of Ottawa, 2017).

The statistical spreadsheet software Microsoft Excel 2007 was used to manage data and export a dataset for the statistical analysis software StataSE 14.0. The collision database consisted of 10,267 records, of which 7,441 occurred at RLC intersections. Of the 10,267 collision cases (48 intersections), 10 were classified as fatal (0.1% of all collisions), 2,585 were classified as serious injury (25.2% of all collisions) and 7,671 as property-damage only (PDO) (74.7% of all collisions), as listed in Table 4.2.

Table 4.2 – Summary of collision database by classification and impact type for RLC and non-RLC intersections

Collision Classification	Angle	App-roa- ching	Rear- end	Side- swipe	Single vehicle	Turning move- ment	Other/ unknown	Grand Total	Percent
Fatal injury	8	-	-	-	-	2	-	10	0.10%
Non-fatal injury	712	7	977	60	216	602	12	2,586	25.19%
PDO	1,434	16	3,359	1,023	320	1,358	161	7,671	74.72%
Grand Total	2,154	23	4,336	1,083	536	1,962	173	10,267	100%

The traffic collision data collected reflected a period before and after the RLCs were installed. Previous work found that at least three, and preferably five years of data is the preferred before and after time period to smooth out any random fluctuations, as well as providing sufficient evidence of any trend or change in an established pattern of collisions (Chen *et al.*, 2012).

A cumulative graph of the collisions by impact types which occurred during the study period was created in Figure 4.4. The corresponding table of the calculations is found in Appendix A (Table C). The graph identifies the most prevalent collision impact types per intersection per year being the rear-end, angle and the turning movement collisions. Not surprisingly, these three collision impact types are also part of Ottawa's RLC site selection criteria (presented earlier in Table 2.1). Sideswipe collisions account for the fourth highest impact type and accounts for over 10% of the total collisions so it will be investigated further. Therefore, this thesis will focus on these four impact types (representing nearly 93% of all collisions) in the statistical analysis performed in the next chapters.

Of the 7,441 collisions at the 34 RLC intersections, 8 were classified as fatal (0.11% of all collisions), 1,844 were classified as serious injury (24.8% of all collisions)

Figure 4.4 – Common collision impact types in Ottawa, ON

and 5,589 as property-damage only (PDO) (75.1% of all collisions). The number of collisions was converted to an average annual number of collisions per intersection for the periods before and after the installation of RLCs. Results for the RLC and non-RLC intersections are presented in Table 4.3.

Table 4.3 – Average number of collisions (per intersection per year) by classification and type for RLC & Non-RLC intersections

Collision Impact Type	RLC INTERSECTIONS									
	Total collisions		Rear-end		Angle		Turning movement		Sideswipe	
	Before	After	Before	After	Before	After	Before	After	Before	After
Total	14.18	16.72	5.00	7.88	3.82	3.08	3.03	2.69	1.35	1.96
Fatal	0.0172	0.0151	-	-	0.0138	0.0151	0.0034	-	-	-
Injury	3.59	4.04	1.14	1.73	1.24	1.01	0.83	0.83	0.09	0.10
PDO	10.58	12.67	3.86	6.15	2.57	2.06	2.20	1.86	1.27	1.87
Collision Impact Type	NON-RLC INTERSECTIONS									
	Total collisions		Rear-end		Angle		Turning movement		Sideswipe	
	Before	After	Before	After	Before	After	Before	After	Before	After
Total	14.42	6.72	2.21	2.79	1.53					
Fatal	0.0102	-	0.0051	0.0051	-					
Injury	3.79	1.54	0.78	0.99	0.08					
PDO	10.62	5.18	1.43	1.79	1.45					

As can be seen from the results, the chosen non-RLC intersections have similar frequencies to the RLC intersections to be comparable when analyzing in the next

chapters. Detailed counts of the number of before and after collisions per intersection for both the RLC intersections and non-RLC intersections can be found in Appendix A.

Two sample t-tests were performed as simple, initial tests to determine if there was a statistically significant change in the mean of collisions between RLC intersections and non-RLC intersections chosen as the control sites. The two-sample t-test still works when the assumption of normality is violated, but only if the underlying distribution is not highly skewed (Minitab Statistical Software, 2017). A p -value of 0.05 or less indicates that any observed differences are unlikely to be due to random variation alone (Kloeden *et al.*, 2009). The full output of the results is presented in Appendix A. A summary of the results is as follows:

- The total collisions' t-test was statistically significant concluding that collision frequencies differed and are unlikely due to random variation alone (an increase from 14.18 to 16.72).
- The traffic volumes' t-test concluded that the before and after differed (an increase in traffic volume which is probably trend related, from 10.31 to 10.48; this could mean that accident frequencies caused by RLC installation will be slightly overstated).
- The rear-end collisions' t-test was statistically significant concluding that collision frequencies differed and are unlikely due to random variation alone (an increase from 5.00 to 7.88).
- The angle collisions' t-test was statistically significant concluding that collision frequencies differed and are unlikely due to random variation alone (a decrease from 3.82 to 3.08).

- The turning movement collisions' t-test was not statistically significant concluding that collision frequencies do **not** differ significantly and is likely due to random variation (turning movement collisions decrease marginally from 3.03 to 2.69 but not significant).
- The sideswipe collisions' t-test was statistically significant concluding that collision frequencies differed and are unlikely due to random variation alone (an increase from 1.35 to 1.96).

However, the standard t-test does not consider relationships among the coefficients. Therefore, further statistical tests will be carried out and presented in Chapter 5.

Only one public report was found, published in 2012 by the City of Ottawa, assessing the overall RLCs performance in the city (Keefe, 2012). The report simply conducted a naïve before-after study and based their policy decisions on those estimations. A naïve before-after study is a simple before-after comparison where the safety effect of a treatment is assessed by directly comparing the collision frequency in the before period with the collision frequency in the after period (Hauer, 1997). This is also referred to as a trend analysis. A summary of results from the City of Ottawa report are presented in Table 4.4. The actual number of collisions used in the counts when calculating the percent difference was not mentioned in the report and number of intersections used in the counts was not mentioned for each year.

Table 4.4 – RLC effect in Ottawa – adapted from Keefe (2012) report

Collision Impact Type	1 yr after	3 yrs after	5yrs after	10 yrs after
Total	-2%	+3%	-8%	-12%
Angle	-3%	-12%	-33%	-29%
Rear-end	+1%	+11%	+8%	+20%

A comparison set of naïve before-after estimates was conducted using the set of data of the RLC intersections from this thesis, presented in Table 4.5. The way the number of collisions was counted was from the exact date each RLC was installed until a year after, which is more accurate than by a simple fiscal year count.

Table 4.5 – RLC effect in Ottawa from database

Collision Impact Type	(34 intersections)			(31 intersections)			(18 intersections)			(7 intersections)		
	average # of collisions		% change*	average # of collisions		% change*	average # of collisions		% change*	average # of collisions		% change*
	Base-year	1 yr after		Base-year	3 yrs after		Base-year	5 yrs after		Base-year	10 yrs after	
Total	15.71	15.00	-4%	16.52	15.74	-5%	18.06	17.83	-1%	17.71	19.39	9%
Angle	3.35	3.15	-6%	3.58	3.42	-5%	4.39	3.47	-21%	4.57	3.61	-21%
Rear-end	6.68	6.38	-4%	6.94	6.96	0%	7.61	8.08	6%	7.29	9.80	35%

* the % change =
$$\frac{(\text{avg.\# of collisions nth year} - \text{avg.\# of collisions base year})}{\text{avg.\# of collisions base year}}$$

It is important to note that the average number of collisions, i.e. for "5 years after", is the average number of collisions from year 1, 2, 3, 4 and 5 after the RLC was installed. The year before the RLC was installed at an intersection was used as the base year for all counts. In the Keefe (2012) report, the base year was the year the RLC was installed. Since the RLC locations have been in place for different lengths of time, only some of the locations can be used for the longer term evaluation. For example, all RLC locations were used to calculate the one year before and after data, but only the seven locations where the red light camera has been in place for over 10 years were used to calculate the 10 year percentage.

There are a few noted differences between the estimations conducted by City of Ottawa and from the data collected in this thesis. The main difference will be from the number of intersections used for each calculation, which was not identified in the City of

Ottawa report. The results in Table 4.5 show that the magnitude of the effect becomes more apparent as the results of more years get analyzed. After a 10 year assessment, results indicate that the angle collisions decrease by 21% and the rear-end collisions rise by about 35%, which in-turn cause the total collisions to increase by 9%.

However, this naïve before-after analysis does not account for possible bias due to RTM and does not account for temporal effects or trends, which are changes taking place independent of the RLC treatment. It is not known what part of the changes can be attributed to the RLC treatment and part due to other influences. Without a control group, it is difficult to establish the cause and effect relationship between the RLC treatment and collisions as an outcome. Therefore, it is not acceptable to base decisions based on the results obtained from this method and more reliable statistical prediction methods will be assessed.

Although the collision summaries in this Section provide some insight on the data, the next step is to gather spatial and geometric data related to the intersections to better understand the trends and patterns. Knowing more about the conditions when collisions happen helps policy makers identify areas for review and create targeted approaches to reducing and ultimately preventing dangerous traffic collisions.

4.3 Selection of Variables

One important goal in model building is to find the best fitting model to describe the relationship between the outcome and a set of independent variables. Data for 11 independent variables (including the treatment variable) were gathered based on site-specific local factors. Descriptive statistics of the explanatory variables are presented in Table 4.6. The sample size should be at least 10 observations per variable, since selection

Table 4.6 – Variable definitions and summary statistics

Dependent Variables					
Description (variable name)	Observations	Mean	Std.Dev.	Min.	Max.
Number of total collisions (<i>totalcollisions</i>)	685	14.99	7.74	0	39
Number of angle collisions (<i>angle</i>)	685	6.33	5.39	0	30
Number of rear-end collisions (<i>rearend</i>)	685	3.14	3.00	0	24
Number of turning movement collisions (<i>turningmovement</i>)	685	2.86	3.02	0	17
Number of sideswipe collisions (<i>sideswipe</i>)	685	1.58	1.89	0	10
Independent Variables					
Description (variable name)	Observations	Mean	Std.Dev.	Min.	Max.
Presence of RLC (<i>rlcinstalled2</i>)	685	0.29	0.45	0	1
Natural log of total AADT (<i>lnaadtt</i>)	685	10.42	0.40	8.96	11.20
Presence of a median (<i>median</i>)	685	0.67	0.47	0	1
Presence of a right-turn channelization (<i>channelization</i>)	685	0.42	0.49	0	1
Number of thru lanes (<i>thrulanes</i>)	685	2.26	0.70	1	4
Number of left-turn lanes (<i>leftturn</i>)	685	0.69	0.62	0	2
Fully-protected left-turn signal (<i>fplt</i>)	685	0.37	0.48	0	1
Permitted-protected left-turn signal (<i>pplt</i>)	685	0.27	0.45	0	1
Permitted left-turn signal (<i>plt</i>)	685	0.46	0.50	0	1
Posted speed limit on Road 1 (<i>speed1</i>)	685	54.41	8.38	40	70
Posted speed limit on Road 2 (<i>speed2</i>)	685	54.73	7.34	40	80

bias and model instability become major issues in smaller sample sizes (Sauerbrei *et al.*, 2007).

Drawings of the signalized intersections were not available at the City of Ottawa's traffic engineering department to record the road characteristics. Therefore, a geometry database was created manually using Google Earth images to record road characteristics of the intersections including the number of through lanes, number of left-turn lanes, presence of median, and right-turn channelization. Additional signal timings and posted speed limits of the cross roads of each studied intersection were obtained from the Traffic Operations department at the City of Ottawa.

Average annual daily traffic (AADT) volumes were obtained from the City of Ottawa and used to attempt to adjust for exposure. The entering AADT data for all years in the study period are required in order to conduct a before-and-after study using the EB method. However, the collected data lacked some AADT values for the collected study period. As a result, the missing AADTs were estimated using an annual growth rate of 5%, as used for other projects in Ottawa (Date, 2014).

Since AADT does not necessarily follow a linear distribution, a better approach was to introduce the natural log as the independent variable. Count models need some sort of mechanism to deal with the fact that counts can be made over different observation periods (IDRE, 2001). For example, the number of collisions is recorded for 50 different intersections, however, the vehicles that pass through the intersections can vary greatly. Fifteen collisions for 30,000 vehicles is very different from 15 collisions for 1,500 vehicles. Count models account for these differences by including the log of the exposure variable, which reduces the skew in the AADT data (Statistical Consulting Group, 2007).

When building regression models, the aim is identify influential variables and determine the functional form. The models are fitted using the log-link function in the StataSE Software. The first approach will be including all variables in the model (all-in model) to provide as complete control of confounding as possible within the given data set. This approach is based on the fact that it is possible for individual variables not to reveal strong confounding, but when taken collectively, substantial confounding can be present in the data set (Miettinen, 1976).

However, it may be cautioned that an all-in model may be over-fitted and thus produce numerically unstable parameter estimates. An over-fitted model can cause the regression coefficients, p -values, and R-squared to be misleading (Frost, 2015). When this happens, the regression model becomes tailored to fit the flukes and random noise in the specific sample rather than reflecting the overall population. If another sample gets used, it would have its own flukes, and the original over-fitted model would not likely fit the new data. Instead, the model should approximate the true model for the entire population.

Therefore, the next step is to explore the variables manually using a stepwise backward procedure. The procedure starts from an all-in model, and variables are deleted stepwise starting with the least significant. In case a variable is significant at the 95% confidence interval ($p \leq 0.05$), the variable is kept in the model. If the variable is not significant, the variable is omitted from the model. When this procedure is completed, any variables that have become insignificant ($p > 0.05$) throughout the process are omitted from the model. Variables that reach $p \leq 0.05$ are considered as potentially important.

The Akaike Information Criterion (AIC) will be used to compare the models. The AIC is a measure of model goodness-of-fit adjusted for the number of parameters that can be compared across models (Akaike, 1987; Washington *et al.*, 2003). The criterion provides an estimate of the trade-off between model accuracy and complexity. The model with the lowest AIC model is considered to be the best model. The only restriction is that the traffic volume variable ($\ln aadt$) is always added to the model, irrespective of its impact to the AIC value, because a model that does not incorporate any measure of exposure cannot be credible from a theoretical point of view (Reurings *et al.*, 2006).

In the context of PSM models, the aim is to find a combination of variables that gets balanced between treated and untreated subjects in the matched sample. Brookhart *et al.* (2006) and Pearl (2010) suggested that variables that do not affect exposure but that affect the outcome should always be included in the propensity score model. Therefore, the inclusion of covariates in the model is more liberal than in most traditional settings. For instance, covariates with p -values larger than 0.05 can be included in the propensity score model (D'Agostino, 2007). The inclusion of non-significant variables will not bias the estimates or make them inconsistent, it can, however, increase their variance (Caliendo & Kopeinig, 2005). Although it is not possible to know for sure whether there is an unmeasured confounder or not, the more measured confounders that have been included, the more plausible the assumption.

Correlation of variables in the propensity score model are not considered to be a problem since the goal of the model is to balance the covariates, not to find statistically significant relationships between the covariates and the treatment (Conniffe *et al.*, 2000). In order to have balanced data, the treatment and control groups need to look substantially similar.

4.4 Spatial Data

Distance variables obtained from the ArcMAP 10.4.1 software, based on the three closest RLC intersection distances, were added to the panel database. Summary statistics of those three variables (*disthalo1*, *disthalo2*, and *disthalo3*) are presented in Table 4.7. Additional sets of variables were also created to see if any would have an apparent trend on the number of collisions. The first set of variables consists of two variables of a binary response of whether or not the closest RLC intersection is within 0 m to 500 m or 500 m

to 1000 m. The second set of variables also consists of two variables of a binary response of whether or not there are more than two RLCs between 0 m to 500 m and between 500 m to 1000 m. The last variable in Table 4.7 consists of a binary response variable determining whether or not there are three RLCs within a 1 km zone. These variables were created to determine if there is a significant distance where the RLC sites would spillover to non-RLC intersections.

Table 4.7 – Summary of distance halo variables

Description (<i>variable name</i>)	Observations	Mean	Std. Dev.	Min.	Max.
Distance halo to closest RLC int. – measure 1- (<i>disthalo1</i>)	685	690.46	886.04	74.98	6117.09
Distance halo to 2nd closest RLC int. -measure 2- (<i>disthalo2</i>)	685	2201.17	2262.52	127.78	11214.45
Distance halo to 3rd closest RLC int. -measure 3- (<i>disthalo3</i>)	685	3554.78	3251.39	486.33	13823.69
Binary where "1" if closest RLC is within 0 to 500 m (<i>closestrlc0to500</i>)	685	0.4350	0.4961	0	1
Binary where "1" if closest RLC is within 500 to 1000 m (<i>closestrlc500to1000</i>)	685	0.1679	0.3740	0	1
Binary where "1" if two or more RLCs installed within 500 -1000 m Binary where "1" if two or more RLCs installed within 0 to 500 m (<i>twoormorerlc0to500</i>)	685	0.0628	0.2427	0	1
Binary where "1" if two or more RLCs installed within 500 to 1000 m (<i>twoormorerlc500to1000</i>)	685	0.0204	0.1416	0	1
Binary where "1" if three RLCs are installed within 1000 m (<i>Threewithin1000</i>)	685	0.0832	0.2764	0	1

Next, time-halo variables were created and added to the database. Variables with several different timing sequences were created and examined to see if any have an effect on the frequency of collisions. A summary of the time-halo descriptive statistics are found in Table 4.8.

The first count variable created (*timehaloyr*) was a simple time trend by year from installation year (1, 2, 3, 4, etc.) to determine if the number of collisions change as the

Table 4.8 – Summary of time-halo variables

Description (<i>variable name</i>)	Observations	Mean	Std. Dev.	Min.	Max.
Time trend (1,2,3,4..) (<i>timehaloyr</i>)	685	6.5596	4.0711	0	14
Cumulative count of RLCs installed (<i>numcam</i>)	685	13.4502	11.4363	0	34
Binary variable where a "1" being a year where a RLC was installed (<i>timehalo</i>)	685	0.4252	0.4945	0	1
Time trend that resets when new RLCs get installed (<i>timehalo2</i>)	685	2.0321	2.3998	0	7

years pass by. This is to examine whether drivers are more aware or indifferent to the presence on RLCs with the progression of years. The second count variable created (*numcams*) was a cumulative count of the number of RLCs as they were installed by year to answer the question of whether the increase in number of RLCs have an impact on the frequency of collisions. A third binary variable (*timehalo*) was created having "1" for the years where RLCs were installed (year 2000, 2001, 2008, 2010, and 2011) and "0" for the years with no cameras installed. This variable would examine if the years the RLCs get installed are any different than other years with no new installations. The fourth count variable created (*timehalo2*) resets at "0" for the years that RLCs get installed and is a continuous count adding one up for every year with no new installations. These different time-halo variables will be tested to find out if the presence of RLCs is substantial in both the short and long-term, as these types of variables have not been examined before related to RLCs.

It is important to understand spillovers and the overall effect on the entire population. This analysis will examine whether the RLC treatment creates benefits to surrounding intersections or by diverting the dangers to them. It will also shed light on how intersections respond to the treatment over time.

4.5 Cost Data

Two types of cost data were used in the economic evaluation of the RLCs: the RLC costs and the social costs of collisions. The RLC costs consist of the capital, maintenance and operational costs of the RLCs. The social costs of collisions are the direct and indirect social cost savings from a reduction in the number of vehicle collisions following the installations of the RLCs.

4.5.1 RLC Costs

Currently the RLC sites in the city of Ottawa are on a lease/operate/maintain basis from the vendor Traffipax under contract. The exact RLC vendor cost is confidential, but according to Mayor Jim Watson *"the city contracts the cameras' operation and monitoring to an outside company at a cost of about \$35,000 annually"* (Dodge, 2016). This cost estimate includes the installation, operation and maintenance of RLC equipment, providing access to vehicle ownership information from MTO, and the agreement with the City of Toronto for processing infraction notices within the Red Light Camera Enforcement Program's Joint Processing Centre.

The City of Ottawa has an annual budget of \$1.25M for its RLC program (City of Ottawa, 2016). According to Mr. Start Edison, Program Manager of Ottawa's Traffic Engineering and Control department, the total costs for the RLC program in Ottawa for 2014 was \$1,189,053 and for 2015 was \$1,251,783 (S. Edison (email communication, Mon 2016-03-14 8:32 AM)). The estimated total RLC cost for the year 2016 is \$1,267,641, based on a Consumer Price Index of 1.27% (Statistics Canada, 2017).

The total number of fines that have been issued on a yearly basis since the program began in 2000 until 2011 were obtained from the City of Ottawa (2012) *"Red*

Light Camera/Roadside Speed Indicator Update" report. For the years 2012 and 2013, an estimated average of 9,200 fines was issued each year (CTV News, 2015). Data obtained from the City of Ottawa shows that almost twice as many vehicles were caught RLR in 2014 compared to 2013. In 2014, 17,186 tickets were issued at intersections with RLCs. The spike coincides with a decision by the City to operate all 34 RLCs every day, and at the same time. Prior to 2014, the number of cameras in operation rotated from site-to-site (CTV News, 2015). In 2015, 17,658 drivers received RLR tickets. During the first three months of 2016, the City mailed 5,266 red-light camera violations (Willing, 2016). The complete number of violations is not out yet for the year 2016, therefore, the same number of tickets from 2015 will be used in the analysis for 2016 to avoid over-estimation.

When the program began in 2000, the fine amount for a RLR violation was \$190 and was then increased in January 2010. The current fine amount set by the province is \$325, including a \$5 service fee and a \$60 victim's surcharge (City of Ottawa, 2012). This results in net revenue of \$260 per red-light violation being returned to the municipality. A summary of the annual number of RLR violations, costs of violations and the annual estimated net revenues is presented in Table 4.9.

The City of Ottawa does not keep track of how many tickets are traceable to each RLC. Krista Tanaka, program manager of road safety and traffic investigations in Ottawa, said, "*The City does not track tickets on an intersection-by-intersection basis because collisions are deemed to be much more important. We don't use tickets as our measure of effectiveness for the cameras*" (Tumilty, 2017).

Table 4.9 – Estimated net revenue (from fines) of the RLC program in Ottawa

Year	Number of RLCs installed	Total Number of RLR Fines Issued	Fine amount per RLR violation	Net revenue from fines*	Annual net estimate of RLR fine revenue
2001	7	4,737	\$ 190	\$ 155	\$ 734,235
2002	7	1,762	\$ 190	\$ 155	\$ 273,110
2003	7	3,253	\$ 190	\$ 155	\$ 504,215
2004	7	2,861	\$ 190	\$ 155	\$ 443,455
2005	7	3,212	\$ 190	\$ 155	\$ 497,860
2006	7	2,572	\$ 190	\$ 155	\$ 398,660
2007	7	5,809	\$ 190	\$ 155	\$ 900,395
2008	18	5,974	\$ 190	\$ 155	\$ 925,970
2009	18	8,873	\$ 190	\$ 155	\$ 1,375,315
2010	31	12,674	\$ 325	\$ 260	\$ 3,295,240
2011	34	9,631	\$ 325	\$ 260	\$ 2,504,060
2012	34	9,200	\$ 325	\$ 260	\$ 2,392,000
2013	34	9,200	\$ 325	\$ 260	\$ 2,392,000
2014	34	17,186	\$ 325	\$ 260	\$ 4,468,360
2015	34	17,658	\$ 325	\$ 260	\$ 4,591,080
2016	34	17,658	\$ 325	\$ 260	\$ 4,591,080

* = cost per fine minus the \$60 victim surcharge and minus the \$5 service fee

4.5.2 Social Costs

Collision victims and the society as a whole are affected by traffic collisions. The social cost of traffic collisions consists of two components used to assign monetary costs, direct and indirect costs (Hanley, 2004). The first component is quite definitive direct costs like property damage, emergency response costs, and material expended in dealing with collisions. The second component is indirect costs which are very abstract and non-tangible estimating the quality of life costs. Quality of life costs includes aspects like physical and mental suffering and permanent cosmetic damage (Hanley, 2004; De Leur, 2010).

The human consequences of collisions are measured by how much society is willing-to-pay to avoid these consequences (Vodden *et al.*, 2007). These are costs that a society is willing to pay to prevent or reduce the risks associated with the occurrence of

collisions, particularly collisions that involve injury and death (i.e. property damage costs, emergency response costs, health services costs, courts and legal costs, tow truck and traffic delay costs).

In 2007, the Transportation Association of Canada published a report entitled *Analysis and Estimation of the Social Cost of Motor Vehicle Collisions in Ontario* (Vodden *et al.*, 2007) which has the most recent social costs available for Ontario. This report advanced an earlier social cost model from Simpson *et al.* (1994) by adding cost components related to traffic delay (i.e. extra time, fuel, and pollution). The average willingness-to-pay social cost is estimated at \$15,700,000 per fatal collision, \$82,000 per injury collision, and \$8,000 per PDO collision (2004 CAD). The details of cost allocation based on the different components are found in Appendix B, adapted from Vodden *et al.* (2007).

Since these values are from 2004, the Consumer Price Index (inflation rates) from 2004 to 2016 were obtained from Statistics Canada (2017) to adjust the costs. The estimated 2016 average willingness-to-pay social cost is estimated at \$19,500,000 per fatal collision, \$101,000 per injury collision, and \$10,000 per PDO collision. A summary of the estimated social costs are found in Table 4.10.

The monetary costs used in Chapter 6 will be based on these base-case costs (2016 CAD). It is important to note, however, that these estimated social collision costs have not been challenged in the economics literature. Therefore, presenting a sensitivity analysis in Chapter 6 will give an impression of the dynamics of the situation.

These social costs of collisions can shed a light on the effect of RLCs as to whether they are reducing the number of collisions, hence the costs to society. The

Table 4.10 – Ontario's estimated social costs of traffic collisions

Year	Inflation Factor*	Base-case values from (Vodden <i>et al.</i> , 2007)		
		PDO	Injury	Fatal
2004	1.9%	\$8,000	\$82,000	\$15,700,000
2005	2.2%	\$8,172	\$83,766	\$16,038,109
2006	1.7%	\$8,308	\$85,154	\$16,303,934
2007	1.9%	\$8,465	\$86,770	\$16,613,222
2008	2.1%	\$8,645	\$88,611	\$16,965,758
2009	0.5%	\$8,691	\$89,079	\$17,055,287
2010	2.5%	\$8,907	\$91,294	\$17,479,475
2011	2.9%	\$9,166	\$93,955	\$17,988,868
2012	1.3%	\$9,287	\$95,190	\$18,225,369
2013	1.0%	\$9,377	\$96,119	\$18,403,323
2014	2.4%	\$9,603	\$98,426	\$18,845,002
2015	1.2%	\$9,718	\$99,607	\$19,071,142
2016	1.8%	\$9,893	\$101,400	\$19,414,423

*Factors obtained from Statistics Canada (2017)

observed number of collisions before and after the RLCs were installed, presented earlier in Table 4.3 of Sec. 4.2, indicated a reduction in angle and turning movement collisions with an increase in rear-end and sideswipe collisions. Since the severities of the collision types differ, it was important to combine both frequency and severity related effects into one cost analysis to determine the overall observed effect of RLCs (i.e. angle and fatal, angle and injury, angle and PDO). Finally, the difference between the social costs of collisions observed before and after-period at the treated intersections were computed as an initial assessment of costs based on the trend.

Table 4.11 and Table 4.12 present the top three intersections that have benefited from the RLC treatment and the top three intersections that have been compromised based on the social costs of the average annual number of observed total collisions before and after the RLC treatment. Results indicate that the intersection that has benefited the most from the RLC treatment in Ottawa is King Edward Ave. and St. Patrick St., by a reduction in cost of an estimated \$3.7 million.

Table 4.11 –Top 3 RLC intersections that benefited after the RLC installation

Benefited			
Intersection Name	Average Annual Total Cost BEFORE RLC	Average Annual Total Cost AFTER RLC	Difference in Cost
KING EDWARD AVE & ST. PATRICK ST	\$ 3,951,520	\$ 180,544	-\$ 3,770,976
CONROY RD & LORRY GREENBERG DR	\$ 3,632,645	\$ 139,116	-\$ 3,493,528
BOOTH ST & OTTAWA RIVER PKWY	\$ 2,567,981	\$ 414,011	-\$ 2,153,970

Table 4.12 –Top 3 RLC intersections that hindered after the RLC installation

Require re-location consideration			
Intersection Name	Average Annual Total Cost BEFORE RLC	Average Annual Total Cost AFTER RLC	Difference in Cost
CYRVILLE RD & INNES RD	\$ 449,671	\$ 5,314,856	\$ 4,865,184
HERON RD & RIVERSIDE DR	\$ 1,187,128	\$ 4,271,590	\$ 3,084,463
BELFAST RD & ST. LAURENT BLVD	\$ 663,914	\$ 1,100,567	\$ 436,653

The intersection that is estimated to have had the least success in reducing the social costs after the RLC installation was the Cyrville Road and Innes Road intersection with an increase of \$4.8 million. The major increase in cost is due to a fatal collision in the post-treatment period. Relocation of RLCs from Table 4.12 need to be studied and considered when evaluation assessments prove that they no longer serve their original purpose.

It is important to note that one of the technical challenges in estimating the benefits and social costs of RLCs at intersections is the extremely rare occurrence of fatal collisions, which account for less than 1 percent of all the collisions but has an most impact on society. The comprehensive cost assigned to a fatality is around 30 times the injury collision costs within the same collision type; thus, one or two fatalities in either

the pre or post-treatment period for a given intersection could greatly affect the cost-related analysis. While this could be legitimate if one could expect repeated similar sites to have the same number of fatalities, this is not likely, due to the rare and random occurrence of fatal collisions.

In a collision-cost research conducted for the State of New Mexico by Hall (1998), the author noted that the main factors determining whether an injury is a fatality rather than a severe injury is probably not affected by roadway-related treatments. They are more likely to be related to factors such as occupant age, restraint use, and type and size of vehicles involved. The author argues that such small numbers of fatalities should not be allowed to affect decisions on roadway-based treatments such as RLCs.

A total of eight fatal collisions took place in the 15 year period for the 34 RLC intersections in Ottawa. A visual representation of the geographical dispersion of the fatal collisions is presented in Figure 4.5. Given that the collision occurrence is random with significant variation over time and space, it is hard to judge whether a specific intersection is safe or safer than other intersections solely based on the RLC presence and frequency of fatal collisions in a given year. A further examination of some potential factors is performed in the next chapter.

Figure 4.5 – RLC intersections with fatal collisions

5. Traffic Safety Evaluation: City of Ottawa Case Study

This chapter presents the main results of the statistical analyses in examining the effect of RLCs on traffic safety using data from the City of Ottawa. Section 5.1 covers the cross-sectional evaluation methods. Section 5.2 presents models with interaction terms followed by Section 5.3 presenting models with spillover effect evaluation. These sections are followed by Section 5.4 presenting the EB method analysis. Section 5.5 presents the case-control analysis results and finally, Section 5.6 presents a summary and comparison of the results.

5.1 Cross-Sectional Evaluation

This section aims to investigate whether some of the variation in the number of traffic collisions is explained in part by the presence of the RLC treatment (by controlling for multiple potential confounding factors). First, to understand the distribution of collisions, a histogram for each collision impact type was plotted confirming that the collisions count data is left-skewed, see Appendix C. This data profile indicates that ordinary least squares (OLS) regression would be inappropriate, since the distribution is non-linear and does not allow for negative values. Since collisions represent a form of count data, it is more appropriate to use a Poisson or a NB based estimation procedure.

The next step was to determine the proper regression model (either Poisson or NB) for estimating the relationship between the intersection attributes and collision experience. The mean and variance were estimated for all collision impact types and the results are presented in Appendix D. The variance for all collision types is larger than the mean, displaying signs of over-dispersion. This confirms that the NB model is more

appropriate than the Poisson model. Therefore, the Poisson models will not be tested any further.

The dependent variable used in the models is the number of collisions per year. Five count variables are used as dependent variables, which are the different collision impact types presented earlier in Table 4.6, which will be testing different outcomes. When it comes to interpreting the regression coefficients, the exponent of the coefficients is calculated as an odds ratio or incidence-rate ratio (IRR) (Buis, 2010). The IRR is the outcome rate while holding all other variables in the model constant. An IRR above (below) 1 implies that the independent variable is positively (negatively) related to the outcome.

An all-inclusive model, with all basic independent variables from Table 4.6, was run first on each collision impact type. The all-inclusive models give an insight to the overall significance and effect of the variables. However, these models were eventually reduced to a best fit model based on the statistical significance of the variables (p -value < 0.05). Model selection was based on comparisons through application of the goodness-of-fit statistical tests using likelihood ratios (LRs) and AIC. All models were checked for multi-collinearity issues (i.e., independent variables that are correlated) and the results did not indicate any correlation issues between the variables. Table 5.1 illustrates a summary of the all-inclusive models and the selected best fit models. The full StataSE output of all models including all their goodness-of-fit parameters is found in Appendix E.

The results indicate that the RLC effect on the total number of collisions is an estimated slight increase of less than 1% (IRR=1.0094). However, the p -value for the

Table 5.1 – NB regression results based on best fit models (IRR coefficients)

Variables	Total		Rear-end		Angle		Turning movement		Sideswipe	
	All-inclusive	Best Fit	All-inclusive	Best Fit	All-inclusive	Best Fit	All-inclusive	Best Fit	All-inclusive	Best Fit
<i>rlcinstalled2</i>	1.0200	1.0094	1.1744**	1.1791**	0.8240**	0.8317*	0.8319*	0.8365*	1.1910	1.1854
<i>lnaad1</i>	1.8523***	1.8568***	3.2585***	3.2921***	0.8661	0.8643	1.5975***	1.5879***	2.7179***	2.6136***
<i>median</i>	0.6665***	0.6798***	0.9893		0.7379**	0.7592**	0.4364***	0.4268***	0.5594***	0.5719***
<i>channelization</i>	1.4449***	1.4369***	1.4925***	1.4821***	1.0853		1.7747***	1.7417***	1.4696**	1.4461**
<i>leftturn</i>	1.1385***	1.1404***	1.0386		1.2619***	1.2644***	0.9233		1.4711***	1.4681***
<i>plt</i>	1.1760***	1.1389**	1.0506		1.0131		1.2614*	1.3181**	1.9306***	1.8557***
<i>fplt</i>	1.0764		1.3124***	1.2805***	0.7143***	0.7288***	0.9389		1.6150***	1.4686***
<i>pplt</i>	1.0787		1.3143***	1.3015***	0.4935***	0.5019***	1.9326***	1.9257***	1.1043	
<i>speed1</i>	1.0064	1.0073***	1.0150***	1.0147***	1.0017		0.9934		0.9968	
<i>speed2</i>	1.0098***	1.0101***	1.0176***	1.0183***	0.9979		1.0056		0.9889	
<i>thrulanes</i>	1.1898***	1.1799***	1.0326		1.3399***	1.3279***	1.1169	1.1448*	1.5524***	1.5016***
<i>_cons</i>	0.0058***	0.0057***	<0.001***	<0.001***	9.9773***	10.2365**	0.0189***	0.0168***	<0.001***	<0.001***
Goodness-of-fit parameters										
AIC	4411	4410	3516	3510	2971	2964	2902	2899	2220	2218
Maximum Likelihood R ²	0.393	0.390	0.501	0.500	0.181	0.179	0.185	0.179	0.212	0.209
Observations	685	685	685	685	685	685	685	685	685	685
RLC EFFECT*:	2.0%	0.9%	17.4%	17.9%	-17.6%	-16.8%	-16.8%	-16.3%	19.1%	18.5%

Exponentiated coefficients = * p<0.05 ** p<0.01 *** p<0.001

* A negative sign indicates a decrease in collisions.

