Safety Effects of Automated Mobile Photo Enforcement

by

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ABSTRACT

This thesis evaluated the safety effects of automated mobile enforcement at both the segment-based level and city-wide level over a period of eight years. For the segment-based evaluation, the before-and-after Empirical Bayes (EB) method was used to account for the regression-to-the-mean effect and other confounding factors. Locally developed safety performance functions and yearly calibration factors for different collision severities/types were developed by using a group of reference urban arterial roads. The results showed consistent reductions in different collision severities/types ranging from 14% to 20%, with the highest reductions observed for severe (i.e. injury and fatal) collisions. The comparison between continuous and discontinuous enforcement strategies on different arterials revealed that continuous enforcement was far more effective in reducing all collision severities and types. Moreover, the thesis also validated the spillover effects on nearby segments. For the city-wide evaluation, generalized linear regression models were adopted to investigate the relationship between the enforcement variables and the monthly number of collisions. It was found that both the deployment hours and the number of issued tickets had an inverse relationship with the collision frequency. The analysis results also suggested that 1,500 hours of deployment should be the threshold to guarantee significant impacts on collision reduction.

PREFACE

The work from Chapter 3 of this thesis is currently under review as R. Li, K. El-Basyouny, A. Kim, "A Before-and-After Empirical Bayes Evaluation of Automated Mobile Speed Enforcement on Urban Arterial Roads". I was responsible for the data collection and analysis as well as the manuscript composition. Professor Karim El-Basyouny and Professor Amy Kim contributed to concept formation and manuscript edits.

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1 INTRODUCTION

1.1 Background

Traffic collision is a serious global issue causing around 1.2 million deaths and around 50 million injuries each year (World Health Organization, 2013). In Canada, there were 2,006 fatalities and 166,725 injuries in 2011 (Transport Canada, 2013). Traffic collisions not only cause harm to victims and their families, it is also a tremendous burden to society as a whole. The estimated total social cost of motor vehicle collisions that occurred in Canadian jurisdictions in 2004 was $63 billion (Transport Canada, 2007). This number was approximately 5% of the gross domestic product (GDP) of Canada in that year. However, these statistics were very likely to be underestimated due to the incomplete official police-reported data.

The unintended and unexpected nature of collisions makes them seem to be random events. Nevertheless, many road collisions can be prevented if drivers always comply with traffic laws. A study in Norway has shown that fatalities could be reduced by 48% if 16 of the most frequent traffic law violations were eliminated (Elvik, 2001). A legislative framework that allows traffic law enforcement to be fairly and properly applied can directly lead to an increase in drivers' compliance. The mechanism of traffic enforcement follows the deterrence theory, which can be further divided into general deterrence and specific deterrence (ESCAPE Consortium, 2003). General deterrence is the impact of the threat of legal punishment on the public at large, while specific deterrence is the impact of actual legal punishment on those who have been apprehended. Speed enforcement is one of the most common types of traffic enforcement that has been adopted by a variety of countries.

The goal of speed enforcement is to improve traffic safety through increasing drivers' compliance to the speed limit. Excessive speed (driving above the speed limit) raises both the frequency and severity of collisions. A faster speed leaves drivers with less time to react to dangerous situations and increases the distance required to stop the vehicle. In accordance with the laws of physics, more kinetic energy needs to be absorbed when colliding at a higher speed, which will cause more harm to the victims. It was revealed that a 5% increase in mean speed may lead to an approximate 10% increase in injury collisions and 20% increase in fatal collisions (OECD, 2006). In Canada, collision statistics suggested that 27% of fatalities and 19% of serious injuries involved speeding (Transport Canada, 2013). In addition, it was found that 90% of pedestrians hit by a vehicle at a speed of 30 km/h could survive, but the percentage dropped to only 20% when the speed was increased to 50 km/h (OECD, 2006).

However, speed violation is a widespread phenomenon across different countries (Elvik, 1997; Goldenbeld & Schagen, 2005). An extensive survey showed that on average 40% to 50% of drivers drove above the speed limit, and the percentage was higher on urban roads than rural roads or motorways in many countries (OECD, 2006). A study based on a national telephone survey of 2,002 Canadian drivers revealed that seven out of ten drivers admitted to having exceeded the speed limit at least occasionally (Transport Canada, 2007). Of the reasons given for speeding, the most common ones (with an agreement of more than 50%) are to avoid being late, belief that the speed limit is unreasonably low, and not paying attention to the driving speed. In addition, one in five drivers committed speeding because they simply enjoy the feeling of driving fast, which was found to be linked to more severe instances of speeding through regression analysis. It can be concluded that although the detrimental effects of speeding are generally agreed upon, the reason and extent of them are underestimated and unclear to the public. Since drivers were also found to have the psychology of keeping up with the flow of traffic (Transport Canada, 2007), it is necessary to enforce the speed limit where speeding significantly contributes to traffic collisions.

Generally, there are two types of speed enforcement: conventional enforcement and automated enforcement. Conventional enforcement is conducted by police with speed measurement devices, such as laser guns. It involves immediate and direct interactions between enforcement officers and violators, which enable the verification of violators to be more objective. At the same time, police have the opportunity to detect suspicious activities and additional offenses, such as impaired driving (NHTSA, 2008). In addition, the enforcement operation is witnessed by a large population of drivers, enhancing the general deterrence of enforcement. However, conventional enforcement may result in traffic congestion at high traffic volume sites and may cause risk to personnel where roadside stopping is dangerous. Most importantly, it is extremely difficult for police to track and record multiple speeding vehicles simultaneously, which diminishes the detection rate as well as the fairness of the operation. Therefore, automated enforcement was proposed as a safer and more accurate alternative to conventional enforcement and was introduced in many countries since the late 1980s (OECD, 2006; Chen et al., 2000).

The automated mechanism of the speed measurement detector and photo camera greatly reduces labour resources. The device can be operated as long as necessary with or without the presence of enforcement officers and can be either fixed at certain site or mobile by mounting it on enforcement vehicle. Mobile enforcement offers much more flexibility in operation than fixed enforcement. Each enforcement device can be easily rotated among multiple enforcement sites at different time periods according to needs, which greatly enlarges the coverage of the enforcement program. Another merit of mobile enforcement is its potential in covert operation. The existence of fixed cameras at specific sites is likely to become public knowledge, especially when the program continues for a long time period. Drivers were observed to slow down near enforcement devices and then speed up to compensate for lost time, which is the so-called "kangaroo effect" (Elvik, 1997). Mobile enforcement devices can be installed in unmarked vehicles and implemented at different sites, thereby increasing the unpredictability of enforcement and creating a wider range of deterrence effects.

The safety effects of automated mobile photo enforcement at both the micro and macro level have been examined by many studies (Goldenbeld & Schagen, 2005; Chen et al., 2000; Luoma et al., 2012; Keall et al., 2001; Carnis & Blais, 2013). Most of these studies adopted an interrupted time-series analysis to evaluate the system-wide effects. In the very few studies that focused on site-based effects, the results were weakened due to the deficiencies in adopted methodologies (i.e., failures to account for the regression-to-the-mean effect and confounding factors, etc.) (Thomas et al., 2008). The deficiencies are usually caused by the difficulty in obtaining a large reference group with similar characteristics as the treatment group. In addition, most study periods of these evaluations were close to the programs' implementation. Some studies found that the effectiveness of the enforcement program was highest during the starting stage but diminished over time (Goldenbeld & Schagen, 2005; Carnis & Blais, 2013). The effectiveness of automated mobile enforcement over a longer time period needs to be further investigated. Finally, a gap exists in the literature on the relationship between deployment resources and safety effects. This knowledge would be valuable for planning and operating an optimized mobile photo enforcement program.

1.2 Objectives of the Thesis

The City of Edmonton's mobile photo radar program was initiated as early as 1993. Currently, there are 10 covert trucks and three overt ones equipped with photo radar devices. More than 1,000 enforcement sites were selected, based on collision, speed, and other criteria, covering different types of roads in the city. The general objective of this thesis is to evaluate the safety effects of the program at both the segment-based and city-wide levels.

For the segment-based evaluation, there are three objectives. First, the thesis will attempt to estimate the effectiveness of automated mobile enforcement on urban arterial roads, using the before-and-after evaluation with Empirical Bayes (EB) adjustment as outlined in the Highway Safety Manual (AASHTO, 2010). Arterial roads handle the heaviest traffic volumes in cities, and the majority of collisions occur on these roads. Although arterial roads have always been important targets for enforcement operations, very few previous studies have explicitly evaluated the safety effects on them. The second objective is to investigate and compare the safety effects of different enforcement strategies by examining changes in collision frequency at continuously enforced sites (i.e., sites that were enforced each year during the after period) and those that are discontinuously enforced sites. This is because the enforcement resources are always limited and it is important to know how to distribute them to achieve better results. Finally, the spillover effect will be investigated by comparing enforced and unenforced arterial segments. This is to examine whether enforcement operations will have impacts on the safety of nearby segments.