RLC treatment variable (*rlcinstalled2*) was 0.801 which is far above the generally accepted maximum threshold of 0.05 that is needed to reject the null hypothesis of no significant effect. This result suggests that the observed difference of the RLC treatment in the total collisions is plausibly a chance finding and that the hypothesis that there is no difference between the treatment and non-treatment intersections cannot be rejected. Failing to reject the null hypothesis according to the standard criteria of statistical significance, however, does not mean definitively that there is no treatment effect (Altman & Bland, 1995). It is important to note however, that it is the size of the effect that determines the importance, not the presence of statistical significance (Crombie & Davis, 2009).

The model coefficients for angle and turning movement collisions show that the RLC has a significant effect in reducing the number collisions by 17% (IRR=0.8317) and 16% (IRR=0.8365), respectively. On the other hand, the presence of a RLC increases the rear-end collisions by 18% (IRR=1.1791) and sideswipe collisions by 19% (IRR=1.1854). The *p*-values were also calculated to assess whether the results are likely to have occurred simply through chance. The *p*-value was <0.05 for the rear-end, angle and the turning movement collision models, suggesting a strong degree of statistical significance; thus the findings are highly unlikely to have arisen by chance. Therefore, the null hypothesis that there is no difference between the treated and non-treatment is strongly rejected. The *p*-value for sideswipe collisions was insignificant (>0.05), suggesting that the observed difference of the RLC treatment in sideswipe collisions is plausibly a chance finding.

To complement the NB models, RENB and FENB regression models were also tested. The models were run on the panel data to model the collisions between intersections as well as over the time (measuring both cross-sectional and time-series effect). Several non-linear panel models were estimated using the xtnbreg command in StataSE, starting with a saturated model that involves all the possible explanatory variables considered in this study. A procedure of eliminating insignificant variables using manual backward method was undertaken and the most parsimonious model was obtained on the basis of minimizing the AIC value.

Table 5.2 presents a summary of the coefficient estimates of the RLC independent variable from the FENB and RENB final models. Not all the estimated coefficients were reported in the table to save space and focus on the RLC treatment effect. Detailed output of the full set of results can be found in Appendix F.

Table 5.2 – FE and RE NB regression results for RLC effect

Collision Impact Type	RLC (<i>rlcinstalled2</i>) variable IRR coefficient			
	Fixed Effect NB	Random Effect NB	Hausman Test: Prob>chi2	Preferred test
Total	-0.01%	0.01%	<0.0001	Fixed effect
Rear-end	23.4%***	23.8%***	0.8780	Random Effect
Angle	model doesn't converge	-28.5%***	N/A	Random Effect
Turning movement	-13.5%	-14.0%	0.2365	Random Effect
Sideswipe	38.9%***	34.5%**	N/A	Random Effect

Exponentiated coefficients = * p<0.05 ** p<0.01 *** p<0.001

The results from the FE and RE models were compared using Hausman's test, which examines whether a significant correlation exists between RE (unique errors u_i) and explanatory variables, the null hypothesis is they are not. In the presence of such correlation, the RE slope estimator is inconsistent; consequently, the FE model should be

chosen over the RE model. If the correlation is insignificant ($p\text{-value} > 0.05$) then it is safe to use RE models (Princeton University Library, 2017; Torres-Reyna, 2007).

The resulting FENB and RENB models for all collision impact types indicate that the models outperform the NB model from the AIC values. The statistically significant p -value of the Hausman for the total collisions model indicates there may be a systematic difference in the coefficients, and the FE model is preferred over the RE model. For the remaining models the RE models were determined to be better fit.

The results of the effect of the RLC on all the collision impact types are in line with the estimates based on the NB regression. They show that after accounting for observable characteristics, the average treatment effect on total collisions is a very slight decrease of under 1%, an increase in rear-end and sideswipe collisions of 24% and 35%, and a decrease in angle and turning movement collisions of 29% and 14%, respectively.

To determine whether the ZINB models provide an improvement over the traditional NB model, ZINB regression was carried out in StataSE. The comparison between the NB and the ZINB models were evaluated using the Vuong test to identify the best fit model. Detailed output of the comparisons between the NB and ZINB models for each collision impact type are available in Appendix G. For all dependent variables, Vuong's test suggested that the standard NB models perform better than the ZINB models for all the collision impact types reviewed. This result suggests that the role of RLCs is much more important to how often collisions occur, but not to whether they occur or not.

Based on the outlined findings, the RENB panel model approach seems to be the most appropriate for the data in this thesis according to the modeling fitness results which

successfully modelled the RLC effect on collision occurrence with correction spatial and temporal changes. Ignoring spatial correlation in collision modeling may lead to biased parameter estimation by not capturing the multivariate nature of the collision data. This modeling technique can be used to model any non-negative integer count data in a form of panel structure in future research.

5.2 Interaction Terms Evaluation

To try to achieve better balance in the models, richer models were specified with interactions between the RLC treatment and the other covariates. Section 5.1 reported the main effects of variables using the FE and RE models and this section includes the main effects plus the interaction terms between the RLC variable and all the covariates in a separate model.

The FE model did not converge for total collisions when interaction term were added. This means the model has too many factors and not a big enough sample size, and cannot be fit, therefore, a RE model was used instead. RE regression models were first run including all the main effects and interaction terms. Next, manual backward selection was performed to eliminate non-significant pair-wise interactions, while forcing the main effects into the model at this stage for interpretation purposes. Once non-significant pair-wise interactions have been eliminated, backwards selection is considered again to eliminate any non-significant main effects that are not involved in remaining interaction terms (Williams, 2016). Details from the StataSE output of the models for all collisions impact types are found in Appendix H.

In order to calculate the predicted value of the dependent variable for each observation, margins were used in StataSE. The way it works is that it calculates the

outcome if all intersections would have a RLC installed (coded as 1), keeping the other variables as they happen to be, and then if all intersections would not have a RLC installed (coded as 0), keeping the other variables as they happen to be. So for each value (i.e. 0 and 1) the margins command calculates what the mean predicted value of the dependent variable would be if all observations had that value for the binary variable. To find out whether this difference is significant, the marginal effects are computed.

To examine the marginal effects, which is the derivative of the mean predicted value with respect to the RLC covariate, the `dydx` option was used in StataSE with the margins command and the results are shown in Table 5.3. The effect of a RLC installed vs. no RLC on total collisions is an average decrease of 0.0467 collisions. This is simply the difference in the predictive margins. The difference is not significant with a *p*-value of 0.2670.

Table 5.3 – Marginal effect of the RLC covariate (xtnbreg* estimates)

Collision impact type	dy/dx Coef.	Std. Err.	z	P>chi2	[95% Conf. Interval]	
Total collisions	-0.0467	0.0420	-1.11	0.2670	-0.1291	0.0357
Rear-end	0.1364	0.0573	2.38	0.0170	0.0241	0.2486
Angle	-0.5334	0.0904	-5.90	<0.0001	-0.7107	-0.3561
Turning movement	-0.5946	0.1304	-4.56	<0.0001	-0.8501	-0.3390
Sideswipe	0.2451	0.0934	2.62	0.0090	0.0620	0.4282

*refers to the StataSE command for FE and RE models

The `dy/dx` coefficient from Table 5.3 was combined with the average annual observed collisions per intersection per year (from Table 4.3) for the post-treatment period to calculate the percent change has the RLC not been installed. Results are shown in Table 5.4.

Similar to the results obtained from the NB analysis in Section 5.1, the RLC seem to have a significant effect in reducing the number of angle and turning movement

Table 5.4 – Impact of RLC in terms of percentage of collision reduction (xtnbreg)

Collision Types & Classification	AAOC ^a (Before RLC)	AAOC ^a (After RLC)	dy/dx Coef. ^b	Effect without RLC (2) – (3)	Percent Change (2) – (4) / (4)
	(1)	(2)	(3)	(4)	(5)
Total Collisions	14.18	16.72	-0.0467	16.77	-0.3%
Rear-end	5.00	7.88	0.1364	7.74	1.8%
Angle	3.82	3.08	-0.5334	3.61	-14.8%
Turning movement	3.03	2.69	-0.5946	3.28	-18.1%
Sideswipe	1.35	1.96	0.2451	1.71	14.3%

^a AAOC = Average annual observed collisions per intersection.

^b Contrast coefficients obtained from Table 5.3.

collisions by 15% and 18%, respectively. By contrast, the number of rear-end and sideswipe collisions increase by 2% and 14%, respectively. The estimation results of the individual interaction terms between each road elements, the RLC, and collision frequencies for each collision impact type uncovered important interactions. The significance of an interaction can be determined if the confidence interval includes 0. If it does, the predictor is not significant (Hilbe, 2008). Detailed output results of the regression models with the interaction terms are available in Appendix H.

Another way to evaluate the significance of the interaction is looking at the graphical plots of the marginal effects. The structure of the significant interactions was summarized graphically (using the marginsplot command in StataSE) by plotting the logits and relative risks from the regression coefficients for main effect and interaction parameters. When the difference in response between RLC and non-RLC intersections was constant throughout the range (slope of lines are parallel and do not cross) this indicates that there is no interaction between the two variables. When RLC has a steeper/or a less steep covariate-curve compared to non-RLC intersections, this indicates that it has an effect with an interaction, given enough statistical power (Joseph, 2016).

Figure 5.1 presents the significant interaction terms between the RLC and the different covariates for the total collisions. Figure 5.2 presents the non-significant interaction terms for the total collisions to show the difference in the lines of the plots. As an example of interpreting the results, looking at graph “a” in Figure 5.1, it can be observed that while non-RLC intersections start out with higher frequency of total collisions when no right-turn channelization is present, RLC intersections surpass the number of total collisions of the non-RLC intersections when there is right-turn channelization.

Results for total collisions indicate that the interaction terms of RLC with right-turn channelization (*rlcinstalled x channelization*), RLC with number of left-turns lanes (*rlcinstalled x leftturn*), RLC with the number of thru lanes (*rlcinstalled x thrulanes*), RLC with median (*rlcinstalled x median*), and RLC with permitted left-turn signals (*rlcinstalled x plt*) turned out to be significant.

On the other hand, it was found that when testing the interaction terms of RLC with speed limit of Road 1 (*rlcinstalled x speed1*), RLC with protected-permitted left-turn signals (*rlcinstalled x pplt*), RLC with fully-protected left-turn signals (*rlcinstalled x fplt*) the difference in response between RLC and non-RLC intersections was constant throughout the range, as seen in Figure 5.2 in graphs f) to h). The slope of lines are parallel and do not cross, confirming that there is no interaction was apparent. Therefore, it could be concluded that these interaction terms are not necessary to be included in the model to help explain the effects of RLC, and did not contribute to explaining the variation in the collision outcomes. Therefore, they were dropped from the final model.

Figure 5.1 – Significant interaction terms for total collisions

Figure 5.2 – Non-significant interaction terms for total collisions

One reason for empirically assessing interactions is that it can provide insight into the mechanisms for the outcome. It is possible to detect intersections for whom an outcome would occur if both exposures are present but would not occur if just one or the other were present.

The estimation results from the models show that site-varying factors coupled with the RLC may significantly influence the collision frequencies by impact type. A summary of the significant interactions between the RLC and the different covariates for the remaining collision impact types are presented in Table 5.5. The percentages of

Table 5.5 – Significant interactions of RLC with different covariates according to collision type and classification (xtnbreg IRR coefficients)

Variables	Total	Rear-end	Angle	TM	Sideswipe
	Determining effects of significant interactions with the RLC				
<i>rlcinstalled2</i>	↓ <1%	↑ 2%	↓ 15%	↓ 18%	↑ 14%
<i>median</i>	↓ 22%		↓ 52%	↓ 45%	↓ 41%
<i>channelization</i>	↑ 27%	↑ 39%			
<i>leftturn</i>	<ul style="list-style-type: none"> • With 1 left-turn lane ↓ 22% • With 2 left-turn lanes ↓ 13% (<i>non-significant</i>) 			<ul style="list-style-type: none"> • With 1 left-turn lane ↑ 66% (<i>non-significant</i>) • With 2 left-turn lanes ↑ 290% 	
<i>plt</i>	↓ 49%		↓ 52%	↓ 75%	↓ 43%
<i>fplt</i>				↓ 75%	
<i>pplt</i>			↓ 51%	↓ 60%	
<i>speed1</i>					
<i>speed2</i>					
<i>thru lanes</i>	<ul style="list-style-type: none"> • With 2 thru lanes ↓ <1% (<i>non-significant</i>) • With 3 thru lanes ↑ 8% (<i>non-significant</i>) • With 4 thru lanes ↓ 38% 			<ul style="list-style-type: none"> • With 2 thru lanes ↓ 20% (<i>non-significant</i>) • With 3 thru lanes ↑ 98% • With 4 thru lanes ↓ 31% (<i>non-significant</i>) 	

increase and decrease are obtained from the IRR values of the interaction effects from the best fit models, which can be found in Appendix H.

As an example of interpreting the results, when looking at total collisions, an intersection with the presence of a median coupled with a RLC would decrease the chance of collisions by 22% (IRR=0.7760). On the other hand, the presence of right-turn channelization coupled with a RLC would increase the chance of total collisions by 27% (IRR=1.2685). Having one designated left-turn lanes would have a significant decrease the number of total collisions by 22% and having two designated left-turn lanes would also decrease the number of collisions by 13%, which was not significant. An intersection

with four thru lanes coupled with a RLC would significantly decrease the total number of collisions by 38%. Having two thru lanes would decrease the number of collisions by less than 1% while having three lanes would increase the number of collisions by 8%, respectively. However, these two values were not statistically significant. Among all the significant variables, the presence of a median is found to be the most influential site-related factor contributing to the reduction of collision frequencies at intersections when coupled with a RLC.

In summary, one of the motivations for examining interactions is to identify which subgroups would benefit most from the RLC treatment when new sites are planned or when resources are limited. In most settings, it is not be possible to treat all intersections. Therefore, it is important to identify the subgroups which the RLC treatment is likely to have the largest effect on and would benefit the most. Even in settings in which resources are not limited and it is possible to treat several intersections at once, it may be the case that the RLC treatment is beneficial for some intersections and harmful for others. In such cases, it is very important to identify those groups for which treatment may be harmful and refrain from treating such intersections.

5.3 Spillover Effect Evaluation

Traffic flow outside of the immediate treatment zone and on alternate routes must be monitored to determine possible spillover effects. It is possible that drivers may choose alternative routes to avoid RLC sites, therefore, the collision reduction at RLC sites may include the effect induced by a reduced traffic flow. The benefits of RLCs will therefore be overestimated without controlling for the change in traffic flow. A NB regression model was run to check if there has been a redistribution of traffic flow caused by the

RLC installations so that vehicle volume decrease in treated sites and increase in the surrounding area. Results indicated that change in traffic patterns was not significant.

Next, the time and distance halo variables were incorporated in the NB and RENB models with the interaction terms to assess whether the presence and number of the RLCs at a range of distances (from 0 m to 500 m and 500 m to 1 km) from an intersection affects the frequency of collisions at the control intersections. The complete output of the models can be found in Appendix I.

The direction, statistical significance and magnitude of the RLC coefficients in the NB regression best fit models were unaffected from previous findings by the introduction of variables to control for time and distance-halos. Table 5.6 presents the marginal effect of the RLC covariate. Next, the marginal effect was used in Table 5.7 to estimate the impact of the RLC presence on the number of collisions.

Table 5.6 – Marginal effect of the RLC covariate (nbreg* estimates)

Collision impact type	dy/dx Coef.	Std. Err.	z	P>chi2	[95% Conf. Interval]	
Total collisions	0.8846	0.6495	1.36	0.1730	-0.3883	2.1575
Rear end	0.6358	0.4529	1.40	0.1600	-0.2518	1.5234
Angle	-0.4067	0.2715	-1.50	0.1340	-0.9387	0.1254
Turning movement	-0.2567	0.2600	-0.99	0.3240	-0.7663	0.2530
Sideswipe	0.2616	0.3054	0.86	0.3920	-0.3369	0.8601

*refers to the StataSE command for NB regression models

The model estimations indicate a reduction in collisions resulting from the presence of the RLC for angle collisions by 12%, and turning movement collisions by 9%. Rear-end collisions are estimated to increase by 9%, and sideswipe collisions increase by 15%. Based on these estimations the effect of the RLC on total collisions is estimated at an increase of 6%. The coefficient for the RLC effect was not significant in the models.

Table 5.7 – Impact of RLC in terms of percentage of collision reduction (nbreg)

Collision Impact Type	AAOC ^a (Before RLC)	AAOC ^a (After RLC)	dy/dx Coef.	Effect without RLC (2) -(3)	Percent Change ^b (2)-(4) / (4)
	(1)	(2)	(3)	(4)	(5)
Total Collisions	14.18	16.72	0.8846	15.84	5.6%
Rear end	5.00	7.88	0.6358	7.24	8.8%
Angle	3.82	3.08	-0.4067	3.49	-11.7%
Turning movement	3.03	2.69	-0.2567	2.95	-8.7%
Sideswipe	1.35	1.96	0.2616	1.70	15.4%

^a AAOC = Average annual observed collisions per intersection.

^b Contrast coefficients obtained from Table 5.6.

The RENB best fit models, which can be found in Appendix I (Table A and Table B), lacked significance for the RLC coefficient for the total collisions model, the rear-end model and the turning movement model. The magnitude of the RLC effect on all models seemed to be underestimated based on the previous model estimations. Also, the direction of the RLC coefficient was the opposite of previous findings for the sideswipe collision impact type.

The results of the best fit model estimations are presented in Table 5.8. The RENB regression lumps the data of all the years of each intersection together when estimating a difference between the RLC and non-RLC intersections. Since there is a low number of comparable non-RLC intersections in this dataset, inferences might not be accurate using this method. Therefore, the NB regression will be used to better assess the spillover effects.

Examination of possible spillover effects of the RLC program demonstrated a moderate, yet significant, effect on collisions. Control intersections within 500 m of RLC

Table 5.8 – Best fit regression models with time and distance halo variables (IRR coefficients)

Variables	Total		Rear-end		Angle		Turning movement		Sideswipe	
	nbreg	xtnbreg, re	nbreg	xtnbreg, re	nbreg	xtnbreg, re	nbreg	xtnbreg, re	nbreg	xtnbreg, re
<i>rlcinstalled2</i>	1.3217	1.3946	0.8926	1.1853	3.5431**	2.0091**	4.8251***	1.1457	1.4105	1.7296*
<i>lnaad</i>	1.7490***	1.5541***	3.0504***	2.0208***	0.9445	1.0696	1.5684***	1.3274*	1.8796***	1.7035**
<i>median</i>	0.70654***	0.62274***	1.7350***	1.8668**	0.6991***	0.6854	0.3222***	0.56255**	0.5310***	0.5716*
<i>channelization</i>	1.3639***	1.5410***	1.0304	1.2650	1.3925***	1.4162	1.9992***		1.6995***	1.8077*
<i>thrulanes</i>	2	0.9896	0.9665	0.4656***	0.4609**	1.8955***	1.6186	1.2160	1.6501*	1.5230
	3	1.2091	1.2899	0.4004***	0.4176**	2.7636***	2.6110**	1.1655	4.2988***	2.5098*
	4	2.4615***	1.7048*	0.6015***	0.5350	6.9723***	2.2002	2.2385***	10.4617***	3.1516*
<i>leftturn</i>	1	1.1286*	1.0693	0.7974**	0.6606*	1.2021*	1.3190	1.0634	1.1575	0.8535
	2	1.3267***	1.5196*	0.6885**	0.8184	1.5403**	2.0103*	1.0595	3.8621***	2.0753*
<i>plt</i>	1.1531**	1.3597*	1.2715***	1.4899*	1.1045	1.5067*	1.0033		1.9071***	1.9600**
<i>fplt</i>	1.2826***	1.3686**	1.9535***	2.2936***	0.6308***		1.2384		1.8436***	1.4781
<i>pplt</i>	1.1460**	1.2783*	1.4745***	1.8103***	0.6365***	0.7202	1.6049***	2.2991***	2.0032***	
<i>speed1</i>	50	1.1518		1.6721***	1.3996	1.5225**		0.5886*	0.8718	
	60	1.0990		0.9185	0.7126	1.7733***		0.8379	0.6037**	
	70	1.1868		2.4424***	2.3533***	0.9959		0.4282***	0.6667*	
<i>speed2</i>	50	1.5268***	1.7065**	0.5207***	0.5768*			5.5721***	3.3765**	4.3011***
	60	1.5499***	1.7675***	0.9480	1.2572			3.3628***	2.4991*	3.9709***
	80	1.2026	1.5158	0.1096***	0.0644**			15.5214***	3.9743	0.9361
<i>rlcinstalled2##median</i>	0.7628*		0.7132		0.5259*				0.3385***	
<i>rlcinstalled2##channeliza-n</i>	1.3140***	1.2719**	2.0445***	1.5862***	0.6473*				1.8658**	
<i>rlcinstalled2##leftturn</i>	1	0.7143***	0.7729**	0.6812**	0.6932*	1.8286**		0.5124***	0.3915***	
	2	0.9033	0.8813	0.7158	0.6874*	1.8592		1.1301	0.2362***	
<i>rlcinstalled2##thrulanes</i>	2	0.9662	1.0001			1.0436		0.4962*	1.4454	
	3	1.0055	1.0710			1.5140		0.5536	0.9460	

4	0.4257***	0.6013*			0.1844***		0.1844***		0.2753*	
rlcinstalled2##plt	0.7678*				0.2004***		0.7143		0.5302**	
rlcinstalled2##fplt			1.3137		0.3903**		0.5441**		2.9095***	
rlcinstalled2##pplt					0.1931***					
rlcinstalled2##speed1	50	0.9116					0.4288**			
	60	0.7828*					0.3225***			
	70	1.0962					1.0164			
rlcinstalled2##speed2	50									
	60									
	80									
numcams			1.0095***	1.0092***	0.9841***	0.9877***			1.0243***	1.0212***
timehalo									1.2218*	1.1944*
timehalo2	1.0142*	1.0111*	1.0242*	1.0244**						
closestRLC0to500			0.40512***	0.4129***			1.6955***			
closestRLC500to1000	1.2454***		0.84199*				1.4874**		1.4960**	
Twoormore0to500	1.2498*		3.856***	4.4274***			.4747***			
Twoormore500to1000	0.4555***				0.2345***		0.3918***		0.07438***	
Threewithin1000			2.5960***	3.4619***					1.6357*	
_cons	0.0178***	0.1060**	.00005***	.01233***	2.7013	2.5563	0.0082***	0.1393	0.00009***	0.0030**
Goodness-of-fit Parameters										
Observations	685	685	685	685	685	685	685	685	685	685
Log-likelihood	-2131	-2055	-1632	-1574	-1411	-1369	-1357	-1314	-1012	-994
chi ²	464	160	701	284	260	73	300	50	334	106
AIC	4328	4163	3323	3209	2879	2773	2775	2655	2090	2031

Exponentiated coefficients = * p<0.05 ** p<0.01 *** p<0.001

equipped intersections tend to have around 60% fewer rear-end collisions, but an increase of 70% of turning movement collisions. A RLC intersection within 500 m to 1 km away from a specific intersection reduced rear-end collisions by 15%, but increases turning movement collisions by an estimated 48% and also increases sideswipe collisions movement by around 50%. Therefore, evidence of collision migration was found for turning movement and sideswipe collisions.

The presence of two or more RLC intersections within a 500 m zone in relation to another intersection is estimated to reduce the turning movement collisions by 53% but massively increases the rear-end collisions by 380%. This result can be expected as drivers will not take as many risks in making a turning movement knowing that there are several RLCs around and rear-end collisions would increase due to drivers stopping abruptly and the vehicle behind them not expecting them to stop. Having two or more RLCs within a 500 m to a 1 km distance seems to have better results on collision reductions, where there is an estimated decrease in angle collisions by 77%, a reduction in turning movement collisions by 61% and a reduction in sideswipe collisions by 92%. Other factors (not considered in this thesis) such as land-use around each specific intersection, local traffic management and driver negligence knowing that they have passed the RLC site may have been factors in increasing collisions at further intersections.

There was a minor, yet significant, time-halo effect evident in the rear-end, angle and sideswipe collisions. There was no apparent time-halo effect for turning movement collisions. As the number of RLCs increased throughout the city (*numcams*), the rear-end collisions have increased only negligibly at less than 1% and the sideswipe collisions increased by 2%. The angle collisions on the other hand decreased by around 2%. The

specific years that have a set of RLCs installed (*timehalo*) seem to have an effect of increasing rear-end collisions by 2%. The years after the installation years (*timehalo2*) seem to have an increase on the number sideswipe collisions of around 22%. Therefore, when accounting for collisions due to time, the RLC effect overall seems to have a more affirmative safety effect in angle collision reductions but an increase in rear-end and sideswipe collisions.

Interaction effects from the NB regression models including the time and distance-halo variables also demonstrated that site-varying factors coupled with the RLC may significantly influence the collision frequencies by impact type. An updated summary of the significant interactions between the RLC and the different covariates for the collision impact types are presented in Table 5.9 based on the improved best fit models from this Section. The percentages of increase and decrease are obtained from the IRR values of the interaction effects from Table 5.8. They are almost identical to the effects presented in the previous section in Table 5.5. Variations in the results from the time and distance-halo variables were within a few percentages. Results of the interaction terms from the RENB spillover models can be found in Appendix I (Table C).

In summary, the significant reduction in collisions up to a distance of 1 km from RLC sites indicates that RLCs have a generalized effect on drivers' behaviors at intersections that extends beyond RLC. These results give confidence that spillovers exist and gives some sense of the mechanisms through which RLCs can operate. When these findings are not accounted for, the safety effects at the treatment sites and overall sites could be considerably underestimated. It is important to consider the geographic distribution of the RLC sites, as some of the sites were in close proximity to each other,

Table 5.9 – Significant interactions from spillover models (nbreg)

Variables	Total	Rear-end	Angle	TM	Sideswipe
	Determining effects of significant interactions with the RLC				
<i>rlcinstalled2</i>	↑ 6%	↑ 9%	↓ 12%	↓ 9%	↑ 15%
<i>median</i>			↓ 48%		↓ 77%
<i>channelization</i>	↑ 42%	↑ 39%	↓ 46%		↑ 86%
<i>leftturn</i>	<ul style="list-style-type: none"> • With 1 left-turn lane ↓ 32% • With 2 left-turn lanes ↓ 17% (non-significant) 	<ul style="list-style-type: none"> • With 1 left-turn lane ↓ 32% • With 2 left-turn lanes ↓ 29% (non-significant) 	<ul style="list-style-type: none"> • With 1 left-turn lane ↑ 82% • With 2 left-turn lanes ↑ 85% (non-significant) 	<ul style="list-style-type: none"> • With 1 left-turn lane ↓ 49% • With 2 left-turn lanes ↑ 13% (non-significant) 	<ul style="list-style-type: none"> • With 1 left-turn lane ↓ 61% • With 2 left-turn lanes ↓ 77%
<i>plt</i>			↓ 80%	↓ 75%	↓ 43%
<i>fplt</i>	↑ 21%		↓ 71%	↓ 75%	
<i>pplt</i>			↓ 81%	↓ 60%	
<i>speed1</i>	<ul style="list-style-type: none"> • At 50km/hr speed limit ↓ 18% • At 60km/hr speed limit ↓ 28% • At 70km/hr speed limit ↓ 2% 			<ul style="list-style-type: none"> • At 50km/hr speed limit ↓ 58% • At 60km/hr speed limit ↓ 68% • At 70km/hr speed limits ↑ <1% 	
<i>speed2</i>					
<i>thru lanes</i>	<ul style="list-style-type: none"> • With 2 thru lanes ↑ <1% (non-significant) • With 3 thru lanes ↑ 5% (non-significant) • With 4 thru lanes ↓ 56% 		<ul style="list-style-type: none"> • With 2 thru lanes ↑ <1% (non-significant) • With 3 thru lanes ↑ 51% (non-significant) • With 4 thru lanes ↓ 82% 	<ul style="list-style-type: none"> • With 2 thru lanes ↓ 51% • With 3 thru lanes ↓ 45% • With 4 thru lanes ↓ 82% (non-significant) 	<ul style="list-style-type: none"> • With 2 thru lanes ↑ 44% • With 3 thru lanes ↓ 6% • With 4 thru lanes ↓ 73%

possibly reducing their effectiveness. A model that explicitly incorporates spillover effects is important for forecasters to evaluate the impact of wider benefits on policy.

5.4 Empirical Bayes Evaluation

The average collision frequency of comparison sites and the variation around this average are brought into the EB procedure by the SPF models, using trend data from all the non-RLC intersections. The SPF models represent the change in mean collision frequency as AADT increases or decreases. These models estimate what the average safety performance (in yearly collision frequency) is expected to be at a group of typical signalized intersections representing a range of traffic volumes. A negative binomial model was applied to estimate the SPFs and the results are presented in Table 5.10, following examples from Hauer *et al.* (2001), Council *et al.* (2005), Hagen (2014), and Weber (2015).

Table 5.10 – SPF models (calculated from full set of non-RLC intersections)

Model	Variable	Coefficient	Std. Error	Over-dispersion parameter	SPF Model Form
Total	AADT	4.54E-05	5.07E-06	0.1819	$5.62E-01 * AADT^{4.54E-05}$
	Intercept	5.62E-01	1.71E-01		
Rear-end	AADT	6.56E-05	6.53E-06	0.1589	$-1.07 * AADT^{6.56E-05}$
	Intercept	-1.07E+00	2.41E-01		
Angle	AADT	2.48E-05	7.82E-06	0.1692	$-3.54E-01 * AADT^{2.48E-05}$
	Intercept	-3.54E-01	2.66E-01		
Turning Movement	AADT	2.90E-05	8.04E-06	0.2182	$-4.17E-01 * AADT^{2.90E-05}$
	Intercept	-4.17E-01	2.73E-01		
Sideswipe	AADT	2.59E-05	6.81E-06	0.3908	$-5.91E-01 * AADT^{2.59E-05}$
	Intercept	-5.91E-01	2.80E-01		

For total collisions, the estimate of the constant regression parameter is 0.5621, and the estimate of the AADT regression parameter 4.54E-05. This means that at an intersection with AADT of 40,000 vehicles per day, then one should expect $0.562 \times 40000^{4.54E-05} = 0.5623$ collisions/(intersection-year). Here AADT plays the role of one trait value, no additional trait values are represented in the SPF. The AADT

was the only factor used in the model following Hauer (2001) and the Synectics (2003) report conducted for intersections in Ontario, which included Ottawa. However in that report the effect of the RLC treatment was combined with police enforcement.

Next, based on the SPF models developed in Table 5.10 and the over-dispersion parameters derived from those models, the number of expected collisions had the RLC treatment not been installed was estimated using the weighted adjustment equations (Eq. 3.5 and 3.6) on the predictive model estimate, as discussed earlier in Section 3.1.2. Detailed results of the different collision impact types for each individual intersection along with the equations used are presented in Appendix J.

Results in Table 5.11 presents summaries of the evaluation of the effect of the RLC treatment based on the percentage differences between the expected number of collisions had the treatment not been installed and the observed post-treatment number of collisions averaged over the 34 RLC sites. This procedure accounts for regression-to-the-mean effects that result from the natural tendency to select for treatment those sites with high observed crash frequencies.

Table 5.11 – Expected number of collisions from the calculated SPFs

Collision Impact Type/Classification	AAOC^a (Before RLC)	AAOC^a (After RLC)	Expected collisions AFTER if RLC were not installed (EB model calculation)	% change^b
Total Collisions	514	513	503	1.8%
Rear-end	192	230	194	15.7%
Angle	142	95	147	-53.8%
Turning movement	101	87	106	-22.2%
Sideswipe	46	62	49	20.9%

^a AAOC = Average annual observed collisions for 34 RLC intersections.

^b Percent change between AAOC after RLC and effect without RLC.

Models based on the collision impact types show a reduction in angle collisions by 53% and a reduction in turning movement collisions by 22%. On the other hand, total

collisions increased by just over 1% and rear-end collisions also increased by 15%.

The accuracy of the developed models and results are subject to the characteristics of the non-RLC intersections adopted in this thesis. It has to be noted that the difference in the estimation of the SPF model and the dispersion parameter can produce different results when the EB procedure is applied. Since collision patterns usually vary in different geographical areas, the SPFs must be calibrated to reflect local conditions. Non-treatment sites should be chosen that have similar characteristics to the RLC sites. These models can also be transferred to other cities by recalibrating and checking the results against known points in the new city to develop a multiplier (Bissonette and Cramer 2008). This recalibration will adapt the model to local conditions. The estimated model and results from these analyses can assist decision makers in the transportation area to allocate funds on safety improvements that could have the most benefit in terms of RLC collision reduction.

5.5 Case-Control Evaluation

In the first step of the PSM, the logit model of Eq. (3.11) was estimated using StataSE 14.2 statistical software's user-written command `psmatch2` which includes algorithms for common support graphing and covariate imbalance testing (`pstest`) (Leuven and Sianesi, 2003) in order to estimate the propensity scores. Here the propensity score is the probability that the intersection received the RLC treatment. With matching, different sets of variables were tested and the one with the best balance was chosen. After the confirmation of the balance of covariates, the ATT was estimated using the StataCorp (2013) `teffects` command. Detailed output of all the models run can be found in Appendix K.

Although the `teffects` package constructs a propensity score and calculates a treatment effect with a one-line command, it does not present details regarding the propensity scores. Hence, the `psmatch2` command was carried out first in order to compare covariate distributions across our matched groups to ensure that adequate balance has been obtained before calculating treatment effects.

A logit regression was run with the RLC treatment as the outcome variable and the potential confounders as explanatory variables. Next, the StataSE software matches the RLC and non-RLC intersections based on their propensity scores for each observation. To check the region of common support, which is the overlap in range of propensity scores across treatment and comparison groups, a visual inspection of the frequency distributions of the propensity scores for the RLC and non-RLC intersections before and after matching is shown in Figure 5.3.

The overlap indicates that observations from both groups are available across the range of the propensity score, making it possible to perform reasonable comparisons. The area of overlap identifies intersections that have comparable propensity scores among treated and untreated subjects, and are therefore better candidates for inclusion in a comparative analysis. The results from the common support show that seven treatment observations were not used. These are the ones that no good matches were found for, the closest control case for each of them had a propensity score that was more than 0.01 away from them. So these results are based on the 192 treatment cases for which there were good matches. Conversely, the amount of non-overlap of these two curves identifies intersections who have a very low probability of treatment and are never treated. Detailed results of the output from StataSE are found in Appendix K.

Figure 5.3 – Distribution and matching of the propensity scores estimation between RLC and non-RLC intersections for total collisions

Next, the matching procedure was checked to see if the propensity score across the groups was able to balance the distribution of the relevant covariates in both the treatment and control group. A visual representation for checking the covariate imbalance is shown in Figure 5.4 to determine if the matching made the treatment and control groups of covariates more alike.

In order to determine whether the propensity score successfully balanced the data on observed covariates, the proposed maximum standardized differences for specific covariates range from 10 to 25 percent is considered a balance (Austin, 2009; Stuart *et al.*, 2013). There is no rule regarding how much imbalance is acceptable in a propensity score.

Figure 5.4 – Percent standardized bias of covariates before and after matching

As seen in Figure 5.4, the propensity score test showed a significant reduction in bias in the majority of covariates after matching. If a variable is thought to be related to the outcome but not the treatment, including it in the propensity score should reduce the overall bias (Brookhart *et al.*, 2006; Austin, 2011). This expectation is because there is a chance that a variable related to the outcome is also related to treatment. If it is not accounted for in the propensity score, it is an unmeasured confounder and will bias the treatment effect (Brookhart *et al.*, 2006). Therefore, it is beneficial to include all variables that are potentially related to the outcome and evaluate the balance by the overall model standardized mean bias before and after matching (Garrido *et al.*, 2014). The mean bias of the overall model was 16.1% in the unmatched model and 9.8% in the matched model, indicating a good match.

Finally, to estimate the ATT of the RLCs on the different collision impact types, the `teffects ipwra StataSE` command was used as a doubly-robust estimation. The estimation algorithm is built up of two parts: (1) a logit model to predict treatment status

as a function of number of total collisions, angle collisions, rear-end collisions, and turning movement collisions (which can be found in Appendix K for each collision impact type under the StataSE psmatch2 command), (2) a linear regression to model the outcome of each collision type, using the explanatory variables. This method guards against a misspecification of the propensity score. It performs multivariable regression analysis on a sample weighted by the propensity score. As long as either the propensity score or the regression model is specified correctly, the treatment effect estimates will not be biased (Allison, 2015). The results of the estimated ATT are presented in Table 5.12.

Table 5.12 – Impact of RLC (ATT) from PSM method on different collision impact types

Collision impact type	ATT coef.	Std. Err.	z	P>chi²	[95% Conf. Interval]		Balance test (tebalance overid)
Total collisions with spillover variables	-1.8096	0.8185	-2.21	0.0270	-3.4139	-0.2052	0.1829
Total collisions	-0.3629	0.6144	-0.59	0.5550	-1.5671	0.8413	0.1829
Rear-end	0.8366	0.4379	1.91	0.0560	-0.0217	1.6948	0.6555
Angle	-0.7164	0.2601	-2.75	0.0060	-1.2262	-0.2066	0.1719
Turning movement	-0.7058	0.2450	-2.88	0.0040	-1.1860	-0.2257	0.1401
Sideswipe	0.1231	0.1953	0.63	0.5290	-0.2598	0.5059	0.2142

The results of the total number of collisions indicate that if all intersections had RLCs there would be 0.3629 collisions less than the average of collisions that would occur if none of the intersections had RLCs. However, the estimation is non-significant. The impact of the of RLCs on reducing collisions in angle and turning movement impacts was significant reductions of 0.7164 and 0.7058, respectively. On the other hand, intersections with RLCs had a significant increase in rear-end collisions by 0.8366, and a non-significant slight increase in sideswipe collisions of 0.1231.

Imai and Ratkovic (2014) derived a test for balance by viewing the restrictions imposed by balance as over-identifying conditions. This test was implemented using the `tebalance overid` command in StataSE, which tests whether the above treatment models balanced the covariates for all the collision impact types. This balance test uses the χ^2 test for balance. When the $\text{Prob} > \chi^2$ is greater than 0.05 the null hypothesis cannot be rejected that the IPWRA model balanced all covariates (Stata Manual, 2016). The `tebalance overid` estimates were all insignificant after matching indicating that no systematic differences remained in the distribution of covariates between the RLC and non-RLC intersections after matching, which means the models are balanced.

The ATT coefficients were used to estimate the percent change of collisions due to the RLC effect. The results are presented in Table 5.13, indicating a decrease of 19% in angle collisions and a decrease of 21% in turning movement collisions and an increase rear-end collisions and sideswipe collisions by 12% and 7% respectively. The total collisions seems to decrease by 2% here since the decrease in angle and turning movement exceed the increase in rear-end and sideswipe. Results are in line with the findings of the other approaches explored in the previous sections.

In summary, this novel technique (the PSM) has a number of advantages: (1) the derivation of the propensity score in the absence of outcome data avoids the potential for inappropriate skewing of estimates of the treatment effect on outcome during the development of a multivariable model. (2) The PSM can also avoid modeling assumptions involving extrapolations that may occur when the joint distribution of covariates has substantial differences between treatment groups. (3) In instances where the outcome is rare compared to the baseline covariates (i.e. if modeling fatal collisions)

Table 5.13 – Impact of RLC (PSM ATT) in terms of percentage of collision reduction

Collision Impact Type	AAOC ^a (Before RLC)	AAOC ^a (After RLC)	ATT Coef. ^b	Effect without RLC (2) -(3)	Percent Change (2)-(4) / (4)
	(1)	(2)	(3)	(4)	(5)
Total collisions with spillover variables	14.18	16.72	-1.8096	18.5296	-9.8%
Total collisions	14.18	16.72	-0.3629	17.0829	-2.1%
Rear-end	5.00	7.88	0.8366	7.0434	11.9%
Angle	3.82	3.08	-0.7164	3.7964	-18.9%
Turning movement	3.03	2.69	-0.7058	3.3958	-20.8%
Sideswipe	1.35	1.96	0.1231	1.8369	6.7%

^a AAOC = Average annual observed collisions per intersection.

^b ATT coefficients of PSM models from Table 5.12.

and the sample size is not sufficient to take into account the multiple covariates, propensity score methods may be more appropriate.

5.6 Comparison of Results from the Statistical Methods

A comparison of results from the previous five sections (Section 5.1-5.5) was carried out to find out if there are any major differences in the results obtained from the different statistical methods applied. The summary of the RLC effect from each method in presented Table 5.14 indicates that while the estimated counterfactual number of collisions varied slightly across the different statistical methods, the direction and magnitude of the RLC effect were similar and consistent for the most part.

Table 5.14 – Summary of the results from the different statistical approaches

Collision Impact Type	Estimated Effect of RLCs on Collisions					
	NB	RENB	RENB w/ Interaction variables	NB w/ interaction & spillover variables	EB	PSM
Total Collisions	0.9%	0.01%	-0.3%	5.6%	1.8%	-2.1%
Rear-end	17.9%	23.8%	1.8%	8.8%	15.7%	11.9%
Angle	-16.8%	-28.5%	-14.8%	-11.7%	-53.8%	-18.9%
Turning movement	-16.3%	-14.0%	-18.1%	-8.7%	-22.2%	-20.8%
Sideswipe	18.5%	34.5%	14.3%	15.4%	20.9%	6.7%

Note: A negative sign indicates a reduction in collisions.

In addition to demonstrating the value of using multiple evaluation methods, these results show the effects and potential value of using RLCs to affect collision profiles for critical intersections. The different methods all indicate that while RLCs mainly reduce the overall collision frequencies modestly, this aggregate effect is the result of a substantial decrease in angle and turning-movement collisions that is partly offset by an increase in rear-end and sideswipe collisions. From a safety perspective, therefore, RLCs can be seen as a valuable instrument for managing traffic safety problems in urban areas.

The consistency in results is an important finding confirming that the PSM methodology appears to be a viable alternative to the EB methodology, which is the current method most commonly used in traffic safety assessments. It is important to note that there is a difference in the data requirement for the EB and PSM methods. Although both methods rely on a large sample of untreated control sites, the EB method further requires that the untreated sites must be representative of the treated sites in order to estimate the SPFs, which constrains the application of the EB method. Using multiple modeling techniques that address the different deficiencies in the different methods adds to the robustness and confidence in the evaluation results of the different traffic-related treatments. A summary of the different approaches and what they adjust for is presented in Table 5.15.

Therefore, it is suggested that when estimating treatment effects in future research using observational data, the PSM method is preferred to regression-based methods for several practical reasons:

- (1) Unlike regression-based methods, where the researcher is usually tempted to continually modify the regression model to achieve the desired outcome, in the PSM

Table 5.15 – What the different statistical methods adjust for

Statistical Method	Adjustment for Selection Bias	Adjustment for Other Covariates
RLC effect on outcome in naive before-after analysis	No	No
Regression of RLC effect on outcome and control variables in NB modeling	No	Yes
Regression of RLC effect on outcome and control variables in EB modeling	Yes	Yes (only when control variables are used)
Propensity score matched sample, doubly-robust method (regression of RLC effect on outcome and covariates within sample matched by propensity score -teffects ipwra-)	Yes	Yes

method the propensity score is estimated and a matched sample is constructed without any reference to the outcome.

(2) In the PSM method, the outcomes are explicitly compared between treated and untreated subjects that have a similar distribution of observed baseline covariates. In the regression-based methods, the degree of overlap between the distributions of baseline covariates for the two groups may be difficult to assess. In a setting in which there is a strong separation between the two groups, a naïve analyst may proceed with a regression-based analysis without being aware that the fitted regression model is interpolating between two distinct populations. While in the PSM method, if there are substantial differences in baseline covariates between treated and untreated subjects, it restricts the analysis to comparing outcomes between the minority of treated and untreated subjects who have similar covariate patterns. Or the analysis can get discontinued concluding that treated and untreated subjects are so different that a meaningful comparison of outcomes between the two groups is not plausible.

(3) It is simpler to determine whether the propensity score model has been adequately specified conditional on the propensity score, but much more difficult to

determine whether the regression model has been correctly specified (Austin, 2011). To assess whether the propensity score model has been adequately specified, the distribution of measured baseline covariates is compared between treated and untreated subjects. In contrast, it is much more difficult to determine whether the regression model relating treatment selection and baseline covariates to the outcome has been correctly specified. Goodness-of-fit measures do not allow one to determine the degree to which the fitted regression model has successfully eliminated systematic differences between treated and untreated subjects. Thus, regression models are unable to reconstruct counterfactuals as accurately.

Finally, the greater analytical flexibility and confidence that can be acquired through multiple assessment methods can also help to identify combinations of treatments that can enhance the safety benefits of different traffic management techniques. By examining more specifically the conditions in which RLCs are associated with certain types of collisions, policy-makers can combine treatments to create the best conditions for reducing collision frequencies by impact type.

6. Economic Evaluation: City of Ottawa Case Study

This chapter presents results of the economic analysis of the RLCs. Section 6.1 presents the benefit calculations details. Section 6.2 present results of the benefit-cost models. The objective of a benefit-cost analysis is to quantifying the RLC program costs versus the economic safety benefits to determine the return on road safety investment.

6.1 Benefit-Cost Model

The last objective used to gauge the success of the RLC implementation is to assess whether it achieves the desired return on investment. To determine this, the NPV and BCR are calculated according to Equation 3.9 and 3.10. The first step in calculating the NPV and the BCR is to convert the treatment effect into an annualized reduction (or increase) in collisions, based on the statistical analysis results performed in Chapter 5. The reductions (or increases) are then converted into annual benefits (or detriments) using average collision cost values.

To do this, the frequency of the collision impact types and severities were combined into one cost analysis to determine the overall observed effect of RLCs. The observed frequency of collisions and the estimated reduction or increase in frequency of collisions based on the effectiveness of the RLC (obtained from the PSM method from Table 5.13) were multiplied by the social collision costs by collision severity. The costs were annualized for the calculation of net benefit per year. Results are presented in Table 6.1.

The annual total safety benefit for the RLC program is calculated by summarizing the products of the number of fatal and injury collisions reduced by the

Table 6.1 – Annual cost of collisions by impact type

Collision Impact Type	# of RLC sites	Number of collisions			Cost of collisions			Total Weighted Cost
		Annual number of Fatal collisions after RLC	Annual number of Injury collisions after RLC	Annual number of PDO collisions after RLC	Cost of fatal collisions	Cost of injury collisions	Cost of PDO collisions	
Total collisions with spillover effect (observed)	34	0.21	55.83	175.35	\$ 4,046,626	\$ 5,661,396	\$ 1,753,538	\$ 11,461,560
Total collisions (PSM with spillover counterfactual would have been 9.8% increase)	34	0.23	61.28	192.48	\$ 4,441,818	\$ 6,214,287	\$ 1,924,788	\$ 12,580,894
Difference between (observed - counterfactual)		-0.02	-5.45	-17.13	-\$ 395,193	-\$ 552,891	-\$ 171,250	-\$ 1,119,334
Total collisions (observed)	34	0.21	55.83	175.35	\$ 4,046,626	\$ 5,661,396	\$ 1,753,538	\$ 11,461,560
Total collisions (PSM counterfactual would have been 2.1% increase)	34	0.21	57.02	179.08	\$ 4,132,590	\$ 5,781,665	\$ 1,790,789	\$ 11,705,044
Difference between (observed – counterfactual)		0.00	-1.19	-3.73	-\$ 85,965	-\$ 120,268	-\$ 37,251	-\$ 243,484
Rear-end collisions (observed)	34	0.00	23.92	85.10	\$ –	\$ 2,425,306	\$ 851,043	\$ 3,276,348
Rear-end collisions (PSM counterfactual would have been 11.9% decrease)	34	0.00	18.73	66.66	\$ –	\$ 1,899,591	\$ 666,569	\$ 2,566,161
Difference between (observed – counterfactual)		0.00	5.18	18.45	\$ –	\$ 525,714	\$ 184,474	\$ 710,188

Angle collisions (observed)	34	0.21	13.91	28.51	\$ 4,046,626	\$ 1,410,061	\$ 285,072	\$ 5,741,759
Angle collisions (PSM counterfactual would have been 18.9% increase)	34	0.26	17.06	34.97	\$ 4,963,410	\$ 1,729,518	\$ 349,656	\$ 7,042,585
Difference between (observed – counterfactual)		-0.05	-3.15	-6.46	-\$ 916,785	-\$ 319,457	-\$ 64,584	-\$ 1,300,826
Turning movement collisions (observed)	34	0.00	11.47	25.73	\$ –	\$ 1,163,301	\$ 257,260	\$ 1,420,560
Turning movement collisions (PSM counterfactual would have been 20.8% increase)	34	0.00	13.86	31.07	\$ –	\$ 1,405,100	\$ 310,733	\$ 1,715,833
Difference between (observed – counterfactual)		0.00	-2.38	-5.35	\$ –	-\$ 241,800	-\$ 53,473	-\$ 295,273
Sideswipe collisions (observed)	34	0.00	1.32	25.87	\$ –	\$ 133,956	\$ 258,650	\$ 392,606
Sideswipe collisions (PSM counterfactual would have been 6.7% decrease)	34	0.00	1.23	24.13	\$ –	\$ 124,980	\$ 241,319	\$ 366,299
Difference between (observed – counterfactual)		0.00	0.09	1.73	\$ –	\$ 8,976	\$ 17,331	\$ 26,307

RLC program, multiplied by the corresponding percent reduction/increase value for the collision type based on the statistical analysis results. The results revealed that from a positive aggregate economic benefit the annual safety benefit of the RLC program (34 sites) approximated a net cost reduction of \$ 1,119,334. It is estimated that the RLC program in Ottawa prevents 5.5 injury collisions and 17.1 PDO collisions annually.

The collision reduction benefits include the avoided collision costs associated with a 19% reduction in angle collisions (savings >\$1,300,000), a 21% reduction in turning movement collisions (savings >\$295,000) and the revenue from issued citations (\$2.2million). However, the RLC presence is estimated to increase the rear-end collision frequencies by 25% (a loss >\$710,000) and sideswipe collisions by 7% (a loss >\$26,000).

Tanaka said, "*Red-light cameras are known to increase the incidence of rear-end collisions, but that those crashes are less likely to be serious than right-angle collisions, which red-light cameras help prevent.*" (Tumilty, 2017). Unless there are specific records indicating the severity level of the injury and PDO of every collision and by victim, this is a critical assumption made by the Program Manager of road safety and traffic investigations in Ottawa. The cost estimation results in Table 6.1 shows otherwise when breaking down the costs of the angle and rear-end collisions by the collision classification. Beyond a collision being fatal, danger lie in the types of injuries a person may suffer. During rear-end collisions, a person could also suffer whiplash, broken bones, sprains and strains, head trauma, cuts, bruising and more.

The assumption that all angle collisions are more severe than rear-end collisions would require assigning a cost to each level of injury, then subdividing the combined injury category in more detail. According to the data stored by the City of Ottawa,

records show that collision severities are recorded for the overall collision and not by victim. The three general categories recorded are: (1) Fatal (2) Non-fatal injury and (3) PDO.

When strictly looking at the cost of injury collisions and the cost of PDO collisions in Table 6.1, results indicate that there is a major increase in the observed rear-end collision costs (due to the increase in frequency) that do not negate the savings in angle collision costs. Rear-end collisions have around double the frequency of injury collisions than angle collisions and almost triple the frequency of PDOs. What creates a major difference in cost between these two collision impact types is the fatal collisions. As discussed earlier in Section 4.4.2, due to the small numbers of fatal collisions related to the angle collisions, a small change in the total count of these types of collisions could have a significant effect on outcomes due to their high social cost.

Next, the costs of installing and operating RLCs were contrasted with the monetary value of benefits brought about by collision reduction and prosecution, and the results are shown in Table 6.2. Scenarios 1 and 2 present the benefits of collision reduction based on the total number of collisions without considering the spillover effects and Scenarios 3 and 4 consider the spillover effects. Scenario 3 and 4 will be discussed further since they presented a better model fit with the spillover terms (from Section 5.5).

In terms of net benefits, Scenario 3 presents the cost savings from the reduction in the total number of collisions at RLC intersections (including the spillover effects) plus the fine revenue minus the RLC annual costs which yields \$4.4 million in savings. Had the fine revenue not been considered as part of the savings, the RLC annual costs would have exceeded the savings by over \$148,000, as presented in Scenario 4 of Table 6.2.

Table 6.2 – Summary of social costs and benefits

Scenario	Annual RLC costs	Annual fine revenue (from Table 4.8)	Collision reduction benefit (from Table 6.1)	Net benefits	BCR
Scenario 1	\$1,267,641	-\$4,591,080	-\$243,484	-\$3,566,923	3.81
Scenario 2	\$1,267,641	not considered	-\$243,484	\$1,024,157	0.19
Scenario 3	\$1,267,641	-\$4,591,080	-\$1,119,334	-\$4,442,773	4.50
Scenario 4	\$1,267,641	not considered	-\$1,119,334	\$148,307	0.88

Note: a negative cost indicates a saving

However, these costs are still covered by the City of Ottawa's annual RLC budget of approximately \$1 million, which was discussed earlier in Section 4.5.1.

The benefit-cost ratio equals the annual net benefits divided by the annual RLC costs. The benefit-cost ratio for Scenario 1 is 4.50, which exceeds 1.0, meaning that the RLC program's benefits exceed its costs. Hence, the RLC program generated a considerable net benefit for Ottawa. Based on these findings, running the RLC program at the 34 intersections in Ottawa proves to be a benefit socially and economically.

To assess the impacts spread over future years, the net impacts in each year need to be discounted to a present value. Results from Scenario 3 were used since they consider the spillover effects and the benefit from the fine revenues. The economic safety benefits were calculated for the RLC intersections over the 5-year benefit accrual timeframe and converted into NPV. The results are presented in Table 6.3. All costs are in present value terms and are discounted at a rate of 5% over 5 years.

Results indicate that the estimated \$1.3 million investment made annually to install, maintain and operate RLCs generates a return of more than three times this amount after one year. The NPV of the benefits is summed for the 5-year service life of the RLC program (until the next contract renewal) yielding an estimated revenue of \$18

Table 6.3 – Annual monetary benefits associated with the RLC treatment for each of the five years of service life

Year	1	2	3	4	5
Discount rate	5%	5%	5%	5%	5%
Estimated Benefits	-\$5,710,414	-\$5,710,414	-\$5,710,414	-\$5,710,414	-\$5,710,414
Estimated Costs	\$1,267,641	\$1,267,641	\$1,267,641	\$1,267,641	\$1,267,641
Benefit-Cost Ratio	4.50	4.50	4.50	4.50	4.50
Discount Factor	0.952	0.907	0.864	0.823	0.784
Discounted Benefits	-\$5,438,489	-\$5,179,514	-\$4,932,870	-\$4,697,972	-\$4,474,259
NPV (discounted benefits-costs)	-\$4,170,848	-\$3,911,873	-\$3,665,229	-\$3,430,331	-\$3,206,618
Sum of 5 year discounted benefits and costs=	-\$18,384,898				

million. This calculation again proves that the RLC program in Ottawa is a benefit socially and economically in the long term.

6.2 Sensitivity Analysis

Various assumptions and estimations were made and used in the base-case analysis of this thesis. These assumptions and estimations introduce potential error and uncertainty to the conclusions. The potential bias is partially addressed by conducting a sensitivity analysis in this section. Ranges of plausible scenarios and assumptions related to the estimated collision reduction frequencies and the social costs were altered to test the robustness of the base-case conclusions. Table 6.4 presents the alternate values considered and provides brief descriptions of the rationales.

Assumptions regarding the collision reduction estimations based on the RLC treatment were tested. Parameter values were selected from probable ranges estimated from the different statistical methods performed in Chapter 5. The estimated social collision costs (from Table 4.9) have not been challenged in the economics literature. The

Table 6.4 – Alternative values for sensitivity analysis

Variable	Base-case	Alternative values	Rationale
Expected total collisions	-2.1%	-2.1% and 5.6%	Min. and max. estimates obtained from the different statistical approaches (Table 5.12)
Expected rear-end collisions	11.9%	1.8% and 23.8%	
Expected angle collisions	-18.9%	-11.7% and -53.8%	
Expected turning movement collisions	-20.8%	-8.7% and -22.2%	
Expected sideswipe collisions	6.7%	6.7% and 34.5%	
Value of PDO collision	\$10,000	\$9,792* and \$11,000**	From: *(Pitel and Solomon, 2013) – Based on Canada-wide average social costs of collisions (calculated from Table 12 and 13 ** (de Leur, 2010) – Ontario costs report Table 7.2 *** (Vodden <i>et al.</i> , 2007) – Exhibit III-5 Lower and upper scenarios
Value of injury collision	\$101,000	\$ 78,781* and \$134,000**	
Value of fatal collision	\$19,500,000	\$9,230,000*** and \$24,250,000***	

base-case for social costs used in the thesis includes the most plausible assumptions gathered from previous studies and represents the outcome that has the highest probability of occurring. Ranges of plausible social cost scenarios are tested for robustness of the base-case conclusions. These tested scenarios can be treated as one of a number of possible values that can be selected in a model which can address the potential for under-reporting and misreporting of collisions. These errors could also have materially affected the conclusion of the study. The sensitivity analysis gives an impression of the dynamics of the situation.

One of the main concerns is that fatalities represent a small proportion of the total collisions, less than 1 percent, yet the comprehensive and human capital cost assigned to a fatality is around 30 times the injury collision costs within the same collision impact type. Thus, one or two fatalities in either the before or after-period for a given intersection could greatly affect the cost-related analysis. While this influence could be

legitimate if one could expect repeated similar samples to have the same number of fatalities, this is not likely, due to the rare and random occurrence of fatal collisions.

Table 6.5 presents a summary of the sensitivity analysis, and detailed estimations can be found in Appendix L. Results from the sensitivity analysis suggests that the base case analysis results are robust for all plausible alternate assumptions. The resulting net present benefits ranged from \$2.7 million under the most conservative RLC effect assumptions, to \$3.6 million based on the highest social costs scenario. For comparison and illustration purposes, the base-case results are also presented in the table as the first column next to the various scenarios. These sensitivity cost estimates could be used for RLC safety program implementation funding or further treatment-development research efforts.

Table 6.5 – Summary of sensitivity analysis

Collision Impact Type	Base Case	Cost		RLC Effectiveness	
		High Scenario	Low Scenario	Highest Reduction Scenario	Lowest Reduction Scenario
Total collisions	-\$ 243,484	-\$ 307,367	-\$ 170,817	-\$ 243,484	\$ 640,701
Rear-end collisions	\$ 389,153	\$ 491,875	\$ 322,791	\$ 59,262	\$ 779,771
Angle collisions	-\$ 1,083,493	-\$ 1,365,322	-\$ 622,712	-\$ 3,089,066	-\$ 671,786
Turning movement collisions	-\$ 295,273	-\$ 378,358	-\$ 240,223	-\$ 315,364	-\$ 123,589
Sideswipe collisions	\$ 26,307	\$ 30,926	\$ 23,945	\$ 26,307	\$ 134,664
Annual RLC costs	\$ 1,267,641	\$ 1,267,641	\$ 1,267,641	\$ 1,267,641	\$ 1,267,641
Annual fine revenue	-\$ 4,591,080	-\$ 4,591,080	-\$ 4,591,080	-\$ 4,591,080	-\$ 4,591,080
Collision reduction benefit	-\$ 243,484	-\$ 307,367	-\$ 170,817	-\$ 243,484	\$ 640,701
NPV (benefit-cost)	-\$ 3,566,923	-\$ 3,630,806	-\$ 3,494,256	-\$ 3,566,923	-\$ 2,682,738
Benefit-cost ratio	3.81	3.86	3.76	3.81	3.12

7. Guidelines, Conclusions and Recommendations

The first section of this concluding chapter provides planners, managers, administrators, law enforcement, and policy makers with an overview of guiding principles that will support them in the evaluation of the RLC program. Section 7.2 provides a summary of the main findings and Section 7.3 presents recommendations for future research.

7.1 Guidelines for Practical Implementation

The following guidelines, formulated based on the results of this thesis, list a selection of relevant tools and sets out a number of key observations so that a RLC program can be tailored to the needs of a particular jurisdiction. These guidelines apply to all municipalities that are currently using the RLC treatment or are planning to use this treatment:

1. Traffic collisions are relatively infrequent events and, if collision statistics are analyzed for a limited number of intersections or for only a short period of time, trends may be missed or misinterpreted. Large reductions in collisions for what appears to be a high risk area may, in fact, be no more than a RTM effect. Using data for a more extended (three to five year) period will be more beneficial so that a meaningful change in the series will likely be detected, thus, ensuring that resources are not inefficiently invested.
2. Program evaluation activities should begin long before RLC is implemented. It is important to get baseline collision data that represent the time before driver behavior was influenced by any RLCs in the area. It is helpful to collect data before the marketing and media campaign begins because the campaign can influence driver behavior.

3. Since policy decisions are mainly based on the results found from the treatment analysis, it is important to ensure that the statistical tests utilized are not biased. Both NB regression analysis and EB analysis can lead to misleading results when the covariate distributions in the treatment and control groups are different. Thus, traditional regression models are unable to reconstruct counterfactuals. Matching methods provide the comparison of treated and control groups with similar covariate distributions, to avoid extrapolation in regression models when there is little or no overlap in distributions. This thesis raises concerns about placing heavy reliance on the results of traditional regression methods. Policymakers should be well advised to place less reliance on regression, and to facilitate replication of already conducted studies with a more robust research design and utilize better quality data to avoid missing opportunities for better researched policy.

4. The application of FE and RE panel count modeling techniques should be used to model any non-negative integer count data in a form of panel structure in future research. It measures both cross-sectional and time-series effect, as it did in this thesis, modeling the collisions between intersections as well as over the time.

5. RLCs were found to be more beneficial at intersections with a higher frequency of angle and turning movement collisions to rear-end and sideswipe collisions. Where RLCs are installed, rear-end collisions should be especially closely monitored, since drivers tend to react unpredictably when they notice it's a RLC intersection, leading to a greater risk of rear-end collisions. The high increase in rear-end collisions may negate any benefit realized from the expected decrease in angle collisions, and may be cause for a relocation study of the RLC to an alternative location. Therefore, focusing on target collisions is determined to be more valuable than simply examining total collisions.

Presenting results related to the total collisions only may not give a clear picture of the effect of the intervention because the increases in rear-end collisions can offset reductions in the main target group of angle collisions.

6. There are a number of practical and theoretical considerations resulting from the interaction terms. It is to be expected that RLC performance will not be the same for all intersections. There may be other traffic and geometrical factors that contribute to a successful RLC application. Such information should be useful for establishing site selection criteria for future RLC locations. It is important to identify the subgroups of intersections in which the treatment is likely to have the largest effect since resources are usually limited to treat only a small fraction of the population. Methods for assessing additive interaction can help determine which subgroups would benefit most from treatment. This thesis presents some potentially valuable implications on program attributes that impact preferences for RLC programs. Given the variation in intersection characteristics, following these guidelines will help increase the likelihood of the RLC program's success for a City similar to Ottawa, ON:

➤ **To reduce rear-end collisions:**

- ✓ Installing RLCs at intersections with one dedicated left-turn lanes reduces rear-end collisions by an estimated 32%
- ✗ Avoid installing RLCs at intersections with right-turn channelization, which were found to increase rear-end collisions by an estimated 39%.

➤ **To reduce angle collisions:**

- ✓ Installing RLCs at intersections with a median reduces angle collisions by an estimated 48%.

- ✓ Installing RLCs at intersections with right-turn channelization reduces angle collisions by an estimated 46%.
- ✓ Installing RLCs at intersections with protected-permitted left-turn signals reduces angle collisions by an estimated 81%.
- ✓ Installing RLCs at intersections with 4 thru lanes reduces angle collisions by an estimated 82%.
- ✗ Avoid installing RLCs at intersections with only 1 dedicated left-turn lane as they increase angle collisions by an estimated 82%.

➤ **To reduce turning movement collisions:**

- ✓ Installing RLCs at intersections with 1 dedicated left-turn lanes reduces turning movement collisions by an estimated 49%.
- ✓ Installing RLCs at intersections with a permitted left-turn signal reduces turning movement collisions by an estimated 75%.
- ✓ Installing RLCs at intersections with 2 thru lanes reduces turning movement collisions by an estimated 51%.
- ✓ Installing RLCs at intersections with 60km/h posted speed limit reduces turning movement collisions by an estimated 68%.
- ✗ Avoid installing RLCs at intersections with 70km/h posted speed limit as they increase turning movement collisions by a little over 1%.

➤ **To reduce sideswipe collisions:**

- ✓ Installing RLCs at intersections with a median reduces sideswipe collisions by an estimated 77%.

- ✓ Installing RLCs at intersections with permitted left-turn signals reduces sideswipe collisions by an estimated 43%.
- ✓ Installing RLCs at intersections with 4 thru lanes reduces sideswipe collisions by an estimated 73%.
- ✗ Avoid installing RLCs at intersections with right-turn channelization, which were found to increase sideswipe collisions by an estimated 86%.
- ✗ Avoid installing RLCs at intersections with 2 thru lanes as they increase sideswipe collisions by an estimated 44%.

These intersection characteristics should be factors to consider when planning for new RLC installations or when studying relocations.

7. Installing a RLC at an intersection where there are other intersections at a very close proximity of under 500 m increases turning movement collisions by an estimated 70%, but reduces the rear-end collisions by 60%. Having a RLC intersection within 500 m to 1 km away from a specific intersection reduced rear-end collisions by 15%, but increases turning movement and sideswipe collisions by an estimated 48% and 50%, respectively. It is also important to consider the geographic distribution of the RLC sites, as having several RLC sites in close proximity to each other can possibly reduce their effectiveness. Having more RLCs condensed within a zone of under 500 m would have a massive impact in increasing the rear-end collisions and not having any significant effect in reducing angle collisions. Having two or more RLCs within a 500 m to a 1 km distance seems to have better results on collision reductions, where there is an estimated decrease in angle collisions by 77%, a reduction in turning movement collisions by 61% and a reduction in sideswipe collisions by 92%. There should be a balanced use of RLCs

throughout a jurisdiction. In many cases, unveiling the mechanisms behind the spillover effects will lead to a better understanding of how the program works in general.

8. Relocation consideration of RLCs should be considered if evaluation assessments prove that they no longer serve their original purpose. These evaluations should be based on collision reductions and social cost savings. It would be useful to regularly review what is happening at individual locations, and not overall totals of all intersections combined for a city, in order to determine the on-going suitability and need for RLCs at each specific intersection. This review should include an examination of the level of RLR violations and collisions at each intersection, any changes to street furniture, road traffic or construction and other relevant considerations. Such a periodic review will provide additional insight into program operations and may serve to identify appropriate modifications to the program. This analysis could lead management to rotate RLCs rather than installing new RLCs at other high-frequency collision intersections. RLC installment and relocation decisions represent a major policy action, with serious repercussions for public safety.

The guidelines in this section provide direction on the development of policies for traffic safety outcomes. This includes the need for ongoing evaluations and the development of a traffic safety plan that includes appropriate interventions and proper impact assessments methods to base the policy decisions. The development of RLC policy follows the same process, and should be considered as part of broader road safety policy development. These set of guidelines aim to assist in this key policy effort by enhancing such decisions using rigorous research and novel methods.

7.2 Conclusions

Road collisions place a great burden on individuals, property and society. Research shows that many drivers routinely violate the red-light signals, placing themselves and other road users at risk for serious collisions. One of the key enforcement initiatives to assist and facilitate enforcement against RLR is RLCs. The methodologies, population sizes, and data sources used to assess effectiveness of RLC programs have varied, which may lead to flawed collision frequency predictions and incorrect inferences relating to the factors that determine the frequency of collisions. At the present time, there is a lack of clear guidelines to use when evaluating the decision to install RLCs at specific intersections.

Contributions of this thesis to the literature include: (1) correcting for the site-selection bias of traditional methodologies by using a novel methodology (propensity score matching); (2) utilizing the fixed-effect and random-effect panel regressions to account for the spatial and temporal correlations in the data; (3) identifying how RLC effectiveness varies by site characteristics by using interaction terms; (4) measuring spillover distances and times resulting from the presence of RLCs; (5) applying benefit-cost methodology supported by economic analysis and sensitivity analysis using these new estimation methods; and (6) establishing guidelines for effective implementation of the RLC treatment. Data from signalized intersections in the City of Ottawa were used to conduct the analyses.

This thesis first explored the suitability of traditional observational models (i.e. variations of the NB and the EB methods). Statistical tests such as the Vuong test and the AIC, were calculated to identify the best fit models. Based on the final model estimates

and incident rate ratios, the safety effects of the RLCs and other control variables were evaluated. Next, a comparison of results from different safety evaluation methods was conducted to establish a framework for assessing and evaluating the regional conditions necessary to make proper decision on using RLCs. The results of EB collision-frequency analyses at the treated intersections indicate that RLCs have effects similar in direction but somewhat smaller in magnitude than those indicated in the NB regression. The PSM method was introduced in attempt to create equivalent treatment and control groups by summarizing relevant pre-treatment characteristics of each subject into a single-index variable, the propensity score. Then, matching subjects in the untreated comparison pool to subjects in the treatment group based on values of the propensity score.

While the results varied a bit across the different methods, the direction and magnitude were remarkably consistent. The results found that the RLC program in the City of Ottawa was effective overall with a total collision reduction of 10%, with an estimated net economic benefit of approximately \$4.4 million per year (including spillover effects and fine revenues). The collision reduction benefits include the avoided collision costs associated with a 19% reduction in angle collisions (savings >\$1,300,000), a 21% reduction in turning movement collisions (savings >\$295,000) plus the revenue from issued citations. However, the RLC presence is estimated to increase the rear-end collision frequencies by 25% (a loss >\$710,000) and sideswipe collisions by 7% (a loss >\$26,000). The final benefit-cost ratio which includes the total annual collision reduction benefits, the spillover effects and annual fine revenue is 4.50. Based on these findings, running the RLC program at the 34 intersections in Ottawa proves to be a benefit socially

and economically. These results are robust to all plausible scenarios tested in the sensitivity analysis.

The main strength of this thesis, which sets it apart from previous research, lies in the development of a procedure for estimating more accurately the actual benefits of RLC deployment by adjusting covariates between the treated and control groups. The PSM method allows scholars to reconstruct counterfactuals using observational data. Misspecified models using observational data sometimes produce biased estimators. One source of such bias is that the two samples lack distribution overlap, and regression analysis cannot tell researchers the distribution overlap between two samples. PSM should be used, at least as a robust test to justify the findings estimated by regression models.

This thesis has presented evidence to suggest that conventional approaches to account for RTM effects that rely on regression techniques could lead to over/under optimistic assessments of the value of road safety measures, suggesting that benefit-cost decisions may not be optimal. It is recommended here that a PSM approach is adopted which is statistically more appropriate to handling casualty data and flexible enough to allow confounding factors to be incorporated more rigorously with the end result of more reliable estimates of the impacts of road safety measures.

This thesis has also demonstrated the value of including the interaction effects to provide site selection criteria for future RLC site selection. Site selection issues are extremely important, where the aim is to generate maximum return in terms of casualty reduction. It would be very impulsive to conclude that RLCs are uniformly effective in reducing traffic collisions, as did many other studies. Hence a treatment decision based

on the average treatment effect for the entire population can be misleading and should be dependent on site characteristics. Since RLCs are usually costly, it is desirable that the RLC program is operated in a way that maximizes effectiveness with limited resources. By revealing patterns of the RLC treatment effects, and any other traffic and geometrical factors that contribute to a successful RLC application, policy makers can install cameras at sites most likely to benefit from the treatment to improve the cost-effectiveness of the program.

The safety benefits extend beyond the immediate vicinity of the RLC intersections, evidenced by a significant spillover effect in the reduction of angle and turning movement collisions in the zones where RLCs are present. Recognizing that collisions 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 thesis confirms the importance of implementing RLCs on a case-by-case basis only after a careful review of the collision patterns and geometric/operational characteristics at each intersection. The procedure developed as part of the thesis also helps to identify intersections, presently without enforcement, that are likely to benefit from the RLC treatment.