For the city-wide evaluation, there are two objectives. The first objective is to examine the relationship between monthly enforcement statistics and city-wide collisions through the generalized linear model. The enforcement statistics include the deployment hours and the number of issued tickets, representing the scales of general and specific deterrence, respectively. At the same time, the marginal safety effects of increasing 1,000 deployment hours and 10,000 issued tickets are estimated in terms of collision reduction. The second objective is to investigate the threshold for deployment hours that can result in a significant impact on collision reduction. This threshold can be set as the minimum requirement for future enforcement operation.

1.3 Thesis Structure

The remainder of this thesis is organized into the following chapters:

Chapter 2 provides a literature review in three sections related to the topics of this thesis. The first section describes the extent and nature of the speeding problem and explains the mechanism of enforcement. The second section explains why Empirical Bayes is a more advanced method than the naïve or comparison group methods in conducting before-and-after evaluation. The last section summarizes the microscopic and macroscopic safety effects of automated mobile enforcement based on previous studies.

Chapter 3 presents the data, methodology, and results of the segment-based evaluation. The results include the overall safety effects of the enforcement program, the comparison between the continuously enforced and discontinuously enforced segments, and the spillover effects of the enforcement.

Chapter 4 provides the data, methodology, and results of the city-wide evaluation. The relationship between the monthly enforcement statistics and the number of collisions is revealed, and the marginal effects of deployment hours and issued tickets are estimated. A threshold for the minimum number of deployment hours is proposed in order to ensure the effectiveness of the enforcement program.

2 LITERATURE REVIEW

2.1 Enforcement and Safety

2.1.1 Speeding is a Road Safety Problem

The automobile has conquered the world at a rapid pace since its inception in 1886. The adoption of the revolutionary assembly line by Henry Ford in 1913 opened the era of the mass production of automobiles (Williams et al., 1993). The number of registered vehicles in the world increased from 4.2 million in 1916 to 1.5 billion in 2010, while the global population increased from around 2 billion to 7 billion during the same period (Mäkinen et al., 2003). Even in the first decade of the 20th century, the problems caused by speeding raised a need for regulations on roads. Frank Elliott in *The Times* mentioned the following:

> Motorists have shown from the beginning that they will not comply with any law which causes them inconvenience (such as the speed limit), or which, though easy to obey, they are not forced to obey (such as the regulation for number-plates). If that is to be their attitude, let us accept it for the time, and counter it by increased police activity, especially by the provision of more mobile police, until it is brought home to their minds that compliance with the law is their necessary contribution to the common wealth (Leerink, 1938).

Elliott's words convey two important messages. The first one is that it is of human nature to commit speeding in exchange for reduced travel time. The second one is that this behaviour can hardly be eliminated without enforcement intervention.

The first speed limit law specifically for automobiles was enacted in Connecticut, United States, on May 21, 1901, regulating the maximum speed to be 19 km/h on urban roads and 24 km/h on rural roads. As Elliott mentioned nearly one century ago, people are always reluctant to follow rules that cause them immediate inconvenience. Speeding has always been a prevalent phenomenon in many countries. A survey conducted by the Working Group in 2004 clearly revealed the extent of the speeding problem (OECD, 2006). Questionnaires were sent to the OECD/ECMT countries (Organisation for Economic Co-operation and Development/European Conference of Ministers of Transport), and the results were shown in Table 2-1. It can be observed that speeding is common among the drivers of passenger cars regardless of country or road type. On average, the percentage of speeding drivers is between 40% and 50%, but it can be as high as 80% on some motorways and urban roads.