In conclusion, the results obtained in this thesis provide an important step forward toward optimizing a systematic, statistically defensible approach to identifying the impacts of the RLC. A series of issues related to RLCs addressed in this research have not been investigated in depth before, such as how effectiveness varies by site characteristics and under what conditions RLCs perform most effectively. This thesis

contributes to the literature by applying novel causal methods and utilizing spatial analysis to estimate treatment effects of RLCs on traffic safety to help set guidelines for practical implementation.

7.3 Recommendations for Future Research

This thesis addressed some of the gaps in the literature on the casual link between the RLC treatment and road safety. In this section, further recommendations for future research efforts are suggested below:

- This thesis, as well as all reports in Ontario assessing social costs, was based on data outlining the social cost figures from the year 2004 for different collision classifications. There is a considerable need to develop new and updated social cost estimates to be used in all treatment effect analysis as part of a larger effort of producing more accurate cost estimates.
- Additional variables that may influence intersection safety need to be investigated when running causal models. Some variable suggestions that would be useful to consider in future studies include: pavement conditions, visibility of road markings, sizes of the LED red lights on the traffic signals, seatbelt use, and drunk/impaired driver status.
- An analysis similar to the one performed in this thesis should be conducted on a larger number of intersections (perhaps the entire collision database of all intersections in the city). Such study would allow a further, more accurate exploration of the determinants of intersection-collision frequencies.
- Impacts of signal timing need to be studied further to determine how signal timing parameters, particularly cycle length and coordination, influence the safety effects

of RLCs and traffic patterns in the field. Knowledge on the effects of cycle length is limited. Cycle length is needed to provide some measure of the number of red phases (and thus the number of opportunities for RLR) in a given time period. Also, longer red phases might induce more RLR. The length of the phasing during the AM and PM peak should also be reviewed. With respect to signal coordination, a review of whether or not the treated signal approach is part of a set of coordinated signals that lead to queuing of vehicles. Poorly coordinated traffic signals may lead to driver frustration and in turn RLR at signalized intersections.

- A finding in the literature requires further investigation from Huey and Ragland (2007) and Nambisan and Karkee (2010). The finding states that intersections with signal progression, typically provided for pedestrians, where through vehicles can see the countdown, have a lower likelihood of rear-end collisions. Such progression decreases the amount of stops and starts vehicles have to make, which is a decreasing rear-end collision potential. In future studies, the possibility of using progression on all intersection approaches that are in close proximity to other signalized intersections should be explored. Data in this thesis did not cover any signal-progression information. Such information would be valuable when analyzing all intersections in the city.

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Appendix A – Descriptive Data

Table A – Non-RLC intersections

Number	Non-RLC Intersection
1	ALBION RD & HUNT CLUB RD
2	BANK ST & CATHERINE ST
3	BANK ST & RIVERSIDE DR S
4	BASELINE RD & HERON RD
5	BLAIR RD & OGILVIE RD
6	BRIDLE PATH DR & HUNT CLUB RD
7	CARLING AVE & MERIVALE RD
8	COLONEL BY DR & HAWTHORNE AVE
9	CONROY RD & HUNT CLUB RD
10	GREENBANK RD & STRANDHERD DR
11	INDUSTRIAL AVE & ST. LAURENT BLVD
12	KING EDWARD AVE & MURRAY ST
13	LEMIEUX ST & ST. LAURENT BLVD
14	PINECREST RD & RICHMOND RD

Table B – Demographics of Ottawa, Ontario, Canada

Year	Population	Registered Vehicles	Licensed Drivers
1999	769,511	413,892	560,852
2000	786,975	430,547	566,517
2001	806,560	441,625	572,240
2002	817,585	441,169	578,020
2003	825,783	445,120	588,694
2004	830,910	446,250	589,816
2005	836,505	453,168	594,640
2006	845,917	462,406	613,700
2007	855,257	473,384	620,654
2008	868,095	485,973	626,000
2009	883,741	498,120	635,000
2010	899,016	508,389	635,112
2011	912,248	515,784	653,324
2012	924,404	520,942	659,857
2013	934,300	526,151	666,456

Table C – Summary of collision database by impact type per intersection per year

Impact Type	Cumulative		Estimated per intersection		Estimated per intersection per year	
	Non-RLC	RLC	Non-RLC (14 int)	RLC (34 int)	Non-RLC (14 int)	RLC (34 int)
Angle	433	1721	30.9	50.6	2.2	3.5
Approaching	6	18	0.4	0.5	0.0	0.0
Other	56	116	4.0	3.4	0.3	0.2
Rear end	1318	3018	94.1	88.8	6.7	6.2
Sideswipe	300	783	21.4	23.0	1.5	1.6
Single vehicle (other)	166	370	11.9	10.9	0.8	0.8
Turning movement	547	1415	39.1	41.6	2.8	2.9
Grand Total	2826	7441	201.86	218.85	14.42	15.22

T-TESTS

```
. ttest totalcollisions if rlcint == 1, by(rlcinstalled2)
```

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	290	14.18276	.485923	8.27497	13.22636	15.13916
1	199	16.72362	.6046996	8.530338	15.53114	17.9161
combined	489	15.21677	.3827501	8.463885	14.46473	15.96881
diff		-2.540859	.7713636		-4.056471	-1.025248

```
diff = mean(0) - mean(1)                                t = -3.2940
Ho: diff = 0                                           degrees of freedom = 487
```

```
Ha: diff < 0                Ha: diff != 0                Ha: diff > 0
Pr(T < t) = 0.0005          Pr(|T| > |t|) = 0.0011          Pr(T > t) = 0.9995
```

```
. *conclude accident rates differ (total accident numbers increase from 14.18 to 16.72)
. ttest lnaadt if rlcint == 1, by(rlcinstalled2)
```

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	290	10.31352	.0266794	.4543338	10.26101	10.36603
1	199	10.48448	.0280652	.3959085	10.42913	10.53982
combined	489	10.38309	.0198619	.4392137	10.34407	10.42212
diff		-.1709534	.0397233		-.2490035	-.0929032

```

diff = mean(0) - mean(1)                                t = -4.3036
Ho: diff = 0                                             degrees of freedom = 487

```

```

Ha: diff < 0                Ha: diff != 0                Ha: diff > 0
Pr(T < t) = 0.0000          Pr(|T| > |t|) = 0.0000        Pr(T > t) = 1.0000

```

```

. *conclude traffic volumes differ (going up, probably trend, from 10.31 to 10.48; this
could mean that accident rates caused by rlc installation will be overstated)
. ttest angle if rlcint == 1, by(rlcinstalled2)

```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	290	3.82069	.1966391	3.348643	3.433663	4.207716
1	199	3.080402	.2161394	3.049022	2.654171	3.506633
combined	489	3.519427	.1468498	3.24734	3.230892	3.807963
diff		.7402876	.2973416		.1560569	1.324518

```

diff = mean(0) - mean(1)                                t = 2.4897
Ho: diff = 0                                             degrees of freedom = 487

```

```

Ha: diff < 0                Ha: diff != 0                Ha: diff > 0
Pr(T < t) = 0.9934          Pr(|T| > |t|) = 0.0131        Pr(T > t) = 0.0066

```

```

. *conclude accident rates differ (angle accident numbers decrease from 3.82 to 3.08)

```

```

. ttest turningmovement if rlcint == 1, by(rlcinstalled2)

```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	290	3.034483	.1889962	3.218489	2.662499	3.406466
1	199	2.688442	.2333041	3.29116	2.228362	3.148522
combined	489	2.893661	.1469411	3.24936	2.604945	3.182376
diff		.3460405	.2990032		-.2414549	.933536

```

diff = mean(0) - mean(1)                                t = 1.1573
Ho: diff = 0                                             degrees of freedom = 487

```

```

Ha: diff < 0                Ha: diff != 0                Ha: diff > 0
Pr(T < t) = 0.8761          Pr(|T| > |t|) = 0.2477        Pr(T > t) = 0.1239

```

```

. *conclude accident rates DO NOT differ (TM accident numbers decrease marginally from
3.03 to 2.69 but not significant )

```

```

. ttest rearend if rlcint == 1, by(rlcinstalled2)

```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	290	5	.2795158	4.759983	4.449855	5.550145
1	199	7.879397	.4725635	6.666328	6.947494	8.8113
combined	489	6.171779	.2615591	5.783947	5.657858	6.6857
diff		-2.879397	.5167466		-3.894725	-1.864069

```

diff = mean(0) - mean(1)                                t = -5.5722
Ho: diff = 0                                             degrees of freedom = 487

```

```

Ha: diff < 0                Ha: diff != 0                Ha: diff > 0
Pr(T < t) = 0.0000          Pr(|T| > |t|) = 0.0000        Pr(T > t) = 1.0000

```

```
. *conclude accident rates differ (rearend accident numbers increase from 5 to 7.88 )
. ttest sideswipe if rlcint == 1, by(rlcinstalled2)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	290	1.351724	.1121497	1.90984	1.13099	1.572458
1	199	1.964824	.1452035	2.048347	1.67848	2.251168
combined	489	1.601227	.0899143	1.988306	1.42456	1.777894
diff		-.6131	.1810948		-.9689236	-.2572764
diff = mean(0) - mean(1)					t = -3.3855	
Ho: diff = 0					degrees of freedom = 487	
Ha: diff < 0					Ha: diff != 0	
Pr(T < t) = 0.0004					Pr(T > t) = 0.0008	
					Ha: diff > 0	
					Pr(T > t) = 0.9996	

```
. *conclude accident rates differ (sideswipe accident numbers increase from 1.35 to 1.96)
```

Summary of observed collisions – BEFORE and AFTER

Average of Totalcollisions			
		BEFORE	AFTER
	Grand Total		
NON-RLC	14.42		14.42
ALBION RD & HUNT CLUB RD	11.79		11.79
BANK ST & CATHERINE ST	12.50		12.50
BANK ST & RIVERSIDE DR S	12.50		12.50
BASELINE RD & HERON RD	13.07		13.07
BLAIR RD & OGILVIE RD	18.07		18.07
BRIDLE PATH DR & HUNT CLUB RD	16.29		16.29
CARLING AVE & MERIVALE RD	12.07		12.07
COLONEL BY DR & HAWTHORNE AVE	10.14		10.14
CONROY RD & HUNT CLUB RD	14.29		14.29
GREENBANK RD & STRANDHERD DR	16.93		16.93
INDUSTRIAL AVE & ST. LAURENT BLVD	24.29		24.29
KING EDWARD AVE & MURRAY ST	11.21		11.21
LEMIEUX ST & ST. LAURENT BLVD	13.57		13.57
PINECREST RD & RICHMOND RD	15.14		15.14
RLC	14.18	16.72	15.22
ALBERT ST & BOOTH ST	12.91	12.75	12.87
ALBERT ST & KENT ST (OTTAWA)	11.50	12.00	11.93
AVIATION PKWY & OGILVIE RD	16.64	13.75	15.87
BANK ST & HERON RD	22.45	22.50	22.47
BANK ST & HUNT CLUB RD	19.67	25.60	21.79
BANK ST & RIVERSIDE DR N	16.22	15.80	16.07
BASELINE RD & MERIVALE RD	26.22	16.20	22.64

BELFAST RD & ST. LAURENT BLVD	21.89	28.00	24.07
BERRIGAN DR & GREENBANK RD	9.73	11.25	10.13
BLAIR RD & BLAIR RD RAMP 36	16.91	25.25	19.13
BOOTH ST & OTTAWA RIVER PKWY	9.78	10.40	10.00
BRONSON AVE & CARLING AVE	18.00	15.15	15.36
BRONSON AVE & COMMISSIONER ST	14.00	8.75	12.60
CAMPEAU DR & MARCH RD	20.44	18.60	19.79
CARLING AVE & ISLAND PARK DR	10.22	8.80	9.71
CARLING AVE & RICHMOND RD	11.00	14.08	13.86
CATHERINE ST & HWY 417 O'CONN	17.78	12.00	15.71
CATHERINE ST & KENT ST	20.89	23.00	21.64
CHARLEMAGNE BLVD N & TENTH LINE RD	14.56	20.00	16.50
CONROY RD & LORRY GREENBERG DR	3.00	2.50	2.87
COVENTRY RD & ST. LAURENT BLVD	21.00	24.25	23.79
CYRVILLE RD & INNES RD	15.18	14.50	15.00
DRIVEWAY (THE) & ISLAND PARK DR	8.55	8.50	8.53
DUFORD DR & ST. JOSEPH BLVD	8.45	7.00	8.07
EAGLESON RD & HAZELDEAN RD	18.50	16.17	16.50
FISHER AVE & MEADOWLANDS DR	13.27	12.50	13.07
HAWTHORNE AVE & QUEEN ELIZABETH DRWY	8.45	9.00	8.60
HERON RD & RIVERSIDE DR	27.50	29.33	29.07
JOCKVALE RD & STRANDHERD DR	3.82	5.50	4.27
KING EDWARD AVE & ST. ANDREW ST	4.00	1.50	3.64
KING EDWARD AVE & ST. PATRICK ST	25.50	9.00	23.14
MEADOWLANDS DR & MERIVALE RD	20.00	23.00	22.57
RUSSELL RD & WALKLEY RD	21.89	30.40	24.93
SAUNDERSON DR & SMYTH RD	4.17	5.50	4.36
Grand Total	14.28	16.72	14.99

Average of Rearend			
	BEFORE	AFTER	Grand Total
NON-RLC	6.72		6.72
ALBION RD & HUNT CLUB RD	5.86		5.86
BANK ST & CATHERINE ST	3.07		3.07
BANK ST & RIVERSIDE DR S	3.86		3.86
BASELINE RD & HERON RD	8.50		8.50
BLAIR RD & OGILVIE RD	11.00		11.00
BRIDLE PATH DR & HUNT CLUB RD	8.64		8.64
CARLING AVE & MERIVALE RD	3.21		3.21
COLONEL BY DR & HAWTHORNE AVE	2.43		2.43
CONROY RD & HUNT CLUB RD	9.21		9.21

GREENBANK RD & STRANDHERD DR	6.57		6.57
INDUSTRIAL AVE & ST. LAURENT BLVD	14.64		14.64
KING EDWARD AVE & MURRAY ST	4.50		4.50
LEMIEUX ST & ST. LAURENT BLVD	5.93		5.93
PINECREST RD & RICHMOND RD	6.71		6.71
RLC	5.00	7.88	6.17
ALBERT ST & BOOTH ST	3.55	3.25	3.47
ALBERT ST & KENT ST (OTTAWA)	1.00	0.33	0.43
AVIATION PKWY & OGILVIE RD	4.73	6.75	5.27
BANK ST & HERON RD	8.55	11.25	9.27
BANK ST & HUNT CLUB RD	10.33	15.00	12.00
BANK ST & RIVERSIDE DR N	4.11	5.20	4.50
BASLINE RD & MERIVALE RD	12.89	11.80	12.50
BELFAST RD & ST. LAURENT BLVD	5.56	9.40	6.93
BERRIGAN DR & GREENBANK RD	6.09	7.00	6.33
BLAIR RD & BLAIR RD RAMP 36	10.36	14.00	11.33
BOOTH ST & OTTAWA RIVER PKWY	2.78	3.40	3.00
BRONSON AVE & CARLING AVE	5.00	4.69	4.71
BRONSON AVE & COMMISSIONER ST	1.55	1.00	1.40
CAMPEAU DR & MARCH RD	12.89	11.00	12.21
CARLING AVE & ISLAND PARK DR	1.11	1.60	1.29
CARLING AVE & RICHMOND RD	6.00	7.46	7.36
CATHERINE ST & HWY 417 O'CONN	2.67	1.60	2.29
CATHERINE ST & KENT ST	0.78	1.60	1.07
CHARLEMAGNE BLVD N & TENTH LINE RD	6.22	12.80	8.57
CONROY RD & LORRY GREENBERG DR	0.55	1.25	0.73
COVENTRY RD & ST. LAURENT BLVD	7.50	12.67	11.93
CYRVILLE RD & INNES RD	8.00	9.25	8.33
DRIVEWAY (THE) & ISLAND PARK DR	0.73	1.50	0.93
DUFORD DR & ST. JOSEPH BLVD	2.91	2.25	2.73
EAGLESON RD & HAZELDEAN RD	9.50	10.92	10.71
FISHER AVE & MEADOWLANDS DR	2.27	1.75	2.13
HAWTHORNE AVE & QUEEN ELIZABETH DRWY	2.18	3.25	2.47
HERON RD & RIVERSIDE DR	17.50	22.08	21.43
JOCKVALE RD & STRANDHERD DR	0.64	2.25	1.07
KING EDWARD AVE & ST. ANDREW ST	2.92	1.00	2.64
KING EDWARD AVE & ST. PATRICK ST	6.92	3.00	6.36
MEADOWLANDS DR & MERIVALE RD	10.50	9.83	9.93
RUSSELL RD & WALKLEY RD	12.56	20.00	15.21
SAUNDERSON DR & SMYTH RD	0.75	3.00	1.07
Grand Total	5.70	7.88	6.33

Average of Angle			
	BEFORE	AFTER	Grand Total
NON-RLC	2.21		2.21
ALBION RD & HUNT CLUB RD	1.29		1.29
BANK ST & CATHERINE ST	3.50		3.50
BANK ST & RIVERSIDE DR S	4.57		4.57
BASELINE RD & HERON RD	1.43		1.43
BLAIR RD & OGILVIE RD	1.00		1.00
BRIDLE PATH DR & HUNT CLUB RD	1.07		1.07
CARLING AVE & MERIVALE RD	2.57		2.57
COLONEL BY DR & HAWTHORNE AVE	4.71		4.71
CONROY RD & HUNT CLUB RD	1.50		1.50
GREENBANK RD & STRANDHERD DR	1.43		1.43
INDUSTRIAL AVE & ST. LAURENT BLVD	1.57		1.57
KING EDWARD AVE & MURRAY ST	2.36		2.36
LEMIEUX ST & ST. LAURENT BLVD	1.79		1.79
PINECREST RD & RICHMOND RD	2.14		2.14
RLC	3.82	3.08	3.52
ALBERT ST & BOOTH ST	4.36	2.75	3.93
ALBERT ST & KENT ST (OTTAWA)	10.50	9.58	9.71
AVIATION PKWY & OGILVIE RD	2.36	1.50	2.13
BANK ST & HERON RD	3.00	1.25	2.53
BANK ST & HUNT CLUB RD	3.78	3.40	3.64
BANK ST & RIVERSIDE DR N	7.78	6.40	7.29
BASELINE RD & MERIVALE RD	3.33	1.40	2.64
BELFAST RD & ST. LAURENT BLVD	3.44	2.20	3.00
BERRIGAN DR & GREENBANK RD	1.73	1.50	1.67
BLAIR RD & BLAIR RD RAMP 36	3.73	3.75	3.73
BOOTH ST & OTTAWA RIVER PKWY	5.00	3.20	4.36
BRONSON AVE & CARLING AVE	4.00	0.62	0.86
BRONSON AVE & COMMISSIONER ST	5.36	4.50	5.13
CAMPEAU DR & MARCH RD	3.33	3.20	3.29
CARLING AVE & ISLAND PARK DR	5.11	3.00	4.36
CARLING AVE & RICHMOND RD	3.00	3.54	3.50
CATHERINE ST & HWY 417 O'CONN	11.78	7.20	10.14
CATHERINE ST & KENT ST	5.78	7.40	6.36
CHARLEMAGNE BLVD N & TENTH LINE RD	3.00	2.40	2.79
CONROY RD & LORRY GREENBERG DR	1.18	0.25	0.93
COVENTRY RD & ST. LAURENT BLVD	7.50	4.25	4.71
CYRVILLE RD & INNES RD	2.91	2.00	2.67
DRIVEWAY (THE) & ISLAND PARK DR	2.82	2.75	2.80
DUFORD DR & ST. JOSEPH BLVD	2.27	1.25	2.00

EAGLESON RD & HAZELDEAN RD	2.50	1.58	1.71
FISHER AVE & MEADOWLANDS DR	3.73	1.75	3.20
HAWTHORNE AVE & QUEEN ELIZABETH DRWY	3.64	4.25	3.80
HERON RD & RIVERSIDE DR	7.00	2.83	3.43
JOCKVALE RD & STRANDHERD DR	1.55	1.00	1.40
KING EDWARD AVE & ST. ANDREW ST	0.33	0.00	0.29
KING EDWARD AVE & ST. PATRICK ST	8.00	1.00	7.00
MEADOWLANDS DR & MERIVALE RD	3.50	1.33	1.64
RUSSELL RD & WALKLEY RD	2.56	1.60	2.21
SAUNDERSON DR & SMYTH RD	1.67	0.50	1.50
Grand Total	3.17	3.08	3.14

Average of Turning Movement			
	BEFORE	AFTER	Grand Total
NON-RLC	2.79		2.79
ALBION RD & HUNT CLUB RD	3.50		3.50
BANK ST & CATHERINE ST	2.64		2.64
BANK ST & RIVERSIDE DR S	0.64		0.64
BASELINE RD & HERON RD	0.36		0.36
BLAIR RD & OGILVIE RD	2.00		2.00
BRIDLE PATH DR & HUNT CLUB RD	3.93		3.93
CARLING AVE & MERIVALE RD	3.21		3.21
COLONEL BY DR & HAWTHORNE AVE	1.93		1.93
CONROY RD & HUNT CLUB RD	1.93		1.93
GREENBANK RD & STRANDHERD DR	6.36		6.36
INDUSTRIAL AVE & ST. LAURENT BLVD	3.36		3.36
KING EDWARD AVE & MURRAY ST	0.93		0.93
LEMIEUX ST & ST. LAURENT BLVD	3.57		3.57
PINECREST RD & RICHMOND RD	4.71		4.71
RLC	3.03	2.69	2.89
ALBERT ST & BOOTH ST	2.91	4.50	3.33
ALBERT ST & KENT ST (OTTAWA)	0.00	0.58	0.50
AVIATION PKWY & OGILVIE RD	7.55	3.50	6.47
BANK ST & HERON RD	4.45	2.00	3.80
BANK ST & HUNT CLUB RD	1.78	1.40	1.64
BANK ST & RIVERSIDE DR N	1.33	1.00	1.21
BASELINE RD & MERIVALE RD	5.33	0.00	3.43
BELFAST RD & ST. LAURENT BLVD	8.89	11.20	9.71
BERRIGAN DR & GREENBANK RD	0.91	2.25	1.27
BLAIR RD & BLAIR RD RAMP 36	2.00	5.25	2.87
BOOTH ST & OTTAWA RIVER PKWY	1.33	1.80	1.50

BRONSON AVE & CARLING AVE	6.00	5.38	5.43
BRONSON AVE & COMMISSIONER ST	4.91	2.00	4.13
CAMPEAU DR & MARCH RD	1.67	2.60	2.00
CARLING AVE & ISLAND PARK DR	3.11	2.20	2.79
CARLING AVE & RICHMOND RD	1.00	0.62	0.64
CATHERINE ST & HWY 417 O'CONN	0.11	0.60	0.29
CATHERINE ST & KENT ST	9.44	8.80	9.21
CHARLEMAGNE BLVD N & TENTH LINE RD	4.00	3.20	3.71
CONROY RD & LORRY GREENBERG DR	0.73	0.75	0.73
COVENTRY RD & ST. LAURENT BLVD	2.00	1.08	1.21
CYRVILLE RD & INNES RD	0.91	1.25	1.00
DRIVEWAY (THE) & ISLAND PARK DR	4.45	3.75	4.27
DUFORD DR & ST. JOSEPH BLVD	2.36	1.75	2.20
EAGLESON RD & HAZELDEAN RD	2.00	0.83	1.00
FISHER AVE & MEADOWLANDS DR	5.36	5.00	5.27
HAWTHORNE AVE & QUEEN ELIZABETH DRWY	1.64	0.50	1.33
HERON RD & RIVERSIDE DR	1.50	1.75	1.71
JOCKVALE RD & STRANDHERD DR	1.09	1.50	1.20
KING EDWARD AVE & ST. ANDREW ST	0.17	0.00	0.14
KING EDWARD AVE & ST. PATRICK ST	4.42	1.00	3.93
MEADOWLANDS DR & MERIVALE RD	5.00	8.00	7.57
RUSSELL RD & WALKLEY RD	1.67	1.40	1.57
SAUNDERSON DR & SMYTH RD	1.42	0.50	1.29
Grand Total	2.94	2.69	2.86

Average of Sideswipe		
	BEFORE	Grand Total
NON-RLC	1.53	1.53
ALBION RD & HUNT CLUB RD	0.64	0.64
BANK ST & CATHERINE ST	2.00	2.00
BANK ST & RIVERSIDE DR S	2.57	2.57
BASELINE RD & HERON RD	1.79	1.79
BLAIR RD & OGILVIE RD	2.86	2.86
BRIDLE PATH DR & HUNT CLUB RD	0.71	0.71
CARLING AVE & MERIVALE RD	1.71	1.71
COLONEL BY DR & HAWTHORNE AVE	0.29	0.29
CONROY RD & HUNT CLUB RD	0.64	0.64
GREENBANK RD & STRANDHERD DR	1.00	1.00
INDUSTRIAL AVE & ST. LAURENT BLVD	3.07	3.07

KING EDWARD AVE & MURRAY ST	2.14		2.14
LEMIEUX ST & ST. LAURENT BLVD	1.36		1.36
PINECREST RD & RICHMOND RD	0.64		0.64
RLC	1.35	1.96	1.60
ALBERT ST & BOOTH ST	0.73	2.00	1.07
ALBERT ST & KENT ST (OTTAWA)	0.00	0.75	0.64
AVIATION PKWY & OGILVIE RD	0.82	0.50	0.73
BANK ST & HERON RD	4.82	6.00	5.13
BANK ST & HUNT CLUB RD	3.00	5.00	3.71
BANK ST & RIVERSIDE DR N	2.00	2.60	2.21
BASELINE RD & MERIVALE RD	2.44	1.40	2.07
BELFAST RD & ST. LAURENT BLVD	2.00	3.80	2.64
BERRIGAN DR & GREENBANK RD	0.36	0.25	0.33
BLAIR RD & BLAIR RD RAMP 36	0.55	1.00	0.67
BOOTH ST & OTTAWA RIVER PKWY	0.11	1.40	0.57
BRONSON AVE & CARLING AVE	2.00	2.92	2.86
BRONSON AVE & COMMISSIONER ST	0.91	0.75	0.87
CAMPEAU DR & MARCH RD	1.22	0.60	1.00
CARLING AVE & ISLAND PARK DR	0.33	1.40	0.71
CARLING AVE & RICHMOND RD	0.00	1.46	1.36
CATHERINE ST & HWY 417 O'CONN	2.22	1.80	2.07
CATHERINE ST & KENT ST	4.11	5.00	4.43
CHARLEMAGNE BLVD N & TENTH LINE RD	0.44	0.80	0.57
CONROY RD & LORRY GREENBERG DR	0.27	0.00	0.20
COVENTRY RD & ST. LAURENT BLVD	3.50	4.50	4.36
CYRVILLE RD & INNES RD	1.64	1.25	1.53
DRIVEWAY (THE) & ISLAND PARK DR	0.18	0.50	0.27
DUFORD DR & ST. JOSEPH BLVD	0.27	0.50	0.33
EAGLESON RD & HAZELDEAN RD	0.50	1.25	1.14
FISHER AVE & MEADOWLANDS DR	0.73	1.50	0.93
HAWTHORNE AVE & QUEEN ELIZABETH DRWY	0.36	0.25	0.33
HERON RD & RIVERSIDE DR	1.00	1.75	1.64
JOCKVALE RD & STRANDHERD DR	0.09	0.00	0.07
KING EDWARD AVE & ST. ANDREW ST	0.17	0.00	0.14
KING EDWARD AVE & ST. PATRICK ST	5.25	2.50	4.86
MEADOWLANDS DR & MERIVALE RD	1.00	2.00	1.86
RUSSELL RD & WALKLEY RD	2.33	5.60	3.50
SAUNDERSON DR & SMYTH RD	0.17	0.50	0.21
Grand Total	1.42	1.96	1.58

Appendix B – Allocation of Costs

Adapted from : (Vodden *et al.*, 2007)

Total social cost by collision severity is: Fatal—\$11.5 billion; Injury—\$5.0 billion; and PDO— \$1.3 billion. The average social cost by collision severity is: Fatal—\$15.7 million; Injury—\$82 thousand; and PDO—\$8 thousand. The average collision had a social cost of \$77 thousand in 2004.

Exhibit IV-1 Social Cost of motor vehicle collisions in Ontario in 2004 based on willingness to pay medium estimate (2004 million S)

Social costs of collisions in: 2004

Using values (\$000,000) for: 2004

Valuation using: Medium estimate using Willingness to Pay

	Collision Severity			
	Fatal	Injury	PDO	TOTAL
Fatalities:	11,056.80			11056.8
Injuries:				+
Major	41	641.1		682.1
Minor	40.8	1,535.00		1,575.80
Minimal	1.3	80.1		81.4
Total disability	9.2	192.1		201.3
Partial disability	51.3	1,266.80		1318
HUMAN SUB-TOTAL	11,200.40	3,715.10		14,915.40

Other Costs:				
Property damage	17.5	740.9	1045.8	1804.2
Hospital/Health care:				
• ER facility	0.2	6.5	0	6.8
• Hospital stay facility	1.2	11		12.1
• Medical practitioners	4.3	99.7		104
Police	6.1	49.9	29.3	85.3
Courts	0.9	7.3	4.3	12.6
Fire	1.9	89.4		91.3
Ambulance	1.6	27.6		29.1
Towtrucks	0.6	33.2	61.8	95.6
Out of pocket	0.6	56.3	149.3	206.2
Traffic delays:				
• Extra time	120.6	102.2	27.9	250.7
• Extra fuel	10.1	8.6	2.3	21
• Extra pollution	110.7	93.8	25.6	230.2
OTHER SUB-TOTAL	276.30	1,326.40	1,346.30	2,949.10

OVERALL TOTAL (human + other sub-totals)	11,476.70	5,041.50	1,346.30	17,864.50
AVERAGE (\$000)	15.728	81.6	8	77.2

Appendix C – Histogram of collision frequency by collision impact type

RLC INTERSECTIONS (before and after periods)

Total collisions

histogram totalcollisions if rlcint ==1

Rear-end collisions

histogram rearend if rlcint ==1

Angle collisions

histogram angle if rlcint ==1

Turning movement collisions

histogram turningmovement if rlcint ==1

Sideswipe

histogram sideswipe if rlcint ==1

RLC & Non-RLC INTERSECTIONS (total collisions) **Non-RLC INTERSECTIONS**

Appendix D – Means and Variances

. summarize totalcollisions rearend angle turningmovement sideswipe, detail

Totalcollisions					
	Percentiles	Smallest			
1%	1	0			
5%	3	0			
10%	5	0	Obs	685	
25%	10	0	Sum of Wgt.	685	
50%	14		Mean	14.98832	←
		Largest	Std. Dev.	7.735381	
75%	20	39			
90%	26	39	Variance	59.83612	←
95%	29	39	Skewness	.5169208	
99%	36	39	Kurtosis	3.058732	
Rearend					
	Percentiles	Smallest			
1%	0	0			
5%	0	0			
10%	1	0	Obs	685	
25%	2	0	Sum of Wgt.	685	
50%	5		Mean	6.329927	←
		Largest	Std. Dev.	5.387531	
75%	9	27			
90%	14	28	Variance	29.02549	←
95%	16	30	Skewness	1.137234	
99%	21	30	Kurtosis	4.386079	
Angle					
	Percentiles	Smallest			
1%	0	0			
5%	0	0			
10%	0	0	Obs	685	
25%	1	0	Sum of Wgt.	685	
50%	3		Mean	3.144526	←
		Largest	Std. Dev.	3.000169	
75%	4	16			
90%	7	17	Variance	9.001012	←
95%	9	21	Skewness	2.022987	
99%	14	24	Kurtosis	9.907645	
TurningMovement					
	Percentiles	Smallest			
1%	0	0			
5%	0	0			
10%	0	0	Obs	685	
25%	1	0	Sum of Wgt.	685	
50%	2		Mean	2.864234	←
		Largest	Std. Dev.	3.019521	
75%	4	14			
90%	7	14	Variance	9.117505	←
95%	9	15	Skewness	1.593698	
99%	13	17	Kurtosis	5.654614	

Sideswipe					

	Percentiles	Smallest			
1%	0	0			
5%	0	0			
10%	0	0	Obs	685	
25%	0	0	Sum of Wgt.	685	
50%	1		Mean	1.581022	←
		Largest	Std. Dev.	1.891329	
75%	2	9			
90%	4	9	Variance	3.577125	←
95%	5	9	Skewness	1.655795	
99%	9	10	Kurtosis	5.958757	

Appendix E – NB StataSE Output

. ***TOTAL COLLISIONS***

```
. *FULL MODEL*
. nbreg totalcollisions rlcinstalled2 lnaadt channelization median leftturn thrulanes plt
fplt
pplt speed1 speed2, irr
```

```
Negative binomial regression      Number of obs      =      685
                                   LR chi2(11)              =      341.55
                                   Prob > chi2              =      0.0000
                                   Pseudo R2                =      0.0723
```

totalcollisions	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.019958	.0382699	0.53	0.598	.947642	1.097792
lnaadt	1.852272	.0876899	13.02	0.000	1.688136	2.032367
channelization	1.444894	.0591834	8.99	0.000	1.33343	1.565674
median	.6665064	.0308571	-8.76	0.000	.6086904	.729814
leftturn	1.138514	.0317801	4.65	0.000	1.0779	1.202538
thrulanes	1.189767	.033066	6.25	0.000	1.126692	1.256373
plt	1.175951	.0517297	3.68	0.000	1.078811	1.281839
fplt	1.076391	.0506249	1.57	0.118	.9816037	1.180331
pplt	1.07871	.049069	1.67	0.096	.9866989	1.179301
speed1	1.00643	.0021188	3.04	0.002	1.002285	1.010591
speed2	1.009752	.0025644	3.82	0.000	1.004738	1.01479
_cons	.0058145	.0028226	-10.60	0.000	.0022454	.0150566
/lnalpha	-2.20427	.092922			-2.386393	-2.022146
alpha	.1103311	.0102522			.0919608	.1323711

```
LR test of alpha=0: chibar2(01) = 407.85      Prob >= chibar2 = 0.000
```

```
. fitstat
```

```
Measures of Fit for nbreg of totalcollisions
```

```
Log-Lik Intercept Only:    -2363.083      Log-Lik Full Model:      -2192.307
D(672):                    4384.613      LR(11):                  341.554
                                   Prob > LR:                  0.000
McFadden's R2:             0.072      McFadden's Adj R2:      0.067
Maximum Likelihood R2:     0.393      Cragg & Uhler's R2:     0.393
AIC:                       6.439      AIC*n:                  4410.613
BIC:                       -3.156      BIC':                   -269.730
```

```
. *nbreg best fit reduced:
. nbreg totalcollisions rlcinstalled2 lnaadt channelization median leftturn thrulanes plt
speed1 speed2, irr
```

```
Negative binomial regression      Number of obs      =      685
                                   LR chi2(9)              =      338.04
                                   Prob > chi2              =      0.0000
                                   Pseudo R2                =      0.0715
```

totalcollisions	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.009402	.0375249	0.25	0.801	.9384697	1.085695
lnaadt	1.856836	.0866584	13.26	0.000	1.694525	2.034693
channelization	1.436911	.0586502	8.88	0.000	1.326436	1.556586
median	.6797706	.0306337	-8.57	0.000	.6223049	.7425429
leftturn	1.14044	.0318757	4.70	0.000	1.079645	1.204658
thrulanes	1.17991	.0322782	6.05	0.000	1.118312	1.244901
plt	1.138942	.0448	3.31	0.001	1.054435	1.230221

```

      speed1 |      1.00732   .0020645      3.56   0.000      1.003281   1.011374
      speed2 |      1.010096   .0025116      4.04   0.000      1.005186   1.015031
      _cons |      .0057017   .0027121     -10.86   0.000      .0022445   .0144842
-----+-----
      /lnalpha |     -2.199901   .0929008                      -2.381983   -2.017819
-----+-----
      alpha |      .1108141   .0102947                      .0923672   .1329451
-----+-----
LR test of alpha=0: chibar2(01) = 409.91          Prob >= chibar2 = 0.000

```

```
. fitstat
```

```
Measures of Fit for nbreg of totalcollisions
```

```

Log-Lik Intercept Only:   -2363.083   Log-Lik Full Model:   -2194.065
D(674):                   4388.130   LR(9):                 338.037
                               Prob > LR:                 0.000
McFadden's R2:           0.072   McFadden's Adj R2:     0.067
Maximum Likelihood R2:    0.390   Cragg & Uhler's R2:    0.390
AIC:                      6.438   AIC*n:                 4410.130
BIC:                      -12.699   BIC':                  -279.273

```

. ***REAR-END COLLISIONS***

```

. * nbreg on full
. nbreg rearend rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt
pplt speed1 speed2, irr

```

```

Negative binomial regression          Number of obs   =      685
                                      LR chi2(11)       =     476.06
Dispersion      = mean                Prob > chi2      =     0.0000
Log likelihood = -1745.095            Pseudo R2      =     0.1200

```

```

-----+-----
      rearend |      IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      rlcinstalled2 |  1.174396   .0656937      2.87   0.004     1.052446   1.310476
      lnaadt |  3.258538   .2441723     15.76   0.000     2.813453   3.774035
channelization |  1.492513   .0913287      6.54   0.000     1.323829   1.68269
      median |  .9892691   .0716181     -0.15   0.882     .8584041   1.140085
      leftturn |  1.038635   .0432963      0.91   0.363     .9571501   1.127057
      thrulanes |  1.032596   .0437878      0.76   0.449     .9502436   1.122086
      plt |  1.050629   .068674      0.76   0.450     .9242958   1.19423
      fplt |  1.312368   .0912859      3.91   0.000     1.145111   1.504055
      pplt |  1.314319   .0917481      3.92   0.000     1.146255   1.507024
      speed1 |  1.014974   .0031003      4.87   0.000     1.008915   1.021068
      speed2 |  1.017641   .0038088      4.67   0.000     1.010203   1.025133
      _cons |  2.40e-06   1.84e-06     -16.88   0.000     5.34e-07   .0000108
-----+-----
      /lnalpha |     -1.554048   .108908                      -1.767503   -1.340592
-----+-----
      alpha |      .2113906   .0230221                      .1707588   .2616907
-----+-----

```

```
LR test of alpha=0: chibar2(01) = 281.55          Prob >= chibar2 = 0.000
```

```
. fitstat
```

```
Measures of Fit for nbreg of rearend
```

```

Log-Lik Intercept Only:   -1983.123   Log-Lik Full Model:   -1745.095
D(672):                   3490.190   LR(11):                476.056
                               Prob > LR:                 0.000
McFadden's R2:           0.120   McFadden's Adj R2:     0.113
Maximum Likelihood R2:    0.501   Cragg & Uhler's R2:    0.502
AIC:                      5.133   AIC*n:                 3516.190
BIC:                      -897.580   BIC':                  -404.232

```

```
. *nbreg best fit reduced:
```

```
. nbreg rearend rlcinstalled2 lnaadt channelization fplt pplt speed1 speed2, irr
```

```
Negative binomial regression      Number of obs      =      685
                                   LR chi2(7)              =      474.14
Dispersion      = mean            Prob > chi2          =      0.0000
Log likelihood = -1746.0532        Pseudo R2           =      0.1195
```

	rearend	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2		1.179085	.0641182	3.03	0.002	1.059881	1.311696
lnaadt		3.292117	.2419955	16.21	0.000	2.850399	3.802288
channelization		1.482139	.0780839	7.47	0.000	1.336734	1.643361
fplt		1.280509	.0767245	4.13	0.000	1.138625	1.440072
pplt		1.301471	.0856283	4.00	0.000	1.144013	1.480601
speed1		1.014674	.0030301	4.88	0.000	1.008753	1.020631
speed2		1.018268	.0036666	5.03	0.000	1.011107	1.02548
_cons		2.41e-06	1.81e-06	-17.18	0.000	5.50e-07	.0000105
/lnalpha		-1.549936	.1082334			-1.762069	-1.337802
alpha		.2122616	.0229738			.1716892	.2624218

```
LR test of alpha=0: chibar2(01) = 292.35      Prob >= chibar2 = 0.000
```

```
. fitstat
```

```
Measures of Fit for nbreg of rearend
```

```
Log-Lik Intercept Only:    -1983.123      Log-Lik Full Model:      -1746.053
D(676):                    3492.106      LR(7):                  474.139
                               Prob > LR:      0.000
McFadden's R2:             0.120      McFadden's Adj R2:      0.115
Maximum Likelihood R2:     0.500      Cragg & Uhler's R2:     0.501
AIC:                       5.124      AIC*n:                  3510.106
BIC:                       -921.781     BIC':                   -428.434
```

. ***ANGLE COLLISIONS***

```
. * nbreg on full model
```

```
. nbreg angle rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt pplt
speed1 speed2, irr
```

```
Negative binomial regression      Number of obs      =      685
                                   LR chi2(11)             =      136.50
Dispersion      = mean            Prob > chi2          =      0.0000
Log likelihood = -1472.3882        Pseudo R2           =      0.0443
```

	angle	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2		.8239992	.0594871	-2.68	0.007	.7152798	.9492436
lnaadt		.8661252	.0769089	-1.62	0.106	.7277747	1.030776
channelization		1.085338	.0856697	1.04	0.300	.929772	1.266932
median		.7378556	.0647453	-3.46	0.001	.6212697	.8763197
leftturn		1.261866	.0683389	4.29	0.000	1.134788	1.403175
thrulanes		1.339935	.071693	5.47	0.000	1.206536	1.488083
plt		1.013089	.0895683	0.15	0.883	.8519062	1.204767
fplt		.7142611	.0657134	-3.66	0.000	.5964099	.8553998
pplt		.4934816	.0448515	-7.77	0.000	.4129592	.589705
speed1		1.001701	.0044126	0.39	0.700	.9930897	1.010387
speed2		.9978994	.0049612	-0.42	0.672	.9882228	1.007671
_cons		9.977261	9.173026	2.50	0.012	1.645972	60.47839
/lnalpha		-1.096737	.1169352			-1.325926	-.8675482
alpha		.333959	.0390516			.265557	.41998

LR test of alpha=0: chibar2(01) = 208.82 Prob >= chibar2 = 0.000

. fitstat

Measures of Fit for nbreg of angle

Log-Lik Intercept Only:	-1540.638	Log-Lik Full Model:	-1472.388
D(672):	2944.776	LR(11):	136.500
		Prob > LR:	0.000
McFadden's R2:	0.044	McFadden's Adj R2:	0.036
Maximum Likelihood R2:	0.181	Cragg & Uhler's R2:	0.183
AIC:	4.337	AIC*n:	2970.776
BIC:	-1442.993	BIC':	-64.676

. *nbreg best fit reduced:

. nbreg angle rlcinstalled2 lnaadt median leftturn thrulanes fplt pplt , irr

Negative binomial regression	Number of obs	=	685
Dispersion = mean	LR chi2(7)	=	134.88
Log likelihood = -1473.1998	Prob > chi2	=	0.0000
	Pseudo R2	=	0.0438

angle	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	.8316673	.0592187	-2.59	0.010	.7233359	.9562231
lnaadt	.8643373	.0756968	-1.66	0.096	.7280091	1.026195
median	.7591635	.0611176	-3.42	0.001	.6483478	.8889199
leftturn	1.26444	.0674798	4.40	0.000	1.138864	1.403863
thrulanes	1.327941	.0689006	5.47	0.000	1.199538	1.470089
fplt	.7287846	.0565437	-4.08	0.000	.6259758	.8484784
pplt	.5018849	.0425198	-8.14	0.000	.4250992	.5925406
_cons	10.23645	9.146498	2.60	0.009	1.776568	58.98166

/lnalpha	-1.093667	.1166737			-1.322343	-.864991

alpha	.3349858	.039084			.26651	.4210554

LR test of alpha=0: chibar2(01) = 211.45 Prob >= chibar2 = 0.000

. fitstat

Measures of Fit for nbreg of angle

Log-Lik Intercept Only:	-1540.638	Log-Lik Full Model:	-1473.200
D(676):	2946.400	LR(7):	134.877
		Prob > LR:	0.000
McFadden's R2:	0.044	McFadden's Adj R2:	0.038
Maximum Likelihood R2:	0.179	Cragg & Uhler's R2:	0.181
AIC:	4.328	AIC*n:	2964.400
BIC:	-1467.487	BIC':	-89.171

. *TURNINGMOVEMENT COLLISIONS*****

. * nbreg on full model

. nbreg turningmovement rlcinstalled2 lnaadt channelization median leftturn thrulanes plt
fplt pplt speed1 speed2, irr

Negative binomial regression	Number of obs	=	685
Dispersion = mean	LR chi2(11)	=	140.38
Log likelihood = -1437.7798	Prob > chi2	=	0.0000
	Pseudo R2	=	0.0465

turningmovement	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	.8319201	.0708887	-2.16	0.031	.7039632	.9831353
lnaadt	1.597505	.1756352	4.26	0.000	1.287829	1.981647
channelization	1.774666	.1647146	6.18	0.000	1.479493	2.128729
median	.4363698	.0446738	-8.10	0.000	.3570361	.5333316

```

leftturn | .9232845 .0606008 -1.22 0.224 .8118317 1.050038
thrulanes | 1.116897 .0673373 1.83 0.067 .9924175 1.25699
    plt | 1.261375 .121923 2.40 0.016 1.043682 1.524475
    fplt | .9388935 .098942 -0.60 0.550 .763687 1.154296
    pplt | 1.93258 .1871464 6.80 0.000 1.598487 2.3365
speed1 | .9934389 .0045911 -1.42 0.154 .9844811 1.002478
speed2 | 1.005566 .0058379 0.96 0.339 .9941889 1.017074
    _cons | .0189012 .021111 -3.55 0.000 .0021172 .1687366
-----+-----
      /lnalpha | -.6951847 .105285 -1.9015395 -.4888298
-----+-----
      alpha | .4989823 .0525354 .4059442 .6133437
-----+-----
LR test of alpha=0: chibar2(01) = 302.29          Prob >= chibar2 = 0.000

```

```
. fitstat
```

```
Measures of Fit for nbreg of turningmovement
```

```

Log-Lik Intercept Only:   -1507.971   Log-Lik Full Model:   -1437.780
D(672):                   2875.560   LR(11):                 140.382
                               Prob > LR:                 0.000
McFadden's R2:           0.047   McFadden's Adj R2:     0.038
Maximum Likelihood R2:   0.185   Cragg & Uhler's R2:    0.188
AIC:                     4.236   AIC*n:                 2901.560
BIC:                    -1512.210   BIC':                  -68.559

```

```
.
. nbreg turningmovement rlcinstalled2 lnaadt channelization median thrulanes plt pplt ,
irr
```

```

Negative binomial regression          Number of obs   =      685
                                      LR chi2(7)         =     135.20
Dispersion = mean                    Prob > chi2       =     0.0000
Log likelihood = -1440.3706          Pseudo R2       =     0.0448

```

```

-----+-----
turningmovement |          IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
    rlcinstalled2 |   .8365191   .0702191   -2.13   0.033   .7096176   .9861147
      lnaadt |   1.587854   .1680954    4.37   0.000   1.290327   1.953987
channelization |   1.741691   .1598015    6.05   0.000   1.455033   2.084825
      median |   .426751   .0412719   -8.81   0.000   .3530639   .5158172
    thrulanes |   1.144794   .0659107    2.35   0.019   1.022633   1.281547
        plt |   1.318148   .1146117    3.18   0.001   1.111611   1.563059
        pplt |   1.925666   .1562743    8.07   0.000   1.642491   2.257661
        _cons |   .0167683   .0183003   -3.75   0.000   .0019748   .1423832
-----+-----
      /lnalpha |  -.6739772   .1038748   -1.877568   -.4703863
-----+-----
      alpha |   .5096775   .0529426   .4157929   .6247609
-----+-----
LR test of alpha=0: chibar2(01) = 317.09          Prob >= chibar2 = 0.000

```

```
. fitstat
```

```
Measures of Fit for nbreg of turningmovement
```

```

Log-Lik Intercept Only:   -1507.971   Log-Lik Full Model:   -1440.371
D(676):                   2880.741   LR(7):                 135.201
                               Prob > LR:                 0.000
McFadden's R2:           0.045   McFadden's Adj R2:     0.039
Maximum Likelihood R2:   0.179   Cragg & Uhler's R2:    0.181
AIC:                     4.232   AIC*n:                 2898.741
BIC:                    -1533.146   BIC':                  -89.495

```

```
. ***SIDESWIPE COLLISIONS***
```



```
. * nbreg on full model
. nbreg sideswipe rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt
pplt speed1 speed2, irr
```

```
Negative binomial regression      Number of obs      =      685
                                   LR chi2(11)              =     163.56
                                   Prob > chi2              =     0.0000
                                   Pseudo R2                =     0.0694
```

sideswipe	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.191028	.1117738	1.86	0.062	.9909223	1.431542
lnaadt	2.717922	.3452967	7.87	0.000	2.118833	3.486401
channelization	1.469599	.1633105	3.46	0.001	1.181975	1.827214
median	.5594334	.0681646	-4.77	0.000	.4405884	.7103358
leftturn	1.471078	.1061248	5.35	0.000	1.277113	1.694502
thrulanes	1.55236	.1150942	5.93	0.000	1.342404	1.795155
plt	1.930595	.2409146	5.27	0.000	1.511721	2.465532
fplt	1.615044	.2109489	3.67	0.000	1.250273	2.086239
pplt	1.104276	.1380429	0.79	0.428	.8643125	1.410861
speed1	.9968244	.005502	-0.58	0.564	.9860987	1.007667
speed2	.9889366	.0068684	-1.60	0.109	.9755659	1.00249
_cons	.0000178	.0000235	-8.26	0.000	1.32e-06	.000238
/lnalpha	-.7417289	.1423542			-1.020738	-.4627198
alpha	.4762897	.0678019			.3603289	.629569

```
LR test of alpha=0: chibar2(01) = 124.88      Prob >= chibar2 = 0.000
```

```
. fitstat
```

```
Measures of Fit for nbreg of sideswipe
```

```
Log-Lik Intercept Only:    -1178.846      Log-Lik Full Model:      -1097.065
D(672):                    2194.130      LR(11):                  163.563
                                   Prob > LR:                  0.000
McFadden's R2:              0.069      McFadden's Adj R2:      0.058
Maximum Likelihood R2:      0.212      Cragg & Uhler's R2:     0.219
AIC:                        3.241      AIC*n:                  2220.130
BIC:                       -2193.640      BIC':                   -91.739
```

```
. *nbreg best fit reduced:
. nbreg sideswipe rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt,
irr
```

```
Negative binomial regression      Number of obs      =      685
                                   LR chi2(8)              =     160.19
                                   Prob > chi2              =     0.0000
                                   Pseudo R2                =     0.0679
```

sideswipe	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.185355	.1104918	1.82	0.068	.9874258	1.422959
lnaadt	2.613627	.3260831	7.70	0.000	2.046659	3.337657
channelization	1.44609	.1600335	3.33	0.001	1.164115	1.796365
median	.5718935	.0668041	-4.78	0.000	.4548672	.719028
leftturn	1.468092	.1055245	5.34	0.000	1.275176	1.690194
thrulanes	1.501616	.1068001	5.72	0.000	1.306227	1.726233
plt	1.855699	.219677	5.22	0.000	1.471144	2.340305
fplt	1.468589	.1616191	3.49	0.000	1.183655	1.822114
_cons	.0000142	.0000185	-8.62	0.000	1.13e-06	.0001804
/lnalpha	-.7254988	.1408413			-1.001543	-.449455
alpha	.484083	.0681789			.3673123	.6379758

```
LR test of alpha=0: chibar2(01) = 129.19      Prob >= chibar2 = 0.000
```

```
. fitstat
```

```
Measures of Fit for nbreg of sideswipe
```

Log-Lik Intercept Only:	-1178.846	Log-Lik Full Model:	-1098.751
D(675):	2197.502	LR(8):	160.191
		Prob > LR:	0.000
McFadden's R2:	0.068	McFadden's Adj R2:	0.059
Maximum Likelihood R2:	0.209	Cragg & Uhler's R2:	0.215
AIC:	3.237	AIC*n:	2217.502
BIC:	-2209.856	BIC':	-107.956

```
.
```

Appendix F – FE vs. RE StataSE Output

. ***TOTAL COLLISIONS***

```
. totalcollisions rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt
speed1 , irr re
```

```
Random-effects negative binomial regression      Number of obs      =      685
Group variable: id                             Number of groups   =      48
```

```
Random effects u_i ~ Beta                        Obs per group:
                                                min =      14
                                                avg  =     14.3
                                                max  =      15
```

```
Wald chi2(9) =      83.36
Prob > chi2   =      0.0000
Log likelihood = -2081.6357
```

totalcollisions	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.008911	.034777	0.26	0.797	.9430005	1.079428
lnaadt	1.4856	.1092074	5.38	0.000	1.286263	1.71583
channelization	1.522304	.1697601	3.77	0.000	1.223431	1.894189
median	.6539714	.0791896	-3.51	0.000	.5158061	.8291461
leftturn	1.206626	.0944726	2.40	0.016	1.03497	1.406751
thrulanes	1.208493	.0912004	2.51	0.012	1.042334	1.401138
plt	1.381199	.1618842	2.76	0.006	1.097718	1.737888
fplt	1.285999	.1446759	2.24	0.025	1.031525	1.603251
speed1	1.011767	.0058691	2.02	0.044	1.000329	1.023336
_cons	.0952885	.0760335	-2.95	0.003	.0199453	.4552392
/ln_r	3.282267	.2575541			2.77747	3.787063
/ln_s	2.800139	.2512405			2.307717	3.292561
r	26.63608	6.860231			16.07829	44.12663
s	16.44693	4.132136			10.05145	26.91171

```
LR test vs. pooled: chibar2(01) = 215.70          Prob >= chibar2 = 0.000
```

```
. estimates store BFRandom_total
```

```
. xtnbreg totalcollisions rlcinstalled2 lnaadt channelization plt fplt pplt, irr fe
```

```
Conditional FE negative binomial regression      Number of obs      =      685
Group variable: id                             Number of groups   =      48
```

```
Obs per group:
min =      14
avg  =     14.3
max  =      15
```

```
Wald chi2(6) =      59.65
Prob > chi2   =      0.0000
Log likelihood = -1797.5982
```

totalcollisions	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	.9949895	.0354414	-0.14	0.888	.927895	1.066936
lnaadt	1.368036	.1114794	3.85	0.000	1.166096	1.604947
channelization	2.244904	.8394589	2.16	0.031	1.078697	4.671925
plt	12.54959	5.573344	5.70	0.000	5.255406	29.96767
fplt	9.676686	4.298755	5.11	0.000	4.051262	23.11336
pplt	7.13449	3.313479	4.23	0.000	2.871035	17.72913
_cons	.0739633	.0666668	-2.89	0.004	.0126411	.4327597

```
. estimates store Bffixed_total
```

```
. hausman Bffixed_total Bfrandom_total
```

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Bffixed_to~1	Bfrandom_t~1	Difference	S.E.
rlcinstall~2	-.005023	.0088713	-.0138943	.0089777
lnaad	.3133759	.395819	-.0824431	.0351653
channeliza~n	.8086627	.4202247	.3884379	.3569248
plt	2.529688	.322952	2.206736	.4283604
fplt	2.26972	.2515359	2.018184	.4297573

b = consistent under Ho and Ha; obtained from xtbnreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtbnreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = 37.16
 Prob>chi2 = 0.0000

. ***Rearend COLLISIONS***

```
. xtbnreg rearend rlcinstalled2 lnaadt channelization fplt pplt speed2 , irr re
```

Random-effects negative binomial regression Number of obs = 685
 Group variable: id Number of groups = 48

Random effects u_i ~ Beta Obs per group:
 min = 14
 avg = 14.3
 max = 15

Log likelihood = -1610.4136 Wald chi2(6) = 98.58
 Prob > chi2 = 0.0000

rearend	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.238949	.0600354	4.42	0.000	1.126697	1.362385
lnaad	1.967512	.2173921	6.13	0.000	1.584409	2.443247
channelization	1.44516	.2326552	2.29	0.022	1.054099	1.9813
fplt	1.501106	.2718085	2.24	0.025	1.052646	2.140623
pplt	1.524108	.2861125	2.24	0.025	1.054932	2.201949
speed2	1.029409	.0111812	2.67	0.008	1.007726	1.051559
_cons	.0021585	.0029045	-4.56	0.000	.0001544	.030167
/ln_r	2.93412	.3068066			2.33279	3.535449
/ln_s	1.565857	.240776			1.093944	2.037769
r	18.80494	5.769478			10.30665	34.31043
s	4.786774	1.15254			2.986029	7.67347

LR test vs. pooled: chibar2(01) = 259.83 Prob >= chibar2 = 0.000

```
. estimates store Bfrandom_Rear
```

```
. xtbnreg rearend rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt  

pplt speed1 speed2 , irr fe
```

Conditional FE negative binomial regression Number of obs = 685
 Group variable: id Number of groups = 48

Obs per group:
 min = 14
 avg = 14.3
 max = 15

Log likelihood = -1361.5256 Wald chi2(11) = 49.71
 Prob > chi2 = 0.0000

	rearend	IRR	Std. Err.	z	P> z	[95% Conf. Interval]
rlcinstalled2		1.234684	.06217	4.19	0.000	1.118653 1.362751
lnaad		1.871255	.2504416	4.68	0.000	1.4395 2.43251
channelization		2.035007	1.866155	0.77	0.438	.3372811 12.27835
median		1.372049	1.698674	0.26	0.798	.1212087 15.5312
leftturn		.7384626	.4241543	-0.53	0.598	.239563 2.27634
thrulanes		.2633071	.1928093	-1.82	0.068	.0626847 1.106022
plt		17.18604	35.49233	1.38	0.168	.3001156 984.1544
fplt		1.093169	1.416797	0.07	0.945	.0861966 13.86386
pplt		.8136977	1.332419	-0.13	0.900	.0328573 20.15087
speed1		.9938791	.0371239	-0.16	0.869	.9237172 1.06937
speed2		1.096884	.0876635	1.16	0.247	.9378473 1.282889
_cons		.0033124	.0129585	-1.46	0.144	1.55e-06 7.081227

. estimates store fixed_rearend

. hausman fixed_rearend BFRandom_Rear

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed_rear~d	BFRandom_R~r	Difference	S.E.
rlcinstall~2	.2108151	.2142637	-.0034486	.0136884
lnaad	.6266096	.6767696	-.05016	.0755239
channeliza~n	.7104995	.3682199	.3422796	.9027841
fplt	.0890804	.406202	-.3171215	1.283335
pplt	-.2061664	.4214094	-.6275759	1.62669
speed2	.0924732	.028985	.0634882	.079179

b = consistent under Ho and Ha; obtained from xtnbreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtnbreg

Test: Ho: difference in coefficients not systematic

chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = 2.41
 Prob>chi2 = 0.8780

. ***ANGLE COLLISIONS***

. xtnbreg angle rlcinstalled2 lnaadt channelization median leftturn thrulanes plt fplt
 pplt speed1 speed2 , irr re

Random-effects negative binomial regression Number of obs = 685
 Group variable: id Number of groups = 48

Random effects u_i ~ Beta Obs per group:
 min = 14
 avg = 14.3
 max = 15

Log likelihood = -1382.376 Wald chi2(11) = 49.71
 Prob > chi2 = 0.0000

	angle	IRR	Std. Err.	z	P> z	[95% Conf. Interval]
rlcinstalled2		.7150306	.0491449	-4.88	0.000	.6249144 .8181421
lnaad		1.040364	.1473213	0.28	0.780	.7882253 1.373157
channelization		1.356324	.2593466	1.59	0.111	.9324015 1.972987
median		.693824	.1462632	-1.73	0.083	.4589969 1.048791
leftturn		1.420396	.1886487	2.64	0.008	1.094858 1.842727
thrulanes		1.368023	.1843422	2.33	0.020	1.050493 1.781532
plt		1.3437	.2756556	1.44	0.150	.8988369 2.008739

turningmovement	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	.8648481	.0674598	-1.86	0.063	.7422403	1.007709
lnaad	1.237153	.1991701	1.32	0.186	.9023764	1.696129
channelization	1.015656	.4228494	0.04	0.970	.4491227	2.296828
median	.2627005	.1663413	-2.11	0.035	.0759421	.9087396
leftturn	1.381525	.4284546	1.04	0.297	.7522708	2.537133
thrulanes	1.777892	.6247317	1.64	0.102	.8928995	3.540041
plt	1.368898	.7334152	0.59	0.558	.4789858	3.912189
fplt	1.766865	.8537343	1.18	0.239	.6853461	4.555088
pplt	7.689989	4.802918	3.27	0.001	2.260959	26.15523
speed1	.9626528	.0262212	-1.40	0.162	.912608	1.015442
speed2	.9930054	.0263103	-0.26	0.791	.9427542	1.045935
_cons	1.911804	5.035216	0.25	0.806	.0109544	333.6542

```
. estimates store fixed_turningmovement
```

```
. hausman fixed_turningmovement random_turningmovement
```

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed_turn~t	random_tur~t	Difference	S.E.
rlcinstall~2	-.1452014	-.1505678	.0053664	.0067675
lnaad	.2128124	.2708081	-.0579958	.0623007
channeliza~n	.015535	.4208298	-.4052948	.3514847
median	-1.336741	-.876005	-.4607356	.5764989
leftturn	.323188	.0513992	.2717887	.2665104
thrulanes	.5754285	.1718191	.4036094	.3169492
plt	.3140063	.2616782	.0523281	.478947
fplt	.5692068	.1691	.4001068	.4113273
pplt	2.039919	.9900171	1.049902	.573239
speed1	-.0380625	-.0107035	-.027359	.0245242
speed2	-.0070192	.0083616	-.0153809	.0224361

b = consistent under Ho and Ha; obtained from xtnbreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtnbreg

Test: Ho: difference in coefficients not systematic

chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = 13.94
 Prob>chi2 = 0.2365
 (V_b-V_B is not positive definite)

Sideswipe COLLISIONS

```
. xtnbreg sideswipe rlcinstalled2 lnaad channelization median leftturn thrulanes plt  
fplt, irr re
```

Random-effects negative binomial regression Number of obs = 685
 Group variable: id Number of groups = 48

Random effects u_i ~ Beta Obs per group:
 min = 14
 avg = 14.3
 max = 15

Log likelihood = -1019.0869 Wald chi2(8) = 45.22
 Prob > chi2 = 0.0000

sideswipe	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2	1.344971	.1183631	3.37	0.001	1.131889	1.598167
lnaad	1.835545	.3519391	3.17	0.002	1.260548	2.672825
channelization	1.503055	.3761641	1.63	0.103	.9203387	2.45472

median		.5479913	.1405835	-2.34	0.019	.3314391	.9060323
leftturn		1.415549	.2353462	2.09	0.037	1.021894	1.960848
thrulanes		1.50017	.2471232	2.46	0.014	1.08623	2.071854
plt		1.833879	.4664664	2.38	0.017	1.113932	3.019136
fplt		1.703208	.4140313	2.19	0.028	1.057669	2.742745
_cons		.0033278	.0068578	-2.77	0.006	.0000586	.188928

/ln_r		2.939118	.4037653			2.147753	3.730484
/ln_s		1.078573	.248511			.5915002	1.565645

r		18.89918	7.630832			8.565591	41.69928
s		2.94048	.7307416			1.806697	4.785763

LR test vs. pooled: chibar2(01) = 161.18

Prob >= chibar2 = 0.000

. estimates store BFrandoM_SS

. xtnbreg sideswipe rlcinstalled2 lnaadt channelization median leftturn thrulanes plt
fplt pplt speed1 speed2 , irr fe

Conditional FE negative binomial regression
Group variable: id

Number of obs = 685
Number of groups = 48

Obs per group:

min = 14
avg = 14.3
max = 15

Log likelihood = -828.54026

Wald chi2(11) = 30.41
Prob > chi2 = 0.0014

sideswipe		IRR	Std. Err.	z	P> z	[95% Conf. Interval]

rlcinstalled2		1.389411	.1227235	3.72	0.000	1.168547 1.65202
lnaadt		1.388501	.3242052	1.41	0.160	.8786114 2.194299
channelization		14.30891	25.45519	1.50	0.135	.4378648 467.5984
median		.198335	.2153202	-1.49	0.136	.0236212 1.665317
leftturn		.1510241	.2264494	-1.26	0.207	.0079934 2.853379
thrulanes		.1240258	.1764009	-1.47	0.142	.0076358 2.014509
plt		12.54594	18.53453	1.71	0.087	.6934174 226.9925
fplt		32.50525	62.68131	1.81	0.071	.7422395 1423.518
pplt		1.942345	2.462207	0.52	0.600	.1619212 23.29963
speed1		.9699335	.0432112	-0.69	0.493	.8888333 1.058434
speed2		1.383394	.2188109	2.05	0.040	1.014639 1.886166
_cons		4.51e-06	.0000244	-2.28	0.023	1.13e-10 .1807297

. estimates store fixed_sideswipe

. hausman fixed_sideswipe BFrandoM_SS

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed_side	BFrandoM_SS	Difference	S.E.

rlcinstall~2		.3288799	.2963726	.0325073
lnaadt		.3282251	.6073413	-.2791163
channeliza~n		2.660882	.4074996	2.253383
median		-1.617798	-.6014958	-1.016302
leftturn		-1.890316	.3475173	-2.237833
thrulanes		-2.087266	.4055786	-2.492844
plt		2.529397	.6064332	1.922964
fplt		3.481402	.5325136	2.948888

b = consistent under Ho and Ha; obtained from xtnbreg
B = inconsistent under Ha, efficient under Ho; obtained from xtnbreg

Test: Ho: difference in coefficients not systematic

$$\text{chi2}(8) = (b-B)' [(V_b-V_B)^{-1}] (b-B)$$


```
= -42.36      chi2<0 ==> model fitted on these  
              data fails to meet the asymptotic  
              assumptions of the Hausman test;  
              see suest for a generalized test
```

Appendix G – ZINB StataSE Output

. ***TOTAL COLLISIONS***

```
zinb totalcollisions rlcinstalled lnaadt median channelization thrulanes speed2,
inf(rlcinstalled) irr vuong zip
```

```
Zero-inflated negative binomial regression      Number of obs      =      685
                                                Nonzero obs        =      679
                                                Zero obs           =       6
```

```
Inflation model = logit                      LR chi2(6)          =     302.83
Log likelihood = -2204.673                   Prob > chi2         =     0.0000
```

totalcollisions	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
totalcollisions						
rlcinstalled	.9951063	.0339866	-0.14	0.886	.9306744	1.063999
lnaadt	1.875037	.0870775	13.54	0.000	1.711905	2.053714
median	.7179511	.0314397	-7.57	0.000	.6589008	.7822934
channelization	1.38111	.0507531	8.79	0.000	1.285133	1.484254
thrulanes	1.145823	.0293846	5.31	0.000	1.089654	1.204887
speed2	1.009766	.0025156	3.90	0.000	1.004848	1.014708
_cons	.009665	.004546	-9.86	0.000	.0038444	.0242982
inflate						
rlcinstalled	-1.28577	1.351648	-0.95	0.341	-3.93495	1.363411
_cons	-4.565645	.5135863	-8.89	0.000	-5.572256	-3.559035
/lnalpha	-2.20493	.092495	-23.84	0.000	-2.386216	-2.023643
alpha	.1102583	.0101983			.091977	.1321731

```
Likelihood-ratio test of alpha=0: chibar2(01) = 417.98 Pr>=chibar2 = 0.0000
Vuong test of zinb vs. standard negative binomial: z = 1.55 Pr>z = 0.0609
```

. ***REAR-END COLLISIONS***

```
zinb rear-end rlcinstalled lnaadt channelization fplt speed1 , inf(rlcinstalled) irr
vuong zip
```

```
Zero-inflated negative binomial regression      Number of obs      =      685
                                                Nonzero obs        =      619
                                                Zero obs           =       66
```

```
Inflation model = logit                      LR chi2(5)          =     435.21
Log likelihood = -1759.183                   Prob > chi2         =     0.0000
```

rearend	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
rearend						
rlcinstalled	1.226481	.0633322	3.95	0.000	1.108427	1.357109
lnaadt	3.327735	.2440987	16.39	0.000	2.882111	3.84226
channelization	1.54891	.0812588	8.34	0.000	1.397561	1.716651
fplt	1.198171	.064401	3.36	0.001	1.078369	1.331283
speed1	1.014679	.0029354	5.04	0.000	1.008942	1.020449
_cons	6.15e-06	4.71e-06	-15.68	0.000	1.37e-06	.0000276
inflate						
rlcinstalled	-1.213165	3.671331	-0.33	0.741	-8.408843	5.982512
_cons	-4.393972	1.257298	-3.49	0.000	-6.85823	-1.929714


```

      thrulanes |    1.159845    .0662391    2.60    0.009    1.037021    1.297216
            plt |    1.311346    .115588    3.08    0.002    1.103287    1.558641
            pplt |    2.020945    .1695462    8.39    0.000    1.714523    2.382131
            speedl |    .9938945    .004524    -1.35    0.178    .985067    1.002801
            _cons |    .0144313    .0160821    -3.80    0.000    .0016246    .1281956
-----+-----
inflate
  rlcinstalled |    18.27494    20199.76    0.00    0.999   -39572.53    39609.08
            _cons |   -22.72116    20199.76   -0.00    0.999   -39613.52    39568.08
-----+-----
      /lnalpha |   -.7174442    .1234193   -5.81    0.000   -.9593416   -.4755468
-----+-----
            alpha |    .4879979    .0602284                .3831451    .6215451
-----+-----
Likelihood-ratio test of alpha=0: chibar2(01) =   183.13 Pr>=chibar2 = 0.0000
Vuong test of zinb vs. standard negative binomial: z =    0.13 Pr>z = 0.4475

```

. ***SS COLLISIONS***

```

zinb sideswipe rlcinstalled lnaadt median channelization leftturn thrulanes plt fplt ,
inf(rlcinstalled )irr vuong zip

```

```

Zero-inflated negative binomial regression      Number of obs      =          685
                                                Nonzero obs          =          435
                                                Zero obs             =          250

```

```

Inflation model = logit                      LR chi2(8)            =        144.52
Log likelihood = -1098.651                  Prob > chi2           =         0.0000

```

```

-----+-----
      sideswipe |          IRR    Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
sideswipe
  rlcinstalled |    1.175147    .1011541     1.87   0.061     .9927101    1.391111
      lnaadt |    2.567085    .3230318     7.49   0.000     2.005988    3.285126
      median |    .5659645    .065674    -4.91   0.000     .4508339    .7104963
channelization |    1.485314    .1632713     3.60   0.000     1.197433    1.842407
  leftturn |    1.481704    .1064526     5.47   0.000     1.287085    1.705751
  thrulanes |    1.520448    .106941     5.96   0.000     1.324653    1.745184
      plt |    1.816013    .2140129     5.06   0.000     1.441474    2.287869
      fplt |    1.43505    .1579344     3.28   0.001     1.156613    1.780517
      _cons |    .0000165    .0000216    -8.45   0.000     1.29e-06    .0002129
-----+-----
inflate
  rlcinstalled |   -12.23251    115798.9    -0.00   1.000   -226973.8    226949.4
            _cons |   -12.78321    427.8575    -0.03   0.976   -851.3685    825.802
-----+-----
      /lnalpha |   -.7177857    .1400877    -5.12   0.000   -.9923525   -.4432189
-----+-----
            alpha |    .4878313    .0683391                .3707036    .6419666
-----+-----

```

```

Likelihood-ratio test of alpha=0: chibar2(01) =    67.01 Pr>=chibar2 = 0.0000
Vuong test of zinb vs. standard negative binomial: z =   -0.01 Pr>z = 0.5024

```

Appendix H – Models with Interaction Terms

TOTAL COLLISIONS

```
. xtnbreg totalcollisions c.lnaadt i.rlcinstalled2 i.median i.channelization i.thrulanec i.lef
> tturn i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##median rlcinstalled2##channelizatio
> n rlcinstalled2##leftturn rlcinstalled2##thrulanec rlcinstalled2##plt , irr re
```

Fitting negative binomial (constant dispersion) model:

```
Random-effects negative binomial regression      Number of obs      =      685
Group variable: id                             Number of groups     =      48

Random effects u_i ~ Beta                      Obs per group:
                                                min =      14
                                                avg  =     14.3
                                                max  =     15

Wald chi2(26)      =     158.75
Prob > chi2        =     0.0000

Log likelihood = -2055.3945
```

totalcollisions	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
lnaadt	1.53249	.1094531	5.98	0.000	1.332305	1.762755
1.rlcinstalled2	1.343386	.2460804	1.61	0.107	.9381628	1.923637
1.median	.6080691	.0758878	-3.99	0.000	.4761261	.776576
1.channelization	1.531408	.1790652	3.64	0.000	1.217759	1.925842
thrulanec						
2	.9623884	.1683536	-0.22	0.827	.6830415	1.355981
3	1.210443	.2497452	0.93	0.355	.8078296	1.813714
4	1.619663	.4143637	1.88	0.059	.9809778	2.674178
leftturn						
1	1.077081	.1099505	0.73	0.467	.8817714	1.315651
2	1.557594	.2686971	2.57	0.010	1.110748	2.184204
1.plt	1.411503	.1793644	2.71	0.007	1.100314	1.810701
1.fplt	1.369607	.1714541	2.51	0.012	1.071614	1.750465
1.pplt	1.228837	.1466724	1.73	0.084	.9725146	1.552718
speed1						
50	.9220458	.1469514	-0.51	0.611	.6746708	1.260123
60	.9936122	.1422348	-0.04	0.964	.7505301	1.315424
70	1.180765	.2220578	0.88	0.377	.8167409	1.707036
speed2						
50	1.690552	.3160943	2.81	0.005	1.171854	2.438842
60	1.796273	.3138887	3.35	0.001	1.27535	2.529968
80	1.561899	.5676603	1.23	0.220	.7661083	3.184312
rlcinstalled2##median						
1 1	.7760803	.0889926	-2.21	0.027	.619869	.9716579
rlcinstalled2##channelization						
1 1	1.268579	.1153544	2.62	0.009	1.061491	1.516069
rlcinstalled2##leftturn						
1 1	.7754177	.0749924	-2.63	0.009	.6415257	.9372542
1 2	.8748829	.1154927	-1.01	0.311	.6754347	1.133226
rlcinstalled2##thrulanec						
1 2	.9977756	.1445295	-0.02	0.988	.7511642	1.325351
1 3	1.087567	.1765482	0.52	0.605	.7911842	1.494976
1 4	.6159125	.1368261	-2.18	0.029	.3984951	.951952
rlcinstalled2##plt						
1 1	.775767	.0829428	-2.37	0.018	.6291053	.9566197
_cons	.1287522	.0972641	-2.71	0.007	.0292905	.5659566
/ln_r	3.737985	.2739498			3.201053	4.274917
/ln_s	3.167266	.2650913			2.647697	3.686836

```

              r | 42.01325 11.50952                24.55839 71.87416
              s | 23.74249 6.293929                14.12148 39.91834
-----

```

```
LR test vs. pooled: chibar2(01) = 160.81          Prob >= chibar2 = 0.000
```

```
. margins rlcinstalled2
```

```
Predictive margins          Number of obs    =          685
Model VCE      : OIM
```

```
Expression   : Linear prediction, predict()
```

```
-----
              |          Delta-method
              |      Margin Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
rlcinstalled2 |
    0 |      3.190575 .1550743    20.57  0.000     2.886635     3.494516
    1 |      3.143885 .1570026    20.02  0.000     2.836166     3.451604
-----

```

```
. *margins r.rlcinstalled2 ... same results as below:
. margins, dydx(rlcinstalled2)
```

```
Average marginal effects          Number of obs    =          685
Model VCE      : OIM
```

```
Expression   : Linear prediction, predict()
dy/dx w.r.t. : 1.rlcinstalled2
```

```
-----
              |          Delta-method
              |      dy/dx Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
1.rlcinstalled2 | -.0466905 .0420488    -1.11  0.267    -.1291046     .0357236
-----

```

Note: dy/dx for factor levels is the discrete change from the base level.