TABLE 2-1 Percentages of Speeding Drivers of Passenger Cars (OECD, 2006)

	Motorways		Rural Roads		Urban Roads	
	Speed Limit	Above the limit	Speed Limit	Above the limit	Speed Limit	Above the limit
Austria	130 km/h	23%	100 km/h	18%	50 km/h	51%
					30 km/h	78%
Canada	110 km/h	15 to 53%	80 km/h	15 to 45%		
	100 km/h	15 to 81%				
Denmark	110 km/h	72%	80 km/h	61%	50 km/h	60%
Iceland	90 km/h	80%	90 km/h	77%		
Ireland	112 km/h	23%	96 km/h	8%	64 km/h (Arterial Rd)	75%
					48 km/h (Arterial Rd)	86%
					48 km/h (Local St)	36%
Korea	100 or 110 km/h	50%	60 km/h	Not available	50 km/h (Arterial Rd)	73%
Netherlands	100 km/h	45%	80 km/h	Approx. 45%	50 km/h (Local St)	Approx. 45%
	120 km/h	40%				
Portugal	120 km/h	46%	90 km/h	55%	80 km/h (Arterial Rd)	50%
					50 km/h (Collector St)	70%
Sweden	110 km/h	68%	30 to 110 km/h	58% (All state roads)		
Switzerland	120 km/h	38%	80 km/h	24%	50 km/h (Arterial Rd)	21%
United Kingdom	112 km/h	57%	96 km/h	9%	56 km/h (Arterial Rd)	27%
					48 km/h (Local St)	58%
United States	88 to 104 km/h	40 to 70%	88 km/h	47%	56 km/h (Arterial Rd)	73%
					48 km/h (Local St)	74%

As briefly explained in the introduction, higher speed allows less time for drivers to react, leading to an increase in both the frequency and severity of collisions. However, one may argue that although this rationale is logical, it cannot prove that exceeding the speed limit will significantly increase the risk of collisions. It is true that there are differences in driving skills among drivers. Professional racing drivers are able to safely operate a vehicle at a speed higher than speed limit, which is set as the maximum safe speed for the majority of drivers. However, the real risk of speeding does not lie in breaking the speed limit by 1 or 2 km/h but lies in driving without constraints. It is extremely difficult for ordinary drivers to estimate their own maximum safe speed, consequently exposing themselves to dangers when the speed is faster than what they can handle.

A glimpse of the link between speeding and collisions can be seen from the facts that young male drivers were found to have higher propensity for speeding behaviour and were also more likely to be involved in speed-related fatal collisions than other demographics (Clement & Jonah, 1984; Bowie & Walz, 1994; Laapotti & Keskinen, 2004). Cooper (1997) conducted a study to investigate the relationship between speed violations and collisions, using data from approximately two million drivers in British Columbia, Canada. In the study, speed violations were divided into exceed-speed-limit (ESL) and speed-too-fast (STF) (i.e., travelling more than 40 km/h above limit). Both variables were highly significant in logistic collision prediction models, and it was found that the estimates for ESL remained almost identical in models of different severity, while those for STF increased with the severity level. In the second part of the study, drivers were grouped according to the type and number of violations during the four-year period. The group average number of collisions increased regardless of the violation type when the number of violations increased from one to more than three. For the drivers that had only non-speeding violations, the group average number of collisions increased from 0.2 to 0.3. For the drivers with ESL but no STF, the group average number of collisions increased from 0.2 to 0.6. For drivers with STF, the number increased from 0.5 to 1.1. Thus, it can be concluded that speeding, especially serious speeding, is related to more collisions.

Kloeden et al. (2002) developed mathematical curves to describe the relationship between speed and the relative risk in urban areas with a 60 km/h speed limit in Adelaide, Australia. The speeds of passenger vehicles that were involved in injury collisions were compared with those of passenger vehicles not involved in any collisions but travelling in the same direction, at the same location, time of day, day of week, time of year. Modified logistic regression modelling was used to fit the data, and the developed curve with a 95% confidence limit is plotted in Figure 2-1. It can be observed that the relative risk of injury collision involvement increased with speed exponentially, and the risk was found to approximately double for each 5 km/h increase in free travelling speed after exceeding the speed limit. The results confirmed the link between speeding and collisions.