```
.
. margins rlcinstalled2##median rlcinstalled2##channelization rlcinstalled2##leftturn
rlcinstalled2##thrulanes rlcinstalled2##plt
```

```
Predictive margins          Number of obs    =          685
Model VCE      : OIM
```

```
Expression   : Linear prediction, predict()
```

```
-----
              |          Delta-method
              |      Margin Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
rlcinstalled2 |
    0 |      3.190575 .1550743    20.57  0.000     2.886635     3.494516
    1 |      3.143885 .1570026    20.02  0.000     2.836166     3.451604
median |
    0 |      3.566693 .1720228    20.73  0.000     3.229534     3.903851
    1 |      2.995582 .1617697    18.52  0.000     2.678519     3.312645
rlcinstalled2#median |
    0 0 |      3.521736 .1727496    20.39  0.000     3.183153     3.860319
    0 1 |      3.024269 .1623117    18.63  0.000     2.706144     3.342394
    1 0 |      3.643798 .1806064    20.18  0.000     3.289816     3.99778
    1 1 |      2.892832 .1698801    17.03  0.000     2.559873     3.225791
channelization |
    0 |      2.973043 .1625125    18.29  0.000     2.654524     3.291562
    1 |      3.468342 .1661695    20.87  0.000     3.142656     3.794029
rlcinstalled2#channelization |
    0 0 |      3.012012 .1639524    18.37  0.000     2.690671     3.333353
    0 1 |      3.4382 .1675235    20.52  0.000     3.10986     3.76654
    1 0 |      2.865648 .1680032    17.06  0.000     2.536368     3.194928
    1 1 |      3.529733 .1696835    20.80  0.000     3.197159     3.862307
-----

```

leftturn							
0		3.157332	.1643631	19.21	0.000	2.835186	3.479477
1		3.157694	.1616957	19.53	0.000	2.840776	3.474611
2		3.561643	.2104829	16.92	0.000	3.149104	3.974182
rlcinstalled2#leftturn							
0 0		3.114677	.1663639	18.72	0.000	2.788609	3.440744
0 1		3.188931	.1624876	19.63	0.000	2.870461	3.507401
0 2		3.557819	.212312	16.76	0.000	3.141695	3.973943
1 0		3.212783	.1721223	18.67	0.000	2.87543	3.550137
1 1		3.032684	.1666512	18.20	0.000	2.706054	3.359315
1 2		3.522261	.2220801	15.86	0.000	3.086991	3.95753
thrulanes							
1		3.138734	.2238388	14.02	0.000	2.700018	3.57745
2		3.09975	.158251	19.59	0.000	2.789584	3.409916
3		3.354107	.1764307	19.01	0.000	3.008309	3.699905
4		3.480156	.2274989	15.30	0.000	3.034267	3.926046
rlcinstalled2#thrulanes							
0 1		3.141468	.2257595	13.92	0.000	2.698987	3.583948
0 2		3.103131	.1590903	19.51	0.000	2.791319	3.414942
0 3		3.332454	.1796084	18.55	0.000	2.980428	3.684448
0 4		3.623686	.2324895	15.59	0.000	3.168015	4.079357
1 1		3.106768	.2502302	12.42	0.000	2.616325	3.59721
1 2		3.066204	.163282	18.78	0.000	2.746177	3.38623
1 3		3.381697	.1776252	19.04	0.000	3.033558	3.729836
1 4		3.104336	.2550804	12.17	0.000	2.604387	3.604284
plt							
0		3.057369	.1663674	18.38	0.000	2.731295	3.383443
1		3.328262	.1666546	19.97	0.000	3.001625	3.654899
rlcinstalled2#plt							
0 0		3.033091	.1676659	18.09	0.000	2.704472	3.36171
0 1		3.377746	.1672944	20.19	0.000	3.049855	3.705637
1 0		3.102417	.1691715	18.34	0.000	2.770847	3.433987
1 1		3.193169	.1784342	17.90	0.000	2.843444	3.542894

*SIGNIFICANT

```
. quietly margins rlcinstalled2, at(median==(0 1))
```

```
. marginsplot, recastci(rarea) ciopts(color(*.3))
```

Variables that uniquely identify margins: median rlcinstalled2

```
. margins, dydx(rlcinstalled2) at(median==(0 1))
```

Average marginal effects	Number of obs	=	685
Model VCE : OIM			

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.   : 1.rlcinstalled2
```

```
1. at      : median      =      0
```

```
2. at      : median      =      1
```

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.	rlcinstalled2						
	_at						
	1	.1220623	.0732187	1.67	0.095	-.0214437	.2655683
	2	-.131437	.0660273	-1.99	0.047	-.260848	-.0020259

Note: dy/dx for factor levels is the discrete change from the base level.

end of do-file

```
. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"
```

```
. quietly margins rlcinstalled2, at(channelization==(0 1))
```

```
. marginsplot, recastci(rarea) ciopts(color(*.3))
```

```

Variables that uniquely identify margins: channelization rlcinstalled2

. margins, dydx(rlcinstalled2) at(channelization==(0 1))

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

1._at      : channelization      =      0
2._at      : channelization      =      1
-----
|              Delta-method
|              dy/dx      Std. Err.      z      P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinstalled2 |
  _at |
    1 |   -.1463644   .0637786   -2.29   0.022   -.2713683   -.0213606
    2 |    .0915333   .0581665    1.57   0.116   -.022471   .2055375
-----
Note: dy/dx for factor levels is the discrete change from the base level.

```

```

.
end of do-file

. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"

. quietly margins rlcinstalled2, at(leftturn==(0 (1) 2))

. marginsplot, recastci(rarea) ciopts(color(*.3))

Variables that uniquely identify margins: leftturn rlcinstalled2

. margins, dydx(rlcinstalled2) at(leftturn==(0 (1) 2))

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

1._at      : leftturn      =      0
2._at      : leftturn      =      1
3._at      : leftturn      =      2
-----
|              Delta-method
|              dy/dx      Std. Err.      z      P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinstalled2 |
  _at |
    1 |    .0981068   .0781784    1.25   0.210   -.05512   .2513335
    2 |   -.1562466   .0553275   -2.82   0.005   -.2646865   -.0478067
    3 |   -.0355585   .0972589   -0.37   0.715   -.2261824   .1550654
-----
Note: dy/dx for factor levels is the discrete change from the base level.

```

```

.
end of do-file

. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"

. quietly margins rlcinstalled2, at(thrulanes==(2 (1) 4))

. marginsplot, recastci(rarea) ciopts(color(*.3))

Variables that uniquely identify margins: thrulanes rlcinstalled2

. margins, dydx(rlcinstalled2) at(thrulanes==(1 (1) 4))

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```



```

1._at      : thrulanes      =          1
2._at      : thrulanes      =          2
3._at      : thrulanes      =          3
4._at      : thrulanes      =          4

```

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.rlcinstalled2							
	_at						
	1	-.0347002	.1433293	-0.24	0.809	-.3156204	.24622
	2	-.0369271	.0570857	-0.65	0.518	-.148813	.0749587
	3	.0492427	.0678634	0.73	0.468	-.0837672	.1822526
	4	-.5193506	.1632096	-3.18	0.001	-.8392357	-.1994656

Note: dy/dx for factor levels is the discrete change from the base level.

end of do-file

```

. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"

```

```

. quietly margins rlcinstalled2, at(plt==(0 1))

```

```

. marginsplot, recastci(rarea) ciopts(color(*.3))

```

Variables that uniquely identify margins: plt rlcinstalled2

```

. margins, dydx(rlcinstalled2) at(plt==(0 1))

```

```

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

```

```

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```

```

1._at      : plt      =          0
2._at      : plt      =          1

```

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.rlcinstalled2							
	_at						
	1	.0693265	.0566824	1.22	0.221	-.0417689	.1804219
	2	-.1845765	.0791132	-2.33	0.020	-.3396355	-.0295176

Note: dy/dx for factor levels is the discrete change from the base level.

end of do-file

```

. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"

```

```

. quietly margins rlcinstalled2, at(fplt==(0 1))

```

```

. marginsplot, recastci(rarea) ciopts(color(*.3))

```

Variables that uniquely identify margins: fplt rlcinstalled2

```

. margins, dydx(rlcinstalled2) at(fplt==(0 1))

```

```

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

```

```

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```

```

1._at      : fplt      =          0
2._at      : fplt      =          1

```

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	

```
-----+-----
1.rlcinstalled2 |
   _at |
      1 | -.0466905 .0420488 -1.11 0.267 -.1291046 .0357236
      2 | -.0466905 .0420488 -1.11 0.267 -.1291046 .0357236
-----+-----
```

Note: dy/dx for factor levels is the discrete change from the base level.

.
end of do-file

```
. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"
```

```
. quietly margins rlcinstalled2, at(pplt==(0 1))
```

```
. marginsplot, recastci(rarea) ciopts(color(*.3))
```

Variables that uniquely identify margins: pplt rlcinstalled2

```
. margins, dydx(rlcinstalled2) at(pplt==(0 1))
```

```
Average marginal effects      Number of obs      =      685
Model VCE      : OIM
```

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2
```

```
1._at      : pplt      =      0
```

```
2._at      : pplt      =      1
```

```
-----+-----
              |      Delta-method
              |      dy/dx      Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinstalled2 |
   _at |
      1 | -.0466905 .0420488 -1.11 0.267 -.1291046 .0357236
      2 | -.0466905 .0420488 -1.11 0.267 -.1291046 .0357236
-----+-----
```

Note: dy/dx for factor levels is the discrete change from the base level.

.
end of do-file

```
. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"
```

```
. quietly margins rlcinstalled2, at(speed2==(40 (10) 80))
at values for factor speed2 do not sum to 1
r(198);
```

end of do-file

```
r(198);
```

```
. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"
```

```
. quietly margins rlcinstalled2, at(speed1==(40 (10) 70))
```

```
. marginsplot, recastci(rarea) ciopts(color(*.3))
```

Variables that uniquely identify margins: speed1 rlcinstalled2

```
. margins, dydx(rlcinstalled2) at(speed1==(40 (10) 70))
```

```
Average marginal effects      Number of obs      =      685
Model VCE      : OIM
```

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2
```

```
1._at      : speed1      =      40
```

```
2._at      : speed1      =      50
```

```
3._at      : speed1      =      60
```

```
4._at      : speed1      =      70
```

```
-----+-----
              |      Delta-method
```

		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1. rlcinstalled2							
	_at						
	1	-.0466905	.0420488	-1.11	0.267	-.1291046	.0357236
	2	-.0466905	.0420488	-1.11	0.267	-.1291046	.0357236
	3	-.0466905	.0420488	-1.11	0.267	-.1291046	.0357236
	4	-.0466905	.0420488	-1.11	0.267	-.1291046	.0357236

Note: dy/dx for factor levels is the discrete change from the base level.

end of do-file

NON SIG

```
. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"
```

```
. xtnbreg rearend c.lnaadt i.rlcinstalled2 i.median i.channelization i.thrulaness i.leftturn i.
> plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##channelization , irr
```

Fitting negative binomial (constant dispersion) model:

```
Random-effects negative binomial regression   Number of obs   =       685
Group variable: id                          Number of groups  =        48
```

```
Random effects u_i ~ Beta                    Obs per group:
                                             min =       14
                                             avg  =      14.3
                                             max  =       15
```

```
Log likelihood = -1598.9703                  Wald chi2(19)    =     149.03
                                             Prob > chi2      =     0.0000
```

	rearend	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
	lnaadt	1.936407	.2091766	6.12	0.000	1.566921	2.393018
	1.rlcinstalled2	.9975935	.0891039	-0.03	0.978	.8373851	1.188453
	1.median	1.062585	.2200022	0.29	0.769	.7081527	1.59441
	1.channelization	1.310854	.2498042	1.42	0.155	.902286	1.904427
	thrulaness						
	2	.7385447	.2334157	-0.96	0.338	.3975173	1.372137
	3	.6725023	.2448061	-1.09	0.276	.3294861	1.37262

```

      4 | .7068213 .3094912 -0.79 0.428 .2996398 1.667323
leftturn |
      1 | 1.048321 .1719149 0.29 0.774 .7601599 1.445717
      2 | 1.287175 .361411 0.90 0.369 .7424012 2.231704
      |
      1.plt | 1.298995 .2657121 1.28 0.201 .8699467 1.939647
      1.fplt | 1.716497 .3610475 2.57 0.010 1.136584 2.592296
      1.pplt | 1.331785 .2694524 1.42 0.157 .8958094 1.979944
      |
      speed1 |
      50 | .8366068 .2207421 -0.68 0.499 .4988022 1.403183
      60 | .8595634 .2098294 -0.62 0.535 .5327087 1.386967
      70 | 2.00273 .638016 2.18 0.029 1.072636 3.739318
      |
      speed2 |
      50 | .9672 .3068262 -0.11 0.916 .5193838 1.801126
      60 | 1.665909 .4858255 1.75 0.080 .9406263 2.95043
      80 | 1.920101 1.183184 1.06 0.290 .5738595 6.424546
rlcinstalled2#channelization |
      1 1 | 1.392687 .1481322 3.11 0.002 1.130619 1.715501
      |
      _cons | .0119615 .0144864 -3.65 0.000 .0011141 .1284283
-----
      /ln_r | 3.285772 .3281859 2.642539 3.929004
      /ln_s | 1.877734 .2536389 1.380611 2.374857
-----
      r | 26.72961 8.77228 14.04883 50.85632
      s | 6.53867 1.658461 3.97733 10.74948
-----
LR test vs. pooled: chibar2(01) = 202.61 Prob >= chibar2 = 0.000

```

```
. margins rlcinstalled2
```

```

Predictive margins          Number of obs   =       685
Model VCE      : OIM

```

```
Expression   : Linear prediction, predict()
```

```

-----
      |               Delta-method
      |      Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
rlcinstalled2 |
      0 | 2.951536 .2952563 10.00 0.000 2.372844 3.530227
      1 | 3.087906 .2959675 10.43 0.000 2.507821 3.667992
-----

```

```
. *margins r.rlcinstalled2 ... same results as below:
. margins, dydx(rlcinstalled2)
```

```

Average marginal effects          Number of obs   =       685
Model VCE      : OIM

```

```

Expression   : Linear prediction, predict()
dy/dx w.r.t. : 1.rlcinstalled2

```

```

-----
      |               Delta-method
      |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
1.rlcinstalled2 | .1363708 .0572834 2.38 0.017 .0240973 .2486442
-----

```

Note: dy/dx for factor levels is the discrete change from the base level.

```
. margins rlcinstalled2#channelization
```

```

Predictive margins          Number of obs   =       685
Model VCE      : OIM

```

```
Expression   : Linear prediction, predict()
```

```

-----
      |               Delta-method
      |      Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
rlcinstalled2#channelization |
      0 0 | 2.838127 .3043395 9.33 0.000 2.241633 3.434622
      0 1 | 3.108806 .31737 9.80 0.000 2.486772 3.73084
      1 0 | 2.835718 .3078756 9.21 0.000 2.232292 3.439143

```

```

1 1 | 3.437631 .316833 10.85 0.000 2.81665 4.058613
-----

```

```

. quietly margins rlcinstalled2, at(channelization==(0 1))

```

```

. marginsplot, recastci(rarea) ciopts(color(*.3))

```

Variables that uniquely identify margins: channelization rlcinstalled2

```

. margins, dydx(rlcinstalled2) at(channelization==(0 1))

```

```

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

```

```

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```

```

1._at      : channelization =      0

```

```

2._at      : channelization =      1

```

```

-----
              |      Delta-method
              |      dy/dx      Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinstalled2 |
   _at |
   1 | -.0024094   .0893189   -0.03   0.978   -.1774712   .1726523
   2 | .3288256   .0578086    5.69   0.000    .2155229   .4421283
-----

```

Note: dy/dx for factor levels is the discrete change from the base level.

```

.
end of do-file

```

```

. xtnbreg angle c.lnaadt i.rlcinstalled2 i.median i.channelization i.thrulanes i.leftturn i.pl
> t i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##median rlcinstalled2##plt rlcinstalled2##pplt
> , irr

```

Fitting negative binomial (constant dispersion) model:

```

Random-effects negative binomial regression      Number of obs      =      685
Group variable: id                             Number of groups    =      48

```

```

Random effects u_i ~ Beta

```

```

Obs per group:
min =      14
avg =     14.3
max =      15

```

```

Log likelihood = -1371.8761      Wald chi2(21)      =      71.85
                                Prob > chi2      =      0.0000

```

```

-----
              angle |      IRR      Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
              lnaadt |  1.076626   .154983    0.51   0.608    .811956   1.427571
            1.rlcinstalled2 |  1.598521   .4063099    1.85   0.065    .9713175   2.630726
              1.median |  .6440655   .1439257   -1.97   0.049    .4156394   .9980293
-----

```

1.channelization		1.634155	.3345162	2.40	0.016	1.094082	2.440825
thrulanes							
2		1.927561	.6024654	2.10	0.036	1.04463	3.556755
3		3.215375	1.165582	3.22	0.001	1.580042	6.543264
4		2.564371	1.220808	1.98	0.048	1.00868	6.519414
leftturn							
1		1.219535	.2215532	1.09	0.275	.8541932	1.741134
2		1.865167	.5717297	2.03	0.042	1.022819	3.401235
1.plt		1.353603	.3001375	1.37	0.172	.876501	2.090404
1.fplt		.7266561	.1632433	-1.42	0.155	.4678498	1.128629
1.pplt		.6334003	.13648	-2.12	0.034	.4152103	.9662474
speed1							
50		1.09475	.3205495	0.31	0.757	.6167054	1.943354
60		1.46962	.3956364	1.43	0.153	.8670679	2.490904
70		.7084149	.2555858	-0.96	0.339	.3492903	1.436775
speed2							
50		1.469772	.5182663	1.09	0.275	.7363804	2.93358
60		1.209949	.403874	0.57	0.568	.6289858	2.327519
80		.7297715	.4995172	-0.46	0.645	.1907888	2.791393
rlcinstalled2#median							
1 1		.4845125	.1127393	-3.11	0.002	.3070734	.7644828
rlcinstalled2#plt							
1 1		.4841608	.1185386	-2.96	0.003	.2996314	.7823334
rlcinstalled2#pplt							
1 1		.4991649	.1308708	-2.65	0.008	.2985908	.8344717
_cons		1.415376	2.137256	0.23	0.818	.0733726	27.30295
/ln_r		2.848562	.3008054			2.258994	3.43813
/ln_s		1.775826	.2617494			1.262807	2.288845
r		17.26294	5.192784			9.573455	31.12868
s		5.905157	1.545671			3.53533	9.863543

LR test vs. pooled: chibar2(01) = 144.34 Prob >= chibar2 = 0.000

. margins rlcinstalled2

Predictive margins
Model VCE : OIM
Number of obs = 685

Expression : Linear prediction, predict()

		Delta-method				[95% Conf. Interval]	
		Margin	Std. Err.	z	P> z		
rlcinstalled2							
0		2.195495	.2076531	10.57	0.000	1.788503	2.602488
1		1.662107	.2176976	7.63	0.000	1.235427	2.088786

. *margins r.rlcinstalled2 ... same results as below:
. margins, dydx(rlcinstalled2)

Average marginal effects
Model VCE : OIM
Number of obs = 685

Expression : Linear prediction, predict()
dy/dx w.r.t. : 1.rlcinstalled2

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
1.rlcinstalled2		-.5333885	.0904455	-5.90	0.000	-.7106584	-.3561186

Note: dy/dx for factor levels is the discrete change from the base level.

. margins rlcinstalled2##median rlcinstalled2##plt rlcinstalled2##pplt

Predictive margins
Model VCE : OIM
Number of obs = 685


```

Variables that uniquely identify margins: plt rlcinstalled2

. margins, dydx(rlcinstalled2) at(plt==(0 1))

Average marginal effects                                Number of obs    =          685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

1._at          : plt              =          0
2._at          : plt              =          1

-----
              |          Delta-method
              |          dy/dx   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
1.rlcinstalled2 |
   _at |
   1 | -.2019566   .1066862    -1.89   0.058    -.4110577    .0071445
   2 | -.9272949   .1921678    -4.83   0.000    -1.303937   -.550653
-----
Note: dy/dx for factor levels is the discrete change from the base level.

.
end of do-file

. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"

. quietly margins rlcinstalled2, at(pplt==(0 1))

. marginsplot, recastci(rarea) ciopts(color(*.3))

Variables that uniquely identify margins: pplt rlcinstalled2

. margins, dydx(rlcinstalled2) at(pplt==(0 1))

Average marginal effects                                Number of obs    =          685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

1._at          : pplt              =          0
2._at          : pplt              =          1

-----
              |          Delta-method
              |          dy/dx   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
1.rlcinstalled2 |
   _at |
   1 | -.3447224   .0741957    -4.65   0.000    -.4901433   -.1993015
   2 | -1.039541   .2557955    -4.06   0.000    -1.540891   -.5381912
-----
Note: dy/dx for factor levels is the discrete change from the base level.

.

```

```
. xtnbreg turningmovement c.lnaadt i.rlcinstalled2 i.median i.channelization i.thrulanec i.lef
> tturn i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##median rlcinstalled2##leftturn rlc
> installed2##thrulanec rlcinstalled2##pplt rlcinstalled2##plt rlcinstalled2##pplt , irr re
```

Random-effects negative binomial regression
Group variable: id

Number of obs = 685
Number of groups = 48

Random effects u_i ~ Beta

Obs per group:
min = 14
avg = 14.3
max = 15

Log likelihood = -1293.8167

Wald chi2(27) = 88.68
Prob > chi2 = 0.0000

turningmovement	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
lnaadt	1.442173	.2118003	2.49	0.013	1.081454	1.923208
1.rlcinstalled2	2.335753	.9718715	2.04	0.041	1.033368	5.279576
1.median	.5473002	.1453215	-2.27	0.023	.3252452	.9209589
1.channelization	1.563749	.382381	1.83	0.067	.9683317	2.525283
thrulanec						
2	.56305	.2040175	-1.59	0.113	.2767704	1.145445
3	.5672855	.2505551	-1.28	0.199	.2386977	1.348202
4	1.374543	.7373458	0.59	0.553	.4803398	3.9334
leftturn						
1	.7322197	.1699302	-1.34	0.179	.4646206	1.153943
2	.9079109	.3458032	-0.25	0.800	.4303674	1.915345
1.plt	1.122025	.2994075	0.43	0.666	.6650639	1.892963
1.fplt	1.319512	.3522562	1.04	0.299	.7819468	2.226639
1.pplt	2.568731	.6685229	3.62	0.000	1.542375	4.278065
speed1						
50	.8610169	.2977071	-0.43	0.665	.4372184	1.695606
60	.7192228	.2168036	-1.09	0.274	.3983602	1.298527

70		.6834575	.2801847	-0.93	0.353	.3060271	1.526382
speed2							
50		3.993215	1.655316	3.34	0.001	1.772035	8.998562
60		2.703495	1.031545	2.61	0.009	1.279797	5.710972
80		2.72069	2.119264	1.28	0.199	.591073	12.52325
rlcinstalled2#median							
1 1		.5516789	.1385287	-2.37	0.018	.3372456	.9024568
rlcinstalled2#leftturn							
1 1		1.662064	.4473743	1.89	0.059	.9806897	2.816851
1 2		2.930995	1.265281	2.49	0.013	1.25765	6.830779
rlcinstalled2#thrulanes							
1 2		.8099249	.2123895	-0.80	0.421	.4844301	1.354124
1 3		1.982624	.6681211	2.03	0.042	1.024225	3.837826
1 4		.6829643	.3797853	-0.69	0.493	.2296459	2.031128
rlcinstalled2#fplt							
1 1		.2484743	.0945641	-3.66	0.000	.1178506	.523879
rlcinstalled2#plt							
1 1		.2471161	.0956886	-3.61	0.000	.1156905	.5278425
rlcinstalled2#pplt							
1 1		.3994791	.155999	-2.35	0.019	.185821	.8588026
_cons		.0970264	.1491803	-1.52	0.129	.0047659	1.975295
/ln_r		2.408381	.2984384			1.823453	2.99331
/ln_s		1.4105	.2695689			.8821547	1.938845
r		11.11595	3.317427			6.193206	19.95161
s		4.098004	1.104695			2.4161	6.950722

LR test vs. pooled: chibar2(01) = 147.32

Prob >= chibar2 = 0.000

. margins rlcinstalled2

Predictive margins Number of obs = 685

Model VCE : OIM

Expression : Linear prediction, predict()

		Delta-method				[95% Conf. Interval]	
		Margin	Std. Err.	z	P> z		
rlcinstalled2							
0		1.888161	.191952	9.84	0.000	1.511942	2.26438
1		1.293592	.2200469	5.88	0.000	.8623078	1.724876

. *margins r.rlcinstalled2 ... same results as below:

. margins, dydx(rlcinstalled2)

Average marginal effects Number of obs = 685

Model VCE : OIM

Expression : Linear prediction, predict()

dy/dx w.r.t. : 1.rlcinstalled2

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
1.rlcinstalled2		-.5945695	.1303914	-4.56	0.000	-.850132	-.339007

Note: dy/dx for factor levels is the discrete change from the base level.

. margins rlcinstalled2#median rlcinstalled2#leftturn rlcinstalled2#thrulanes rlcinstalled2##p1

> t rlcinstalled2##fplt rlcinstalled2##pplt

Predictive margins Number of obs = 685

Model VCE : OIM

Expression : Linear prediction, predict()

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		

		Margin	Std. Err.	z	P> z	[95% Conf. Interval]	

rlcinstalled2#median							
0 0		2.289413	.2614261	8.76	0.000	1.777027	2.801799
0 1		1.686655	.2111804	7.99	0.000	1.272749	2.100561
1 0		2.090791	.2884539	7.25	0.000	1.525432	2.65615
1 1		.893244	.2691279	3.32	0.001	.365763	1.420725
rlcinstalled2#leftturn							
0 0		2.06	.2352117	8.76	0.000	1.598994	2.521007
0 1		1.748326	.2199342	7.95	0.000	1.317262	2.179389
0 2		1.963391	.3738698	5.25	0.000	1.23062	2.696162
1 0		1.10894	.3252961	3.41	0.001	.4713712	1.746509
1 1		1.305325	.2362809	5.52	0.000	.8422234	1.768428
1 2		2.087673	.441207	4.73	0.000	1.222923	2.952422
rlcinstalled2#thrulanes							
0 1		2.356646	.3791596	6.22	0.000	1.613506	3.099785
0 2		1.782259	.2083433	8.55	0.000	1.373913	2.190604
0 3		1.789753	.2918556	6.13	0.000	1.217727	2.361779
0 4		2.674767	.4169032	6.42	0.000	1.857652	3.491882
1 1		1.761308	.4454177	3.95	0.000	.8883052	2.63431
1 2		.9761072	.2534439	3.85	0.000	.4793663	1.472848
1 3		1.878836	.285391	6.58	0.000	1.31948	2.438192
1 4		1.698116	.5425648	3.13	0.002	.6347091	2.761524
rlcinstalled2							
0		1.888161	.191952	9.84	0.000	1.511942	2.26438
1		1.293592	.2200469	5.88	0.000	.8623078	1.724876
plt							
0		1.913221	.2262493	8.46	0.000	1.469781	2.356662
1		1.622253	.2455011	6.61	0.000	1.141079	2.103426
rlcinstalled2#plt							
0 0		1.835552	.2275525	8.07	0.000	1.389557	2.281547
0 1		1.950687	.240345	8.12	0.000	1.47962	2.421755
1 0		1.87973	.2417407	7.78	0.000	1.405927	2.353533
1 1		.5969681	.3795347	1.57	0.116	-.1469063	1.340843
fplt							
0		1.86038	.2168101	8.58	0.000	1.43544	2.28532
1		1.73313	.2560243	6.77	0.000	1.231332	2.234929
rlcinstalled2#fplt							
0 0		1.785352	.2171952	8.22	0.000	1.359657	2.211046
0 1		2.062614	.253301	8.14	0.000	1.566153	2.559075
1 0		1.707094	.2311639	7.38	0.000	1.254021	2.160167
1 1		.5919404	.400299	1.48	0.139	-.1926313	1.376512
pplt							
0		1.601453	.2046626	7.82	0.000	1.200321	2.002584
1		2.278294	.2699137	8.44	0.000	1.749272	2.807315
rlcinstalled2#pplt							
0 0		1.631994	.2066691	7.90	0.000	1.22693	2.037058
0 1		2.575406	.2654195	9.70	0.000	2.055193	3.095619
1 0		1.286581	.2172105	5.92	0.000	.8608567	1.712306
1 1		1.312399	.4356417	3.01	0.003	.4585574	2.166242

```

. quietly margins rlcinstalled2, at(median==(0 1))

. marginsplot, recastci(rarea) ciopts(color(*.3))

Variables that uniquely identify margins: median rlcinstalled2

. margins, dydx(rlcinstalled2) at(median==(0 1))

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

1._at      : median      =      0
2._at      : median      =      1
-----

```



```

. marginsplot, recastci(rarea) ciopts(color(*.3))

Variables that uniquely identify margins: pplt rlcinstalled2

. margins, dydx(rlcinstalled2) at(fplt==(0 1))

Average marginal effects                                Number of obs    =        685
Model VCE      : OIM

Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

1._at          : fplt          =          0
2._at          : fplt          =          1

```

		Delta-method dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.rlcinstalled2							
	_at						
	1	-.0782577	.1197879	-0.65	0.514	-.3130377	.1565224
	2	-1.470674	.3356136	-4.38	0.000	-2.128464	-.812883

Note: dy/dx for factor levels is the discrete change from the base level.

```

.
end of do-file

```

```
. xtbnreg sideswipe c.lnaadt i.rlcinstalled2 i.median i.channelization i.thrulanec i.leftturn
> i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##median rlcinstalled2##plt , irr re
```

Fitting negative binomial (constant dispersion) model:

Random-effects negative binomial regression
Group variable: id

Number of obs = 685
Number of groups = 48

Random effects u_i ~ Beta

Obs per group:
min = 14
avg = 14.3
max = 15

Log likelihood = -1005.5254

Wald chi2(20) = 86.00
Prob > chi2 = 0.0000

sideswipe	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
lnaadt	1.599357	.2981076	2.52	0.012	1.109911	2.304638
1.rlcinstalled2	2.346709	.5828983	3.43	0.001	1.442214	3.818466
1.median	.5461197	.1402929	-2.35	0.019	.3300824	.9035524
1.channelization	1.788259	.4317228	2.41	0.016	1.114122	2.870305
thrulanec						
2	1.335416	.5251608	0.74	0.462	.6178404	2.886403
3	2.060759	.9003143	1.66	0.098	.8752867	4.851815
4	2.36438	1.319409	1.54	0.123	.791984	7.058596
leftturn						
1	.7791687	.1635962	-1.19	0.235	.5163107	1.17585
2	2.269961	.7788726	2.39	0.017	1.158652	4.447173
1.plt	2.215626	.5929399	2.97	0.003	1.311294	3.743629
1.fplt	2.009333	.5501721	2.55	0.011	1.174859	3.436513
1.pplt	1.447202	.3743688	1.43	0.153	.871639	2.402824
speed1						
50	.7453052	.2607662	-0.84	0.401	.3754197	1.479623
60	.5924486	.1959321	-1.58	0.113	.3098452	1.132809
70	.8071575	.3219307	-0.54	0.591	.3693694	1.763826
speed2						
50	4.89139	2.301503	3.37	0.001	1.945019	12.30101
60	4.676964	2.123513	3.40	0.001	1.920823	11.38782
80	.985934	.8358894	-0.02	0.987	.1871486	5.194086
rlcinstalled2#median						
1 1	.5899685	.1492365	-2.09	0.037	.359345	.9686035
rlcinstalled2#plt						
1 1	.5702723	.1435074	-2.23	0.026	.348241	.9338663
_cons	.0063545	.0127101	-2.53	0.011	.000126	.3203659
/ln_r	3.290336	.3994215			2.507484	4.073188
/ln_s	1.575684	.2780813			1.030654	2.120713
r	26.85189	10.72522			12.27401	58.74393


```

s | 4.834046 1.344258 2.8029 8.337081
-----
LR test vs. pooled: chibar2(01) = 88.05 Prob >= chibar2 = 0.000

. margins rlcinstalled2

Predictive margins                                Number of obs   =      685
Model VCE      : OIM

Expression   : Linear prediction, predict()
-----
|               Delta-method
|               Margin Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
rlcinstalled2 |
  0 | 1.801825 .3646042   4.94  0.000   1.087214  2.516436
  1 | 2.046929 .3679593   5.56  0.000   1.325742  2.768116
-----

. *margins r.rlcinstalled2 ... same results as below:
. margins, dydx(rlcinstalled2)

Average marginal effects                        Number of obs   =      685
Model VCE      : OIM

Expression   : Linear prediction, predict()
dy/dx w.r.t. : 1.rlcinstalled2
-----
|               Delta-method
|               dy/dx Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
1.rlcinstalled2 | .2451035 .093402   2.62  0.009   .062039 .428168
-----
Note: dy/dx for factor levels is the discrete change from the base level.

. margins rlcinstalled2#median rlcinstalled2##plt

Predictive margins                                Number of obs   =      685
Model VCE      : OIM

Expression   : Linear prediction, predict()
-----
|               Delta-method
|               Margin Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
rlcinstalled2#median |
  0 0 | 2.204514 .3990889   5.52  0.000   1.422315  2.986714
  0 1 | 1.599597 .3765267   4.25  0.000   .8616188  2.337576
  1 0 | 2.800895 .4031419   6.95  0.000   2.010752  3.591039
  1 1 | 1.668292 .3950942   4.22  0.000   .8939217  2.442662
rlcinstalled2
  0 | 1.801825 .3646042   4.94  0.000   1.087214  2.516436
  1 | 2.046929 .3679593   5.56  0.000   1.325742  2.768116
plt
  0 | 1.584442 .3825847   4.14  0.000   .83459  2.334295
  1 | 2.216814 .3897619   5.69  0.000   1.452895  2.980734
rlcinstalled2#plt
  0 0 | 1.438318 .3855862   3.73  0.000   .6825829  2.194053
  0 1 | 2.233853 .3913086   5.71  0.000   1.466902  3.000804
  1 0 | 1.940055 .3893423   4.98  0.000   1.176958  2.703151
  1 1 | 2.173948 .41723   5.21  0.000   1.356193  2.991704
-----

.
.
. quietly margins rlcinstalled2, at(median==(0 1))

. marginsplot, recastci(rarea) ciopts(color(*.3))

Variables that uniquely identify margins: median rlcinstalled2

. margins, dydx(rlcinstalled2) at(median==(0 1))

Average marginal effects                        Number of obs   =      685
Model VCE      : OIM

```


Appendix I – Spillover Models

Table A – Marginal effect of the RLC covariate (XTNBREG estimates)

Collision Impact Type	AAOC ^a (Before RLC)	AAOC ^a (After RLC)	ATT Coef.	Effect without RLC (2) -(3)	Percent Change (2)-(4) / (4)
	(1)	(2)	(3)	(4)	(5)
Total Collisions	14.18	16.72	-0.0289	16.75	-0.2%
Rear end	5.00	7.88	0.0158	7.86	0.2%
Angle	3.82	3.08	-0.2676	3.35	-8.0%
Turning movement	3.03	2.69	-0.2433	2.93	-8.3%
Sideswipe	1.35	1.96	-0.1341	2.09	-6.4%

Table B – Impact of RLC in terms of percentage of collision reduction (XTNBREG estimates)

Collision impact type	Coef.	Std. Err.	z	P>chi2	[95% Conf. Interval]	
Total collisions	-0.0289	0.0432	-0.67	0.5040	-0.1136	0.0559
Rear end	0.0158	0.0727	0.22	0.8280	-0.1267	0.1583
Angle	-0.2676	0.1124	-2.38	0.0170	-0.4878	-0.0474
Turning movement	-0.2433	0.0846	-2.87	0.0040	-0.4092	-0.0774
Sideswipe	-0.1341	0.1162	-1.15	0.2490	-0.3619	0.0937

Table C – Significant interactions from spillover models (XTNBREG)

	Total	Rear-end	Angle	TM	Sideswipe
Variables	Determining effects of significant interactions with the RLC				
<i>rlcinstalled2</i>	↓ <1%	↑ <1%	↓ 8%	↓ 9%	↓ 7%
<i>median</i>	↓ 24%		↓ 51%	↓ 45%	↓ 45%
<i>channelization</i>	↑ 27%	↑ 58%			
<i>leftturn</i>	<ul style="list-style-type: none"> With 1 left-turn lane ↓ 23% (significant) With 2 left-turn lanes ↓ 12% 	<ul style="list-style-type: none"> With 1 left-turn lane ↓ 31% With 2 left-turn lanes ↓ 32% 		<ul style="list-style-type: none"> With 1 left-turn lane ↑ 66% With 2 left-turn lanes ↑ 290% (significant) 	
<i>plt</i>	↓ 49%		↓ 50%	↓ 75%	↓ 47%

<i>fplt</i>				↓ 75%	
<i>pplt</i>			↓ 51%	↓ 60%	
<i>speed1</i>					
<i>speed2</i>					
<i>thrulanes</i>	• With 2 thru lanes ↑ <1%			• With 2 thru lanes ↓ 20%	
	• With 2 thru lanes ↑ <1%			• With 3 thru lanes ↑ 98%	
	• With 4 thru lanes ↓ 40%			(significant)	
	(significant)			• With 4 thru lanes ↓ 31%	

TOTAL COLLISIONS

```
. quietly nbreg totalcollisions i.rlcinstalled2 c.lnaadt i.median i.channeliza
> tion i.thrulanes i.leftturn i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstal
> led2##channelization rlcinstalled2##leftturn rlcinstalled2##thrulanes rlcin
> stalled2##speed1 timehalo2 closestrlc500to1000 twoormorerlc0to500 twoormorer
> lc500to1000 , irr
```

```
. estimates store nbred_tot
```

```
. margins, dydx(rlcinstalled2)
```

```
Average marginal effects      Number of obs      =      685
Model VCE      : OIM
```

```
Expression      : Predicted number of events, predict()
dy/dx w.r.t.    : 1.rlcinstalled2
```

```
-----
|              Delta-method
|      dy/dx   Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinsta~2 |   .8845895   .6494631     1.36   0.173    - .3883349    2.157514
-----
```

Note: dy/dx for factor levels is the discrete change from the base level.

```
.
. quietly xtnbreg totalcollisions i.rlcinstalled2 c.lnaadt i.median i.channeli
> zation i.thrulanes i.leftturn i.plt i.fplt i.pplt i.speed2 rlcinstalled2##me
> dian rlcinstalled2##channelization rlcinstalled2##leftturn rlcinstalled2##thr
> ulanes rlcinstalled2##plt timehalo2 , irr re
```

```
. estimates store xtred_tot
```

```
. margins, dydx(rlcinstalled2)
```

```
Average marginal effects      Number of obs      =      685
Model VCE      : OIM
```

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2
```

```
-----
```

	Delta-method				
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
1.rlcinsta~2	-.0288863	.0432441	-0.67	0.504	-.1136433 .0558707

Note: dy/dx for factor levels is the discrete change from the base level.

Table 4 – Total collisions – Best fit NB and XTNBREG regression models

.. estimates table nbred_tot xtred_tot, star stats(N ll chi2 aic) eform

Variable	nbred_tot	xtred_tot
totalcolli~s		
rlcinstall~2		
1	1.3217195	1.3946264
lnaadt	1.7490802***	1.5541226***
median		
1	.70654415***	.62274477***
channeliza~n		
1	1.3639609***	1.5410971***
thrulanes		
2	.98957084	.96645237
3	1.2090767	1.2898934
4	2.4615809***	1.7048099*
leftturn		
1	1.1286712*	1.0692996
2	1.3267685***	1.5196238*
plt		
1	1.1531045**	1.3597128*
fplt		
1	1.2826796***	1.3686435**
pplt		
1	1.1460778**	1.2783462*
speed1		
50	1.1518209	
60	1.0989723	
70	1.1868377	
speed2		
50	1.5268132***	1.7065708**
60	1.5499691***	1.7675537***
80	1.2026245	1.515762
rlcinstall~2#		
channeliza~n		
1 1	1.3140753***	1.2719106**
rlcinstall~2#		
leftturn		
1 1	.71437638***	.77292105**
1 2	.90325873	.88132366
rlcinstall~2#		
thrulanes		
1 2	.96622136	1.0000719
1 3	1.0054985	1.0709724
1 4	.42575169***	.6013825*
rlcinstall~2#		

```

      speed1 |
      1 50 | .91157032
      1 60 | .78285876*
      1 70 | 1.096221
      |
      timehalo2 | 1.0142865*      1.0111222*
      clo~00to1000 | 1.2454336***
      twoo~c0to500 | 1.2498515*
      two~00to1000 | .45557391***
      |
      rlcinstall~2# |
      median |
      1 1 | .76287022*
      |
      rlcinstall~2# |
      plt |
      1 1 | .76785219*
      |
      _cons | .01780892***      .10603182**
      -----
      lnalpha |
      _cons | .0796594***
      -----
      ln_r |
      _cons | 42.361369***
      -----
      ln_s |
      _cons | 23.487028***
      -----
      Statistics |
      N | 685      685
      ll | -2131.193      -2054.5725
      chi2 | 463.78098      160.43862
      aic | 4328.386      4163.145
      -----
      legend: * p<0.05; ** p<0.01; *** p<0.001

```

REAR-END COLLISIONS

```

. quietly nbreg rearend i.rlcinstalled2 c.lnaadt i.median i.channelization i
> .thrulanes i.leftturn i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##ch
> annelization rlcinstalled2##leftturn numcams timehalo2 closestrlc0to500 close
> strlc500to1000 twoormorerlc0to500 threewithinrlc1000, irr

```

```

. estimates store nbred_Rear

. margins, dydx(rlcinstalled2)

```

```

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

```

```

Expression      : Predicted number of events, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```

```

-----
      |              Delta-method
      |      dy/dx      Std. Err.      z      P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinsta~2 |      .635787      .4528545      1.40      0.160      -.2517915      1.523366
-----

```

Note: dy/dx for factor levels is the discrete change from the base level.

```

.
. quietly xtnbreg rearend i.rlcinstalled2 c.lnaadt i.median i.channelization
> i.thrulanes i.leftturn i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##m
> edian rlcinstalled2##channelization rlcinstalled2##leftturn rlcinstalled2##fp
> lt numcams timehalo2 closestrlc0to500 twoormorerlc0to500 threewithinrlc100
> 0, irr re

```

```

. estimates store xtred_Rear

```

```
. margins, dydx(rcinstalled2)
```

```
Average marginal effects
Model VCE      : OIM
```

```
Number of obs   =      685
```

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rcinstalled2
```

		Delta-method				
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.rcinsta~2	.0157898	.0727245	0.22	0.828	-.1267476	.1583273

Note: dy/dx for factor levels is the discrete change from the base level.

Table 5 – RE collisions – Best fit NB and XTNBREG regression models

```
. estimates table nbred_Rear xtred_Rear , star stats(N ll chi2 aic) eform
```

Variable	nbred_Rear	xtred_Rear
rearend		
rcinstall~2		
1	.89256089	1.1853131
lnaad	3.0504547***	2.0208322***
median		
1	1.735048***	1.8668862**
channeliza~n		
1	1.0303979	1.2650365
thrulanes		
2	.46563974***	.4609894**
3	.40045236***	.41764803**
4	.60151293***	.53501934
leftturn		
1	.79740425**	.66061526*
2	.68852284**	.81849696
plt		
1	1.2715977***	1.4899393*
fplt		
1	1.9535483***	2.2936995***
pplt		
1	1.4745987***	1.8103629***
speed1		
50	1.6721987***	1.3996471
60	.91850205	.71262692
70	2.4424213***	2.3533684***
speed2		
50	.52076907***	.57688957*
60	.94801827	1.2571618
80	.10967925***	.06443402**
rcinstall~2#		
channeliza~n		
1 1	2.0445292***	1.5862499***
rcinstall~2#		
leftturn		
1 1	.6812503**	.69327182*
1 2	.71578329	.68744844*

```
. margins, dydx(rlcinstalled2)
```


Average marginal effects	Number of obs	=	685
Model VCE : OIM			

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.   : 1.rlcinstalled2
```

	Delta-method				
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
1.rlcinsta~2	-.2675874	.1123666	-2.38	0.017	-.487822 -.0473529

Note: dy/dx for factor levels is the discrete change from the base level.

Table 6 – Angle collisions – Best fit NB and XTNBREG regression models

```
. estimates table nbred_ANG xtred_ANG, star stats(N ll chi2 aic) eform
```

Variable	nbred_ANG	xtred_ANG
angle		
rlcinstall~2		
1	3.5431872**	2.0091066**
lnaad		
lnaad	.94453224	1.0696891
median		
1	.69911625***	.6854204
channeliza~n		
1	1.39259***	1.4162797
thrulanes		
2	1.8955462***	1.6186821
3	2.7636826***	2.6110058**
4	6.9723665***	2.2002249
leftturn		
1	1.2021044*	1.3190148
2	1.5403007**	2.0103001*
plt		
1	1.1045192	1.5067762*
fplt		
1	.63089873***	
pplt		
1	.63656989***	.72017623
speed1		
50	1.5225393**	
60	1.7733245***	
70	.99586034	
rlcinstall~2#		
median		
1 1	.52595629*	.49733084**
rlcinstall~2#		
channeliza~n		
1 1	.64736805*	
rlcinstall~2#		
leftturn		
1 1	1.8286649**	
1 2	1.8592104	
rlcinstall~2#		
thrulanes		

```

      1 2 | 1.043636
      1 3 | 1.5140256
      1 4 | .18449929***
      |
rlcinstall~2#|
      fplt |
      1 1 | .3903501**
      |
rlcinstall~2#|
      plt |
      1 1 | .20046313*** .50521858**
      |
rlcinstall~2#|
      pplt |
      1 1 | .19319574*** .49981533**
      |
      numcams | .98419811*** .98773174***
two~00to1000 | .23457848***
      _cons | 2.7013395 2.5563184
-----+-----
lnalpha
      _cons | .21031516***
-----+-----
ln_r
      _cons | 16.005896***
-----+-----
ln_s
      _cons | 4.9069048***
-----+-----
Statistics
      N | 685 685
      ll | -1410.5784 -1368.7031
      chi2 | 260.11961 73.004888
      aic | 2879.1569 2773.4062
-----+-----
      legend: * p<0.05; ** p<0.01; *** p<0.001

```

TM COLLISIONS

```

. quietly nbreg turningmovement i.rlcinstalled2 c.lnaadt i.median i.channeliz
> ation i.thrulanes i.leftturn i.pplt i.speed1 i.speed2 rlcinstalled2##lefttur
> n rlcinstalled2##thrulanes rlcinstalled2##speed1 closestrlc0to500 closestr
> lc500to1000 twoormorerlc0to500 threewithinrlc1000, irr

```

```

. estimates store nbred_TM

```

```

. margins, dydx(rlcinstalled2)

```

```

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

```

```

Expression      : Predicted number of events, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```

```

-----+-----
      |              Delta-method
      |      dy/dx      Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinsta~2 |  -.256673      .26002      -0.99   0.324      -.7663029      .252957
-----+-----

```

Note: dy/dx for factor levels is the discrete change from the base level.

```

.
. quietly xtnbreg turningmovement i.rlcinstalled2 c.lnaadt i.median i.channeli
> zation i.thrulanes i.plt i.fplt i.pplt i.speed2 rlcinstalled2##fplt rlcinst
> alled2##plt, irr re

```

```

. estimates store xtred_TM

```

```
. margins, dydx(rlcinstalled2)
```

```
Average marginal effects      Number of obs      =      685
Model VCE      : OIM
```

```
Expression      : Linear prediction, predict()
dy/dx w.r.t.    : 1.rlcinstalled2
```

	Delta-method				
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
1.rlcinsta~2	-.2577941	.0847178	-3.04	0.002	-.423838 -.0917502

Note: dy/dx for factor levels is the discrete change from the base level.

Table 7 – TM collisions – Best fit NB and XTNBREG regression models

```
. estimates table nbred_TM xtred_TM, star stats(N ll chi2 aic) eform
```

Variable	nbred_TM	xtred_TM
turningmov~t		
rlcinstall~2		
1	4.8251392***	1.1665452
lnaadt	1.5684963***	1.3519232*
median		
1	.32223078***	.51569926**
channeliza~n		
1	1.9992597***	1.4020666
thrulanes		
2	1.2160026	.57589228
3	1.1655562	.73928375
4	2.2385955***	1.2555515
leftturn		
1	1.0634158	
2	1.0595387	
pplt		
1	1.6049313***	2.3295742***
speed1		
50	.58861143**	
60	.83790931	
70	.42829683***	
speed2		
50	5.5721621***	3.3178915***
60	3.3628425***	2.3845262*
80	15.521402***	3.2914878
rlcinstall~2#		
leftturn		
1 1	.51248536***	
1 2	1.1300569	
rlcinstall~2#		
thrulanes		
1 2	.4962003*	
1 3	.55358242	
1 4	.18446331***	
rlcinstall~2#		
speed1		
1 50	.42885963**	

```

      1 60 | .32256103***
      1 70 | 1.0163573
      |
clos~c0to500 | 1.69551***
clo~00to1000 | 1.4874452**
twoo~c0to500 | .47477907***
threewi~1000 | .39181553***
      |
      plt |
      1 | 1.1324015
      |
      fplt |
      1 | 1.3879123
      |
rlcinstall~2# |
      fplt |
      1 1 | .51008749***
      |
rlcinstall~2# |
      plt |
      1 1 | .7011513*
      |
      _cons | .00824913*** .13975583
-----+-----
lnalpha
      _cons | .28513275***
-----+-----
ln_r
      _cons | 10.161578***
-----+-----
ln_s
      _cons | 4.0243665***
-----+-----
Statistics
      N | 685 685
      ll | -1357.7229 -1308.531
      chi2 | 300.49627 62.913902
      aic | 2775.4458 2653.0621
-----+-----
      legend: * p<0.05; ** p<0.01; *** p<0.001

```

Sideswipe COLLISIONS

```

. quietly nbreg sideswipe i.rlcinstalled2 c.lnaadt i.median i.channelization
> i.thrulanec i.leftturn i.plt i.fplt i.pplt i.speed1 i.speed2 rlcinstalled2##
> median rlcinstalled2##channelization rlcinstalled2##leftturn rlcinstalled2##t
> hrulanec rlcinstalled2##fplt numcams timehalo closestrlc500to1000 twoorm
> orerlc500to1000 threewithinrlc1000, irr

```

```

. estimates store nbred_SS

```

```

. margins, dydx(rlcinstalled2)

```

```

Average marginal effects      Number of obs      =      685
Model VCE      : OIM

```

```

Expression      : Predicted number of events, predict()
dy/dx w.r.t.    : 1.rlcinstalled2

```

```

-----+-----
      |              Delta-method
      |      dy/dx   Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
1.rlcinsta~2 | .2616188   .3053526    0.86   0.392   -.3368612   .8600988
-----+-----

```

Note: dy/dx for factor levels is the discrete change from the base level.

```

. quietly xtnbreg sideswipe i.rlcinstalled2 c.lnaadt i.median i.channelization
> i.thrulanec i.leftturn i.plt i.fplt i.speed2 rlcinstalled2##median rlcin

```

```
> stalled2##plt numcams timehalo , irr re
```

```
. estimates store xtred_SS
```

```
. margins, dydx(rlcinstalled2)
```

```
Average marginal effects  
Model VCE      : OIM
```

```
Number of obs      =      685
```

```
Expression      : Linear prediction, predict()  
dy/dx w.r.t.    : 1.rlcinstalled2
```

	Delta-method				
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
1.rlcinsta~2	-.1340988	.1162395	-1.15	0.249	-.361924 .0937264

Note: dy/dx for factor levels is the discrete change from the base level.

Table 8 – SS collisions – Best fit NB and XTNBREG regression models

```
. estimates table nbred_SS xtred_SS, star stats(N ll chi2 aic) eform
```

Variable	nbred_SS	xtred_SS
sideswipe		
rlcinstall~2		
1	1.4104522	1.7296013*
lnaad		
lnaad	1.8796183***	1.7035118**
median		
1	.53105652***	.57165781*
channeliza~n		
1	1.6995349***	1.8077294*
thrulanes		
2	1.6501634*	1.5230331
3	4.2988862***	2.509848*
4	10.461728***	3.151605*
leftturn		
1	1.1575648	.8535947
2	3.8621182***	2.075335*
plt		
1	1.9071284***	1.9600677**
fplt		
1	1.8436392***	1.4781529
pplt		
1	2.0032955***	
speed1		
50	.87180779	
60	.60374867**	
70	.66672029*	
speed2		
50	4.3011238***	4.7977254***
60	3.9709218***	4.0734174**
80	.93606752	1.005447
rlcinstall~2#		
median		
1 1	.33854544***	.55485819*
rlcinstall~2#		

```

channeliza~n |
  1 1 | 1.8658096**
rlcinstall~2#|
  leftturn |
    1 1 | .39153894***
    1 2 | .2362356***
rlcinstall~2#|
  thrulanes |
    1 2 | 1.4454009
    1 3 | .94597814
    1 4 | .27538621*
rlcinstall~2#|
  fplt |
    1 1 | 2.9095273***
numcams | 1.0243677*** 1.0212703***
timehalo | 1.2218178* 1.1944303*
clo~00to1000 | 1.4960417**
two~00to1000 | .07438641***
threewi~1000 | 1.6357851*
rlcinstall~2#|
  plt |
    1 1 | .53026664**
_cons | .00009008*** .00306121**
-----
lnalpha
_cons | .16284588***
-----
ln_r
_cons | 35.263987***
-----
ln_s
_cons | 4.3351136***
-----
Statistics
  N | 685 685
  ll | -1012.0685 -994.48228
  chi2 | 333.5558 105.92599
  aic | 2090.1371 2030.9646
-----
legend: * p<0.05; ** p<0.01; *** p<0.001

```

Appendix J – EB Models

How variables were calculated in the following tables:

- [1] Average observed Total collisions/yr BEFORE Cam: count
- [2] Average observed Total collisions/yr After Cam: count
- [3] Predicted w/o cam using SPF Model = $\text{cons_coeff} * \text{AADT}^{\text{coeff}}$
- [4] $\text{weight} = 1 / (1 + ([3] * \text{years}) / \text{overdispersion parameter})$
- [5] Expected Collisions (EB estimate) = $[4] * [3] + (1 - [4]) * [1]$
- [6] Observed % change (before after) = $([2] - [1]) / [1]$
- [7] Observed % change (before after) = $([2] - [5]) / [5]$

SPF Models calculated using nbreg from 14 non-RLC intersections

TOTAL COLLISIONS									
	Intersection	AADT	Average observed Total collisions/yr BEFORE Cam	Average observed Total collisions/yr After Cam	Predicted w/o cam using SPF Model	weight	Expected Collisions (EB estimate)	Observed % change (before after)	% change (expected & observed after)
1	BRONSON AVE & CARLING AVE	43,684	18.0	15.2	0.5623	0.02	17.6	-16%	-14%
2	CARLING AVE & RICHMOND RD	46,299	11.0	14.1	0.5623	0.02	10.8	28%	31%
3	COVENTRY RD & ST. LAURENT BLVD	52,562	21.0	24.3	0.5623	0.02	20.6	15%	18%
4	EAGLESON RD & HAZELDEAN RD	37,775	18.5	16.2	0.5623	0.02	18.1	-13%	-11%
5	HERON RD & RIVERSIDE DR	58,882	27.5	29.3	0.5623	0.02	26.9	7%	9%
6	MEADOWLANDS DR & MERIVALE RD	47,966	20.0	23.0	0.5623	0.02	19.6	15%	18%
7	ALBERT ST & KENT ST (OTTAWA)	50,000	11.5	12.0	0.5623	0.02	11.3	4%	7%
8	BOOTH ST & OTTAWA RIVER PKWY	46,168	9.8	10.4	0.5623	0.02	9.6	6%	9%
9	BASELINE RD & MERIVALE RD	46,821	26.2	16.2	0.5623	0.02	25.7	-38%	-37%
10	CARLING AVE & ISLAND PARK DR	23,533	10.2	8.8	0.5623	0.02	10.0	-14%	-12%
11	CAMPEAU DR & MARCH RD	59,992	20.4	18.6	0.5623	0.02	20.0	-9%	-7%
12	BANK ST & RIVERSIDE DR N	41,598	16.2	15.8	0.5623	0.02	15.9	-3%	0%
13	BELFAST RD & ST. LAURENT BLVD	38,197	21.9	28.0	0.5623	0.02	21.4	28%	31%
14	CHARLEMAGNE BLVD N & TENTH LINE RD	35,827	14.6	20.0	0.5623	0.02	14.2	37%	40%
15	BANK ST & HUNT CLUB RD	50,684	19.7	25.6	0.5623	0.02	19.2	30%	33%
16	CATHERINE ST & HWY 417 O'CONN	50,000	17.8	12.0	0.5623	0.02	17.4	-33%	-31%
17	CATHERINE ST & KENT ST	50,000	20.9	23.0	0.5623	0.02	20.4	10%	13%
18	RUSSELL RD & WALKLEY RD	34,805	21.9	30.4	0.5623	0.02	21.4	39%	42%
19	BRONSON AVE & COMMISSIONER ST	18,746	14.0	8.8	0.5623	0.02	13.7	-38%	-36%
20	FISHER AVE & MEADOWLANDS DR	23,176	13.3	12.5	0.5623	0.02	13.0	-6%	-4%
21	DUFORD DR & ST. JOSEPH BLVD	25,612	8.5	7.0	0.5623	0.02	8.3	-17%	-15%
22	AVIATION PKWY & OGILVIE RD	40,664	16.6	13.8	0.5623	0.02	16.3	-17%	-16%

23	BANK ST & HERON RD	56,511	22.5	22.5	0.5623	0.02	22.0	0%	2%
24	BERRIGAN DR & GREENBANK RD	25,292	9.7	11.3	0.5623	0.02	9.5	16%	18%
25	CONROY RD & LORRY GREENBERG DR	22,615	3.0	2.5	0.5623	0.02	2.9	-17%	-15%
26	JOCKVALE RD & STRANDHERD DR	17,536	3.8	5.5	0.5623	0.02	3.7	44%	47%
27	CYRVILLE RD & INNES RD	55,925	15.2	14.5	0.5623	0.02	14.9	-4%	-2%
28	HAWTHORNE AVE & QUEEN ELIZABETH DRWY	27,065	8.5	9.0	0.5623	0.02	8.3	6%	9%
29	ALBERT ST & BOOTH ST	27,558	12.9	12.8	0.5623	0.02	12.6	-1%	1%
30	DRIVEWAY (THE) & ISLAND PARK DR	19,583	8.5	8.5	0.5623	0.02	8.4	-1%	2%
31	BLAIR RD & BLAIR RD RAMP 36	30,969	16.9	25.3	0.5623	0.02	16.5	49%	53%
32	KING EDWARD AVE & ST. PATRICK ST	33,216	25.5	9.0	0.5623	0.02	25.0	-65%	-64%
33	SAUNDERSON DR & SMYTH RD	49,546	4.2	5.5	0.5623	0.02	4.1	32%	35%
34	KING EDWARD AVE & ST. ANDREW ST	47,702	4.0	1.5	0.5623	0.02	3.9	-63%	-62%
Total			514	513			503	0%	1.82%

REAR END COLLISIONS

	Intersection	AADT	Average observed Rear end collisions/yr BEFORE Cam	Average observed Rearend coll/yr	Predicted w/o cam using SPF Model	weight	Expected w/o cam (EB estimate)	Observed % change	% change (expected & observed after)
1	BRONSON AVE & CARLING AVE	43,684	5.0	4.7	-1.0674	-0.01	5.1	-6%	-7%
2	CARLING AVE & RICHMOND RD	46,299	6.0	7.5	-1.0674	-0.01	6.1	24%	23%
3	COVENTRY RD & ST. LAURENT BLVD	52,562	7.5	12.7	-1.0674	-0.01	7.6	69%	67%
4	EAGLESON RD & HAZELDEAN RD	37,775	9.5	10.9	-1.0674	-0.01	9.6	15%	14%
5	HERON RD & RIVERSIDE DR	58,882	17.5	22.1	-1.0674	-0.01	17.7	26%	25%
6	MEADOWLANDS DR & MERIVALE RD	47,966	10.5	9.8	-1.0674	-0.01	10.6	-6%	-7%
7	ALBERT ST & KENT ST (OTTAWA)	50,000	1.0	0.3	-1.0674	-0.01	1.0	-67%	-67%
8	BANK ST & HUNT CLUB RD	50,684	2.8	7.7	-1.0674	-0.01	2.8	177%	173%
9	BANK ST & RIVERSIDE DR N	41,598	12.9	8.5	-1.0674	-0.01	13.0	-34%	-35%

10	BASILENE RD & MERIVALE RD	46,821	1.1	6.3	-1.0674	-0.01	1.1	467%	456%
11	BELFAST RD & ST. LAURENT BLVD	38,197	12.9	6.4	-1.0674	-0.01	13.0	-50%	-51%
12	BOOTH ST & OTTAWA RIVER PKWY	46,168	4.1	10.1	-1.0674	-0.01	4.2	146%	142%
13	CAMPEAU DR & MARCH RD	59,992	5.6	10.6	-1.0674	-0.01	5.6	91%	88%
14	CARLING AVE & ISLAND PARK DR	23,533	6.2	7.2	-1.0673	-0.01	6.3	16%	14%
15	CHARLEMAGNE BLVD N & TENTH LINE RD	35,827	10.3	12.7	-1.0674	-0.01	10.5	23%	22%
16	CATHERINE ST & HWY 417 O'CONN	50,000	2.7	4.1	-1.0674	-0.01	2.7	54%	52%
17	CATHERINE ST & KENT ST	50,000	0.8	1.6	-1.0674	-0.01	0.8	106%	101%
18	RUSSELL RD & WALKLEY RD	34,805	12.6	15.1	-1.0673	-0.01	12.7	20%	19%
19	ALBERT ST & BOOTH ST	27,558	1.5	1.0	-1.0673	-0.01	1.6	-35%	-36%
20	AVIATION PKWY & OGILVIE RD	40,664	2.3	1.8	-1.0674	-0.01	2.3	-23%	-24%
21	BANK ST & HERON RD	56,511	2.9	2.3	-1.0674	-0.01	3.0	-23%	-24%
22	BERRIGAN DR & GREENBANK RD	25,292	4.7	6.8	-1.0673	-0.01	4.8	43%	41%
23	BLAIR RD & BLAIR RD RAMP 36	30,969	8.5	11.3	-1.0673	-0.01	8.6	32%	30%
24	BRONSON AVE & COMMISSIONER ST	18,746	6.1	7.0	-1.0673	-0.01	6.2	15%	14%
25	CONROY RD & LORRY GREENBERG DR	22,615	0.5	1.3	-1.0673	-0.01	0.6	129%	122%
26	CYRVILLE RD & INNES RD	55,925	0.6	2.3	-1.0674	-0.01	0.7	254%	244%
27	DRIVEWAY (THE) & ISLAND PARK DR	19,583	8.0	9.3	-1.0673	-0.01	8.1	16%	14%
28	DUFORD DR & ST. JOSEPH BLVD	25,612	2.2	3.3	-1.0673	-0.01	2.2	49%	47%
29	FISHER AVE & MEADOWLANDS DR	23,176	3.5	3.3	-1.0673	-0.01	3.6	-8%	-10%
30	HAWTHORNE AVE & QUEEN ELIZABETH DRWY	27,065	0.7	1.5	-1.0673	-0.01	0.7	106%	101%
31	JOCKVALE RD & STRANDHERD DR	17,536	10.4	14.0	-1.0673	-0.01	10.5	35%	34%
32	KING EDWARD AVE & ST. PATRICK ST	33,216	6.9	3.0	-1.0673	-0.01	7.0	-57%	-57%
33	SAUNDERSON DR & SMYTH RD	49,546	0.8	3.0	-1.0674	-0.01	0.8	300%	290%
34	KING EDWARD AVE & ST. ANDREW ST	47,702	2.9	1.0	-1.0674	-0.01	3.0	-66%	-66%
Total			192	230			194	20%	15.69%

ANGLE COLLISIONS

	Intersection	AADT	Average observed Angle collisions/yr BEFORE Cam	Average observed Angle AFTER cam coll/yr	Predicted w/o cam using SPF Model	weight	Expected w/o cam (EB estimate)	Observed % change	% change (expected & observed after)
1	BRONSON AVE & CARLING AVE	43,684	4.0	0.6	-0.3538	-0.03	4.1	-85%	-85%
2	CARLING AVE & RICHMOND RD	46,299	3.0	3.5	-0.3538	-0.03	3.1	18%	14%
3	COVENTRY RD & ST. LAURENT BLVD	52,562	7.5	4.3	-0.3538	-0.03	7.8	-43%	-45%
4	EAGLESON RD & HAZELDEAN RD	37,775	2.5	1.6	-0.3538	-0.03	2.6	-37%	-39%
5	HERON RD & RIVERSIDE DR	58,882	7.0	2.8	-0.3538	-0.03	7.3	-60%	-61%
6	MEADOWLANDS DR & MERIVALE RD	47,966	3.5	1.3	-0.3538	-0.03	3.6	-62%	-63%
7	ALBERT ST & KENT ST (OTTAWA)	50,000	10.5	9.6	-0.3538	-0.03	10.9	-9%	-12%
8	BANK ST & HUNT CLUB RD	50,684	5.0	3.1	-0.3538	-0.03	5.2	-38%	-40%
9	BANK ST & RIVERSIDE DR N	41,598	3.3	3.9	-0.3538	-0.03	3.5	17%	13%
10	BASELINE RD & MERIVALE RD	46,821	5.1	3.1	-0.3538	-0.03	5.3	-39%	-42%
11	BELFAST RD & ST. LAURENT BLVD	38,197	3.3	3.4	-0.3538	-0.03	3.5	2%	-2%
12	BOOTH ST & OTTAWA RIVER PKWY	46,168	7.8	4.9	-0.3538	-0.03	8.1	-37%	-39%
13	CAMPEAU DR & MARCH RD	59,992	3.4	1.8	-0.3538	-0.03	3.6	-48%	-50%
14	CARLING AVE & ISLAND PARK DR	23,533	3.0	4.9	-0.3538	-0.03	3.1	63%	57%
15	CHARLEMAGNE BLVD N & TENTH LINE RD	35,827	3.8	2.5	-0.3538	-0.03	3.9	-34%	-36%
16	CATHERINE ST & HWY 417 O'CONN	50,000	11.8	5.4	-0.3538	-0.03	12.2	-54%	-56%
17	CATHERINE ST & KENT ST	50,000	5.8	7.3	-0.3538	-0.03	6.0	26%	22%
18	RUSSELL RD & WALKLEY RD	34,805	2.6	1.4	-0.3538	-0.03	2.7	-45%	-47%
19	ALBERT ST & BOOTH ST	27,558	5.4	4.5	-0.3538	-0.03	5.6	-16%	-19%
20	AVIATION PKWY & OGILVIE RD	40,664	3.7	1.8	-0.3538	-0.03	3.9	-53%	-55%
21	BANK ST & HERON RD	56,511	2.3	1.3	-0.3538	-0.03	2.4	-45%	-47%

22	BERRIGAN DR & GREENBANK RD	25,292	2.4	1.5	-0.3538	-0.03	2.5	-37%	-39%
23	BLAIR RD & BLAIR RD RAMP 36	30,969	3.0	1.3	-0.3538	-0.03	3.1	-58%	-60%
24	BRONSON AVE & COMMISSIONER ST	18,746	1.7	1.5	-0.3538	-0.03	1.8	-13%	-17%
25	CONROY RD & LORRY GREENBERG DR	22,615	1.2	0.3	-0.3538	-0.03	1.2	-79%	-80%
26	CYRVILLE RD & INNES RD	55,925	1.5	1.0	-0.3538	-0.03	1.6	-35%	-38%
27	DRIVEWAY (THE) & ISLAND PARK DR	19,583	2.9	2.0	-0.3538	-0.03	3.0	-31%	-34%
28	DUFORD DR & ST. JOSEPH BLVD	25,612	3.6	4.3	-0.3538	-0.03	3.8	17%	13%
29	FISHER AVE & MEADOWLANDS DR	23,176	4.4	2.8	-0.3538	-0.03	4.5	-37%	-39%
30	HAWTHORNE AVE & QUEEN ELIZABETH DRWY	27,065	2.8	2.8	-0.3538	-0.03	2.9	-2%	-6%
31	JOCKVALE RD & STRANDHERD DR	17,536	3.7	3.8	-0.3538	-0.03	3.9	1%	-3%
32	KING EDWARD AVE & ST. PATRICK ST	33,216	8.0	1.0	-0.3538	-0.03	8.3	-88%	-88%
33	SAUNDERSON DR & SMYTH RD	49,546	1.7	0.5	-0.3538	-0.03	1.7	-70%	-71%
34	KING EDWARD AVE & ST. ANDREW ST	47,702	0.3	0.0	-0.3538	-0.03	0.4	-100%	-100%
Total			142	95			147	-33%	-53.83%

TURNING MOVEMENT COLLISIONS

	Intersection	AADT	Average observed TurningMvmt collisions/yr BEFORE Cam	Average observed TurningMvmt AFTER cam coll/yr	Predicted w/o cam using SPF Model	weight	Expected w/o cam (EB estimate)	Observed % change	% change (expected & observed after)
1	BRONSON AVE & CARLING AVE	43,684	6.0	5.4	-0.4173	-0.04	6.2	-10%	-14%
2	CARLING AVE & RICHMOND RD	46,299	1.0	0.6	-0.4173	-0.04	1.1	-38%	-42%
3	COVENTRY RD & ST. LAURENT BLVD	52,562	2.0	1.1	-0.4173	-0.04	2.1	-46%	-48%
4	EAGLESON RD & HAZELDEAN RD	37,775	2.0	0.8	-0.4173	-0.04	2.1	-58%	-60%
5	HERON RD & RIVERSIDE DR	58,882	1.5	1.8	-0.4173	-0.04	1.6	17%	11%
6	MEADOWLANDS DR & MERIVALE RD	47,966	5.0	8.0	-0.4173	-0.04	5.2	60%	54%
7	ALBERT ST & KENT ST (OTTAWA)	50,000	0.0	0.6	-0.4173	-0.04	0.0	0%	3605%

8	CARLING AVE & ISLAND PARK DR	23,533	1.3	3.2	-0.4173	-0.04	1.4	140%	129%
9	CHARLEMAGNE BLVD N & TENTH LINE RD	35,827	5.3	0.5	-0.4173	-0.04	5.6	-91%	-91%
10	BASELINE RD & MERIVALE RD	46,821	3.1	2.4	-0.4173	-0.04	3.2	-23%	-26%
11	BANK ST & HUNT CLUB RD	50,684	1.7	2.2	-0.4173	-0.04	1.7	32%	26%
12	BELFAST RD & ST. LAURENT BLVD	38,197	1.3	1.2	-0.4173	-0.04	1.4	-10%	-14%
13	BOOTH ST & OTTAWA RIVER PKWY	46,168	8.9	5.6	-0.4173	-0.04	9.2	-37%	-39%
14	CAMPEAU DR & MARCH RD	59,992	4.0	6.0	-0.4173	-0.04	4.2	50%	44%
15	BANK ST & RIVERSIDE DR N	41,598	1.8	1.9	-0.4173	-0.04	1.9	7%	2%
16	CATHERINE ST & HWY 417 O'CONN	50,000	0.1	0.6	-0.4173	-0.04	0.1	440%	100%
17	CATHERINE ST & KENT ST	50,000	9.4	4.7	-0.4173	-0.04	9.8	-50%	-52%
18	RUSSELL RD & WALKLEY RD	34,805	1.7	4.5	-0.4173	-0.04	1.7	170%	158%
19	HAWTHORNE AVE & QUEEN ELIZABETH DRWY	27,065	4.9	2.0	-0.4173	-0.04	5.1	-59%	-61%
20	JOCKVALE RD & STRANDHERD DR	17,536	5.4	5.0	-0.4172	-0.04	5.6	-7%	-10%
21	CYRVILLE RD & INNES RD	55,925	2.4	1.8	-0.4173	-0.04	2.5	-26%	-29%
22	ALBERT ST & BOOTH ST	27,558	7.5	3.5	-0.4173	-0.04	7.8	-54%	-55%
23	BRONSON AVE & COMMISSIONER ST	18,746	4.5	2.0	-0.4172	-0.04	4.6	-55%	-57%
24	CONROY RD & LORRY GREENBERG DR	22,615	0.9	2.3	-0.4173	-0.04	1.0	148%	135%
25	DRIVEWAY (THE) & ISLAND PARK DR	19,583	0.7	0.8	-0.4172	-0.04	0.8	3%	-3%
26	DUFORD DR & ST. JOSEPH BLVD	25,612	1.1	1.5	-0.4173	-0.04	1.1	38%	31%
27	FISHER AVE & MEADOWLANDS DR	23,176	0.9	1.3	-0.4173	-0.04	1.0	38%	30%
28	BANK ST & HERON RD	56,511	1.6	0.5	-0.4173	-0.04	1.7	-69%	-71%
29	BERRIGAN DR & GREENBANK RD	25,292	2.9	4.5	-0.4173	-0.04	3.0	55%	48%
30	BLAIR RD & BLAIR RD RAMP 36	30,969	4.5	3.8	-0.4173	-0.04	4.6	-16%	-19%
31	AVIATION PKWY & OGILVIE RD	40,664	2.0	5.3	-0.4173	-0.04	2.1	163%	151%
32	SAUNDERSON DR & SMYTH RD	49,546	4.4	1.0	-0.4173	-0.04	4.6	-77%	-78%
33	KING EDWARD AVE & ST. PATRICK ST	33,216	1.4	0.5	-0.4173	-0.04	1.5	-65%	-66%
34	KING EDWARD AVE & ST. ANDREW ST	47,702	0.2	0.0	-0.4173	-0.04	0.2	-100%	-100%
Total			101	87			106	-15%	-22.24%

SIDESWIPE COLLISIONS

	Intersection	AADT	Average observed Sideswipe collisions/yr BEFORE Cam	Average observed Sideswipe AFTER cam coll/yr	Predicted w/o cam using SPF Model	weight	Expected w/o cam (EB estimate)	Observed % change	% change (expected & observed after)
1	BRN SON AVE & CARLING AVE	43,684	0.7	2.0	-0.5916	-0.05	0.8	175%	153%
2	CARLING AVE & RICHMOND RD	46,299	0.0	0.8	-0.5916	-0.05	0.0	#DIV/0!	2533%
3	COVENTRY RD & ST. LAURENT BLVD	52,562	0.8	0.5	-0.5916	-0.05	0.9	-39%	-44%
4	EAGLESON RD & HAZELDEAN RD	37,775	4.8	6.0	-0.5916	-0.05	5.1	25%	18%
5	HERON RD & RIVERSIDE DR	58,882	3.0	5.0	-0.5916	-0.05	3.2	67%	58%
6	MEADOWLANDS DR & MERIVALE RD	47,966	2.0	2.6	-0.5916	-0.05	2.1	30%	22%
7	ALBERT ST & KENT ST (OTTAWA)	50,000	2.4	1.4	-0.5916	-0.05	2.6	0%	-46%
8	CARLING AVE & ISLAND PARK DR	23,533	2.0	3.8	-0.5916	-0.05	2.1	90%	79%
9	CHARLEMAGNE BLVD N & TENTH LINE RD	35,827	0.4	0.3	-0.5916	-0.05	0.4	-31%	-39%
10	BASELINE RD & MERIVALE RD	46,821	0.5	1.0	-0.5916	-0.05	0.6	83%	67%
11	BANK ST & HUNT CLUB RD	50,684	0.1	1.4	-0.5916	-0.05	0.1	1160%	866%
12	BELFAST RD & ST. LAURENT BLVD	38,197	2.0	2.9	-0.5916	-0.05	2.1	46%	38%
13	BOOTH ST & OTTAWA RIVER PKWY	46,168	0.9	0.8	-0.5916	-0.05	1.0	-18%	-24%
14	CAMPEAU DR & MARCH RD	59,992	1.2	0.6	-0.5916	-0.05	1.3	-51%	-54%
15	BANK ST & RIVERSIDE DR N	41,598	0.3	1.4	-0.5916	-0.05	0.4	320%	271%
16	CATHERINE ST & HWY 417 O'CONN	50,000	0.0	1.5	-0.5916	-0.05	0.0	#DIV/0!	100%
17	CATHERINE ST & KENT ST	50,000	2.2	1.8	-0.5916	-0.05	2.4	-19%	-24%
18	RUSSELL RD & WALKLEY RD	34,805	4.1	5.0	-0.5916	-0.05	4.3	22%	15%
19	HAWTHORNE AVE & QUEEN ELIZABETH DRWY	27,065	0.4	0.8	-0.5916	-0.05	0.5	80%	62%
20	JOCKVALE RD & STRANDHERD DR	17,536	0.3	0.0	-0.5915	-0.05	0.3	-100%	-100%
21	CYRVILLE RD & INNES RD	55,925	3.5	4.5	-0.5916	-0.05	3.7	29%	22%
22	ALBERT ST & BOOTH ST	27,558	1.6	1.3	-0.5916	-0.05	1.7	-24%	-28%
23	BRN SON AVE & COMMISSIONER ST	18,746	0.2	0.5	-0.5915	-0.05	0.2	175%	128%
24	CONROY RD & LORRY GREENBERG DR	22,615	0.3	0.5	-0.5916	-0.05	0.3	83%	59%
25	DRIVEWAY (THE) & ISLAND PARK DR	19,583	0.5	1.3	-0.5915	-0.05	0.6	150%	126%

26	DUFORD DR & ST. JOSEPH BLVD	25,612	0.7	1.5	-0.5916	-0.05	0.8	106%	90%
27	FISHER AVE & MEADOWLANDS DR	23,176	0.4	0.3	-0.5916	-0.05	0.4	-31%	-39%
28	BANK ST & HERON RD	56,511	1.0	1.8	-0.5916	-0.05	1.1	75%	63%
29	BERRIGAN DR & GREENBANK RD	25,292	0.1	0.0	-0.5916	-0.05	0.1	-100%	-100%
30	BLAIR RD & BLAIR RD RAMP 36	30,969	0.2	0.0	-0.5916	-0.05	0.2	-100%	-100%
31	AVIATION PKWY & OGILVIE RD	40,664	5.3	2.5	-0.5916	-0.05	5.5	-52%	-55%
32	SAUNDERSON DR & SMYTH RD	49,546	1.0	2.0	-0.5916	-0.05	1.1	100%	86%
33	KING EDWARD AVE & ST. PATRICK ST	33,216	2.3	5.6	-0.5916	-0.05	2.5	140%	126%
34	KING EDWARD AVE & ST. ANDREW ST	47,702	0.2	0.5	-0.5916	-0.05	0.2	200%	146%
Total			46	62			49	35%	20.87%

Appendix K – PSM Output

TOTAL COLLISIONS

```
. teffects ipwra (totalcollisions lnaadt median channelization leftturn thrulanes fplt
plt pplt speed1 speed2) (Llrlcinstalled2 Llrearend Llangle L1TM ), atet
```

```
Iteration 0: EE criterion = 1.541e-16
Iteration 1: EE criterion = 1.602e-28
```

```
Treatment-effects estimation      Number of obs      =      637
Estimator      : IPW regression adjustment
Outcome model  : linear
Treatment model: logit
```

		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
totalcollisions							
ATET							
Llrlcinstalled2							
(1 vs 0)		-.3629016	.6143863	-0.59	0.555	-1.567077	.8412734
POMean							
Llrlcinstalled2							
0		17.32654	.6136502	28.24	0.000	16.12381	18.52927

```
. *with lags - outcome NOT repeated in treatmment
. tebalance overid
```

```
Iteration 0: criterion = .13620852
Iteration 1: criterion = .13748158 (backed up)
Iteration 2: criterion = .13755498 (backed up)
Iteration 3: criterion = .13758405
Iteration 4: criterion = .13816077
Iteration 5: criterion = .13838816
Iteration 6: criterion = .13838825
```

```
Overidentification test for covariate balance
H0: Covariates are balanced:
```

```
chi2(4)      = 6.22605
Prob > chi2   = 0.1829
```

```
. psmatch2 rlcinstalled2 lnaadt median channelization leftturn thrulanes fplt plt pplt
speed1
> speed2, logit common outcome (totalcollisions) ties
```

```
Logistic regression      Number of obs      =      685
                        LR chi2(10)      =      84.15
                        Prob > chi2      =      0.0000
Log likelihood = -370.71141      Pseudo R2      =      0.1019
```

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
rlcinstalled2							
lnaadt		.5202112	.2599367	2.00	0.045	.0107447	1.029678
median		-1.045775	.2579872	-4.05	0.000	-1.551421	-.5401296
channelization		.4969581	.2293971	2.17	0.030	.0473481	.946568
leftturn		.549823	.1609388	3.42	0.001	.2343887	.8652573
thrulanes		.8612656	.1567287	5.50	0.000	.5540831	1.168448
fplt		-1.328941	.3086871	-4.31	0.000	-1.933957	-.7239258
plt		-1.384477	.31272	-4.43	0.000	-1.997397	-.7715569
pplt		-1.390921	.3041415	-4.57	0.000	-1.987028	-.794815
speed1		-.0124766	.011701	-1.07	0.286	-.0354101	.010457
speed2		.0031362	.015014	0.21	0.835	-.0262907	.0325631


```

      _cons | -6.341262   2.688711   -2.36   0.018   -11.61104   -1.071485
-----+-----

```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
totalcollisions	Unmatched	16.7236181	14.2777778	2.44584031	.644721258	3.79
	ATT	16.7760417	15.4479167	1.328125	1.10254263	1.20

Note: S.E. does not take into account that the propensity score is estimated.

```

psmatch2: | psmatch2: Common
Treatment | support
assignment | Off suppo On suppor | Total
-----+-----
Untreated | 0 486 | 486
Treated | 7 192 | 199
-----+-----
Total | 7 678 | 685

```

end of do-file

```

. do "C:\Users\Amal\AppData\Local\Temp\STD04000000.tmp"

. pstest lnaadt median channelization leftturn thrulanes fplt plt pplt speed1 speed2,
both gra
> ph

```

Variable	Unmatched Matched	Mean Treated Control	%bias bias	%reduct bias	t-test t p> t	V(T)/ V(C)
lnaadt	U	10.484	10.39	23.7	2.80 0.005	0.95
	M	10.475	10.468	1.8	0.18 0.855	1.23
median	U	.66332	.66667	-0.7	-0.08 0.933	.
	M	.65104	.6875	-7.7	-0.76 0.449	.
channelization	U	.50754	.38272	25.3	3.02 0.003	.
	M	.48958	.45313	7.4	0.71 0.476	.
leftturn	U	.73367	.6749	9.7	1.13 0.258	0.85
	M	.72396	.80208	-12.9	-1.24 0.215	0.85
thrulanes	U	2.4523	2.1872	38.0	4.56 0.000	1.11
	M	2.3958	2.3333	9.0	0.85 0.394	0.74*
fplt	U	.37688	.36831	1.8	0.21 0.833	.
	M	.35417	.26563	18.3	1.88 0.061	.
plt	U	.38191	.48765	-21.4	-2.53 0.012	.
	M	.39583	.41146	-3.2	-0.31 0.756	.
pplt	U	.17588	.3107	-31.8	-3.63 0.000	.
	M	.18229	.21875	-8.6	-0.89 0.374	.
speed1	U	54.422	54.403	0.2	0.03 0.979	0.82
	M	54.219	52.396	22.2	2.16 0.032	0.83
speed2	U	55.126	54.568	8.1	0.90 0.367	0.53*
	M	54.948	55.469	-7.5	-0.87 0.385	0.95

* if variance ratio outside [0.76; 1.32] for U and [0.75; 1.33] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.105	86.28	0.000	16.1	15.6	79.4*	0.32*	20
Matched	0.030	15.92	0.102	9.8	8.2	41.2*	0.71	20

```
* if B>25%, R outside [0.5; 2]
```

```
.
```

```
. pstest _pscore, density both
```

psmatch2: Propensity Score

TOTAL WITH SPILLOVER

```
. psmatch2 rlcinstalled2 lnaadt median channelization leftturn thrulanes plt p
> plt closestrlc0to500 twoormorerlc0to500 threewithinrlc1000 numcams timehalo
> yr timehalo timehalo2, logit common outcome (totalcollisions) ties
```

Logistic regression

Number of obs = 685

```

Log likelihood = -195.89568
LR chi2(14)      = 433.78
Prob > chi2      = 0.0000
Pseudo R2       = 0.5254

```

rlcinstall~2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
lnaad	.126625	.3708407	0.34	0.733	-.6002095	.8534594
median	-1.601679	.4001783	-4.00	0.000	-2.386014	-.817344
channeliza~n	-.0455128	.3338912	-0.14	0.892	-.6999275	.6089019
leftturn	-.2737637	.2450188	-1.12	0.264	-.7539918	.2064643
thrulanes	1.361598	.2390263	5.70	0.000	.8931152	1.830081
plt	-.4718743	.3284175	-1.44	0.151	-1.115561	.1718123
pplt	-2.604665	.405621	-6.42	0.000	-3.399668	-1.809663
close~c0to500	-3.905904	.471707	-8.28	0.000	-4.830433	-2.981376
twoo~c0to500	.8112562	.70269	1.15	0.248	-.5659909	2.188503
threewi~1000	-1.359991	.6938614	-1.96	0.050	-2.719934	-.0000476
numcams	.1541738	.0408894	3.77	0.000	.074032	.2343157
timehaloyr	.1290936	.103199	1.25	0.211	-.0731727	.3313599
timehalo	.5903213	.6235035	0.95	0.344	-.6317231	1.812366
timehalo2	-.0979062	.1450672	-0.67	0.500	-.3822327	.1864203
_cons	-5.500795	3.883157	-1.42	0.157	-13.11164	2.110053

There are observations with identical propensity score values.
The sort order of the data could affect your results.
Make sure that the sort order is random before calling psmatch2.

Variable	Sample	Treated	Controls	Difference	S.E.
T-stat					
totalcollisions	Unmatched	16.7236181	14.2777778	2.44584031	.644721258
3.79					
ATT		16.4193548	16.8193548	-.4	1.39288183
-0.29					

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2:	psmatch2: Common		
Treatment	support		
assignment	Off suppo	On suppor	Total
Untreated	0	486	486
Treated	44	155	199
Total	44	641	685

```

. pstest lnaadt median channelization leftturn thrulanes plt pplt closestrlc0to
> 500 twoormorerlc0to500 threewithinrlc1000 numcams timehaloyr timehalo timeh
> alo2 , both graph

```

Variable	Unmatched	Mean	%reduct	t-test
V(T)/	Matched	Treated Control	%bias bias	t p> t
V(C)				
lnaad	U	10.484 10.39	23.7	2.80 0.005
0.95	M	10.46 10.584	-31.0 -30.7	-3.14 0.002
2.12*				
median	U	.66332 .66667	-0.7	-0.08 0.933
.	M	.63871 .71613	-16.4 -2211.0	-1.46 0.146
.				

```

channelization      U | .50754 .38272 25.3      | 3.02 0.003 |
> .
M | .45806 .47097 -2.6 89.7 | -0.23 0.821 |
> .
leftturn            U | .73367 .6749 9.7      | 1.13 0.258 |
> 0.85
M | .70968 .50323 34.1 -251.3 | 3.15 0.002 |
> 0.95
thrulanes           U | 2.4523 2.1872 38.0      | 4.56 0.000 |
> 1.11
M | 2.4194 2.7032 -40.7 -7.1 | -3.22 0.001 |
> 0.69*
plt                 U | .38191 .48765 -21.4      | -2.53 0.012 |
> .
M | .4 .35484 9.1 57.3 | 0.82 0.414 |
> .
pplt                U | .17588 .3107 -31.8      | -3.63 0.000 |
> .
M | .22581 .23226 -1.5 95.2 | -0.13 0.893 |
> .
closestrlc0to500    U | .20101 .53086 -72.8      | -8.28 0.000 |
> .
M | .25806 .36774 -24.2 66.8 | -2.09 0.037 |
> .
twoormorerlc0to500  U | .04523 .06996 -10.6      | -1.21 0.226 |
> .
M | .05806 0 24.9 -134.8 | 3.08 0.002 |
> .
threewithinrlc1000 U | .0201 .10905 -36.8      | -3.86 0.000 |
> .
M | .02581 .03226 -2.7 92.7 | -0.34 0.736 |
> .
numcams             U | 23.668 9.5885 137.7      | 17.32 0.000 |
> 1.69*
M | 21.116 21.948 -8.1 94.1 | -0.64 0.526 |
> 1.04
timehaloyr          U | 9.8593 5.3251 128.7      | 15.07 0.000 |
> 0.86
M | 9.1871 9.5161 -9.3 92.7 | -0.87 0.387 |
> 1.25
timehalo            U | .21106 .50617 -64.6      | -7.37 0.000 |
> .
M | .27097 .22581 9.9 84.7 | 0.92 0.359 |
> .
timehalo2           U | .99497 2.4568 -65.9      | -7.53 0.000 |
> 0.67*
M | 1.2774 1.2516 1.2 98.2 | 0.10 0.920 |
> 0.87
-----
> -----
* if variance ratio outside [0.76; 1.32] for U and [0.73; 1.37] for M
-----
> ----
Sample | Ps R2 LR chi2 p>chi2 MeanBias MedBias B R %V
> ar
-----+-----
> ----

```

```

Unmatched | 0.527    435.40    0.000    47.7    34.3    212.2*    0.66
> 33
Matched   | 0.084    35.17    0.001    15.4    9.6    70.9*    0.87
> 33
-----
> ----
* if B>25%, R outside [0.5; 2]

```

```
. pstest _pscore, density both
```

psmatch2: Propensity Score

```
. teffects ipwra (totalcollisions lnaadt median channelization leftturn thrulan
> es plt pplt closestrlc0to500 twoormorerlc0to500 threewithinrlc1000 numca
> ms timehaloyr timehalo timehalo2) (L1rlcinstalled2 L1rearend L1angle L1TM ),
> atet
```

```
Iteration 0: EE criterion = 1.541e-16
Iteration 1: EE criterion = 7.530e-29
```

```
Treatment-effects estimation          Number of obs    =          637
Estimator      : IPW regression adjustment
Outcome model  : linear
Treatment model: logit
```

totalcolli~s	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	

ATET						
L1rlcinsta~2 (1 vs 0)	-1.809597	.8185389	-2.21	0.027	-3.413904	-.2052906

POMean						
L1rlcinsta~2 0	18.77323	.8744502	21.47	0.000	17.05934	20.48712

. **REAR-END**

```
. teffects ipwra (rearend lnaadt median channelization leftturn thrulanes fplt plt pplt
speed1 speed2) (Llrlcinstalled2 Lltotal Lllangle LlTM ), atet
```

```
Iteration 0: EE criterion = 5.421e-16
Iteration 1: EE criterion = 5.489e-29
```

```
Treatment-effects estimation          Number of obs    =          637
Estimator      : IPW regression adjustment
Outcome model  : linear
Treatment model: logit
```

	rearend	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
ATET							
Llrlcinstalled2							
(1 vs 0)		.8365904	.4378877	1.91	0.056	-.0216538	1.694835
POMean							
Llrlcinstalled2							
0		7.345228	.4151367	17.69	0.000	6.531575	8.158881

```
. *with lags - outcome NOT repeated in treatmment
. tebalance overid
```

```
Iteration 0: criterion = .28737384
Iteration 1: criterion = .28776517 (backed up)
Iteration 2: criterion = .28860105 (backed up)
Iteration 3: criterion = .28863217 (backed up)
Iteration 4: criterion = .29015134
Iteration 5: criterion = .29072767
Iteration 6: criterion = .29072869
Iteration 7: criterion = .29072869
```

```
Overidentification test for covariate balance
H0: Covariates are balanced:
```

```
chi2(4)      = 2.43963
Prob > chi2   = 0.6555
```

ANGLE

```
. teffects ipwra (angle lnaadt median channelization leftturn thrulanes fplt plt pplt
speed1 speed2) (Llrlcinstalled2 Lltotal Lllangle LlTM ), atet
```

```
Iteration 0: EE criterion = 5.242e-16
Iteration 1: EE criterion = 3.217e-30
```

```
Treatment-effects estimation          Number of obs    =          637
Estimator      : IPW regression adjustment
Outcome model  : linear
Treatment model: logit
```

	angle	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
ATET							
Llrlcinstalled2							
(1 vs 0)		-.7163951	.2601107	-2.75	0.006	-1.226203	-.2065876
POMean							
Llrlcinstalled2							
0		3.777001	.2227096	16.96	0.000	3.340498	4.213504

```
. *with lags - outcome NOT repeated in treatmment
. tebalance overid
```

```

Iteration 0: criterion = .13436149
Iteration 1: criterion = .13448688 (backed up)
Iteration 2: criterion = .13497559 (backed up)
Iteration 3: criterion = .13502574
Iteration 4: criterion = .13521384
Iteration 5: criterion = .13532566
Iteration 6: criterion = .13532571

```

Overidentification test for covariate balance

H0: Covariates are balanced:

```

chi2(4)      = 6.38958
Prob > chi2   = 0.1719

```

TURNINGMOVEMENT

```

. teffects ipwra (turningmovement lnaadt median channelization leftturn thrulanes fplt
plt pplt speed1 speed2) (L1rlcinstalled2 Lltotal Lltrearend Llangle), atet

```

```

Iteration 0: EE criterion = 2.106e-16
Iteration 1: EE criterion = 3.971e-30

```

Treatment-effects estimation Number of obs = 637

Estimator : IPW regression adjustment

Outcome model : linear

Treatment model: logit

turningmovement	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
ATET					
L1rlcinstalled2					
(1 vs 0)	-.7058494	.2449961	-2.88	0.004	-1.186033 - .2256657
POMean					
L1rlcinstalled2					
0	3.257365	.2513298	12.96	0.000	2.764767 3.749962

```

. *with lags - outcome NOT repeated in treatmment
. tebalance overid

```

```

Iteration 0: criterion = .12586104
Iteration 1: criterion = .12587939 (backed up)
Iteration 2: criterion = .12588737
Iteration 3: criterion = .12592376
Iteration 4: criterion = .12623877
Iteration 5: criterion = .12624265
Iteration 6: criterion = .12624271

```

Overidentification test for covariate balance

H0: Covariates are balanced:

```

chi2(4)      = 6.92125
Prob > chi2   = 0.1401

```

SIDESWIPE

```

teffects ipwra (sideswipe lnaadt median channelization leftturn thrulanes fplt plt pplt
spee
> d1 speed2) (L1rlcinstalled2 Lltotal Lltrearend Llangle L1TM ), atet

```

```

Iteration 0: EE criterion = 5.169e-16
Iteration 1: EE criterion = 7.580e-30

```

Treatment-effects estimation Number of obs = 637

Estimator : IPW regression adjustment

Outcome model : linear
 Treatment model: logit

		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
ATET							
Llrlcinstalled2							
(1 vs 0)		.1230867	.1953355	0.63	0.529	-.2597639	.5059373
POMean							
Llrlcinstalled2							
0		1.955701	.1617246	12.09	0.000	1.638727	2.272676

. tebalance overid

Iteration 0: criterion = .12294952
 Iteration 1: criterion = .12299763 (backed up)
 Iteration 2: criterion = .12300272 (backed up)
 Iteration 3: criterion = .12304102
 Iteration 4: criterion = .12357015
 Iteration 5: criterion = .12362902
 Iteration 6: criterion = .12365356
 Iteration 7: criterion = .12365406
 Iteration 8: criterion = .12365407

Overidentification test for covariate balance
 H0: Covariates are balanced:

chi2(5) = 7.08708
 Prob > chi2 = 0.2142

Appendix L – Sensitivity Analysis

HIGH COSTS

Collision Impact Type	# of RLC sites	Annual number of collisions			Annual cost of collisions			Total Weighted Cost
		Annual number of Fatal collisions after RLC	Annual number of Injury collisions after RLC	Annual number of PDO collisions after RLC	Cost of fatal collisions	Cost of injury collisions	Cost of PDO collisions	
Total collisions (observed)	34	0.21	55.83	175.35	\$ 5,058,282	\$ 7,481,530	\$ 1,928,892	\$ 14,468,703
Total collisions (PSM counterfactual would have been 2.1% increase)	34	0.21	57.02	179.08	\$ 5,165,738	\$ 7,640,464	\$ 1,969,868	\$ 14,776,070
Difference between (observed – counterfactual)		0.00	-1.19	-3.73	-\$ 107,456	-\$ 158,934	-\$ 40,977	-\$ 307,367
Rearend collisions (observed)	34	0.00	23.92	85.10	\$ –	\$ 3,205,039	\$ 936,147	\$ 4,141,186
Rear-end collisions (PSM counterfactual would have been 11.9% decrease)	34	0.00	21.08	75.00	\$ –	2824356.08	824955.10	3649311.17
Difference between (observed – counterfactual)		0.00	2.84	10.11	\$ –	\$ 380,683	\$ 111,192	\$ 491,875
Angle collisions (observed)	34	0.21	13.91	28.51	\$ 5,058,282	\$ 1,863,395	\$ 313,579	\$ 7,235,256
Angle collisions (PSM counterfactual would have been 18.9% increase)	34	0.25	16.53	33.89	\$ 6,012,801	\$ 2,215,025	\$ 372,752	\$ 8,600,578
Difference between (observed – counterfactual)		-0.04	-2.62	-5.38	-\$ 954,518	-\$ 351,630	-\$ 59,174	-\$ 1,365,322

Turning movement collisions (observed)	34	0.00	11.47	25.73	\$ –	\$ 1,537,301	\$ 282,986	\$ 1,820,286
Turning movement collisions (PSM counterfactual would have been 20.8% increase)	34	0.00	13.86	31.07	\$ –	\$ 1,856,839	\$ 341,806	\$ 2,198,645
Difference between (observed – counterfactual)		0.00	-2.38	-5.35	\$ –	-\$ 319,538	-\$ 58,820	-\$ 378,358
Sideswipe collisions (observed)	34	0.00	1.32	25.87	\$ –	\$ 177,022	\$ 284,515	\$ 461,538
Sideswipe collisions (PSM counterfactual would have been 6.7% decrease)	34	0.00	1.23	24.13	\$ –	\$ 165,161	\$ 265,451	\$ 430,611
Difference between (observed – counterfactual)		0.00	0.09	1.73	\$ –	\$ 11,862	\$ 19,065	\$ 30,926

LOW COSTS

Collision Impact Type	# of RLC sites	Annual number of collisions			Annual cost of collisions			Total Weighted Cost
		Annual number of Fatal collisions after RLC	Annual number of Injury collisions after RLC	Annual number of PDO collisions after RLC	Cost of fatal collisions	Cost of injury collisions	Cost of PDO collisions	
Total collisions (observed)	34	0.21	55.83	175.35	\$ 1,925,276	\$ 4,398,525	\$ 1,717,064	\$ 8,040,866
Total collisions (PSM counterfactual would have been 2.1% increase)	34	0.21	57.02	179.08	\$ 1,966,176	\$ 4,491,966	\$ 1,753,541	\$ 8,211,682
Difference between (observed – counterfactual)		0.00	-1.19	-3.73	-\$ 40,900	-\$ 93,440	-\$ 36,477	-\$ 170,817
Rearend collisions (observed)	34	0.00	23.92	85.10	\$ –	\$ 1,884,300	\$ 833,341	\$ 2,717,641
Rear-end collisions (PSM counterfactual would have been 11.9% decrease)	34	0.00	21.08	75.00	\$ –	1660489.52	734360.03	2394849.55
Difference between (observed – counterfactual)		0.00	2.84	10.11	\$ –	\$ 223,810	\$ 98,981	\$ 322,791
Angle collisions (observed)	34	0.21	13.91	28.51	\$ 1,925,276	\$ 1,095,523	\$ 279,142	\$ 3,299,941
Angle collisions (PSM counterfactual would have been 18.9% increase)	34	0.25	16.53	33.89	\$ 2,288,583	\$ 1,302,253	\$ 331,817	\$ 3,922,654
Difference between (observed – counterfactual)		-0.04	-2.62	-5.38	-\$ 363,307	-\$ 206,730	-\$ 52,675	-\$ 622,712

Turning movement collisions (observed)	34	0.00	11.47	25.73	\$ –	\$ 903,807	\$ 251,909	\$ 1,155,715
Turning movement collisions (PSM counterfactual would have been 20.8% increase)	34	0.00	13.86	31.07	\$ –	\$ 1,091,669	\$ 304,270	\$ 1,395,938
Difference between (observed – counterfactual)		0.00	-2.38	-5.35	\$ –	-\$ 187,862	-\$ 52,361	-\$ 240,223
Sideswipe collisions (observed)	34	0.00	1.32	25.87	\$ –	\$ 104,075	\$ 253,270	\$ 357,345
Sideswipe collisions (PSM counterfactual would have been 6.7% decrease)	34	0.00	1.23	24.13	\$ –	\$ 97,101	\$ 236,299	\$ 333,400
Difference between (observed – counterfactual)		0.00	0.09	1.73	\$ –	\$ 6,974	\$ 16,971	\$ 23,945

Turning movement collisions (observed)	34	0.00	11.47	25.73	\$ –	\$ 1,163,301	\$ 257,260	\$ 1,420,560
Turning movement collisions (counterfactual)	34	0.00	14.02	31.44	\$ –	\$ 1,421,553	\$ 314,371	\$ 1,735,925
Difference between (observed – counterfactual)		0.00	-2.55	-5.71	\$ –	-\$ 258,253	-\$ 57,112	-\$ 315,364
Sideswipe collisions (observed)	34	0.00	1.32	25.87	\$ –	\$ 133,956	\$ 258,650	\$ 392,606
Sideswipe collisions (counterfactual)	34	0.00	1.23	24.13	\$ –	\$ 124,980	\$ 241,319	\$ 366,299
Difference between (observed – counterfactual)		0.00	0.09	1.73	\$ –	\$ 8,976	\$ 17,331	\$ 26,307

Turning movement collisions (observed)	34	0.00	11.47	25.73	\$ —	\$ 1,163,301	\$ 257,260	\$ 1,420,560
Turning movement collisions (counterfactual)	34	0.00	12.47	27.96	\$ —	\$ 1,264,508	\$ 279,641	\$ 1,544,149
Difference between (observed – counterfactual)		0.00	-1.00	-2.24	\$ —	-\$ 101,207	-\$ 22,382	-\$ 123,589
Sideswipe collisions (observed)	34	0.00	1.32	25.87	\$ —	\$ 133,956	\$ 258,650	\$ 392,606
Sideswipe collisions (counterfactual)	34	0.00	0.87	16.99	\$ —	\$ 88,009	\$ 169,933	\$ 257,942
Difference between (observed – counterfactual)		0.00	0.45	8.87	\$ —	\$ 45,947	\$ 88,717	\$ 134,664