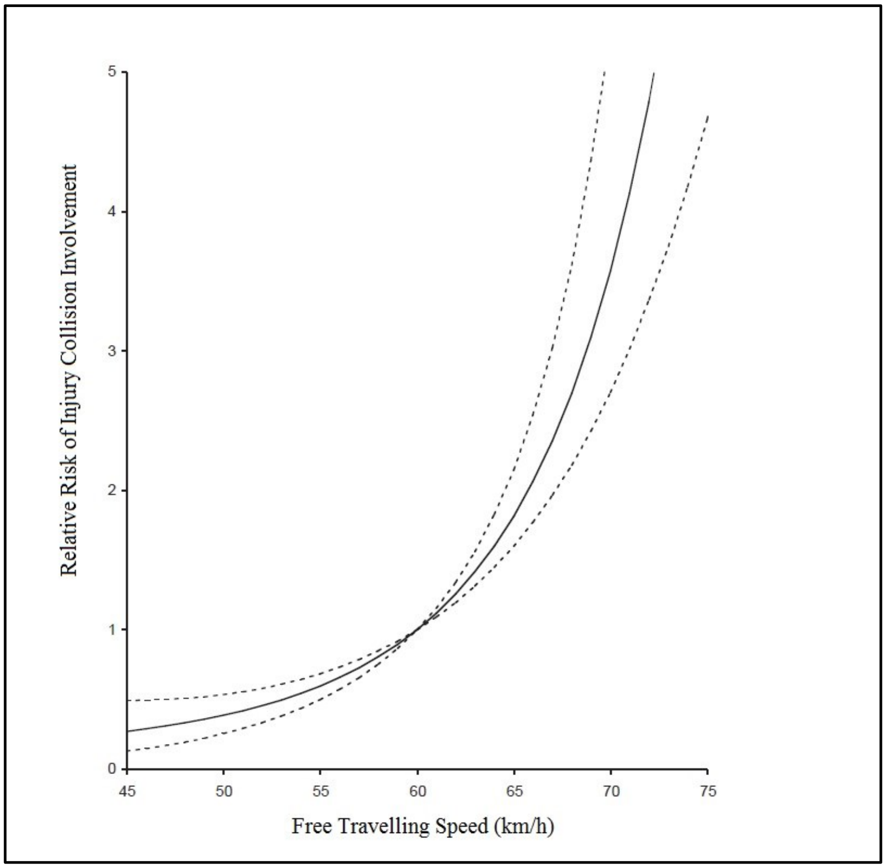

FIGURE 2-1 Relationship between Relative Risk and Speed (Kloeden et al., 2002)

One of the most well-known models established for the relationship between speed and collisions from the road perspective is Nilsson's power model (Nilsson, 1982). The model suggested that change in collisions was correlated with change in speed to a certain degree of power. The basic formula of the model is shown in Equation (2-1). Y denotes the number of collisions and v is the mean speed of traffic. Subscript 0 and 1 represent the before period and the after period, respectively. P is the degree of power needed to be estimated.

$$Y_1 = \left(\frac{v_1}{v_0}\right)^P Y_0 \tag{2-1}$$

The degrees of power P were estimated to be 4, 3, and 2 for fatal collisions, serious casualty collisions (including fatal collisions) and all casualty collisions, respectively (Nilsson, 2004). For example, if the mean speed of traffic reduced from 60 km/h to 50 km/h, the reduction in fatal collisions is estimated to be 52%. Since the formulas were developed based on the results from speed limit changes on rural roads in Sweden from 1967-1972, Cameron and Elvik (2010) examined whether the models were applicable in all road environments with meta-analysis techniques. As shown in Table 2-2, the estimation results indicated that the Nilsson's model performed better for rural highways and freeways than urban roads. Although the estimated degrees of power increased with the collision severity level for urban roads, they were smaller than those for rural roads and freeways. The authors argued that mean speed alone may not be sufficient to represent the complex relationship between speed and safety in an urban environment (Baruya, 1998; Taylor et al., 2000). Several alternative models were introduced for urban roads, which incorporated other speed parameters, such as the coefficient of speed variation, proportion of vehicles exceeding the speed limit, and average speed of speeding vehicles. One more recent study by Elvik (2013) showed that change in collisions was not only related to change in speed but also to initial speed. The results showed that there were more changes in collisions when initial speed was higher.

TABLE 2-2 Degree of Power Estimates for Different Road Environments (Cameron & Elvik, 2010)

	Rural roads/Freeways		Urban/Residential roads	
	Best estimate	95% confidence interval	Best estimate	95% confidence interval
Fatal collisions	4.1	(2.9, 5.3)	2.6	(0.3, 4.9)
Casualties with fatal injury	4.6	(4.0, 5.2)	3	(-0.5, 6.5)
Collisions with serious injury[1]	2.6	(-2.7, 7.9)	1.5	(0.9, 2.1)
Casualties with serious injury	3.5	(0.5, 5.5)	2	(0.8, 3.2)
Collisions with slight injury[2]	1.1	(0.0, 2.2)	1	(0.6, 1.4)
Casualties with slight injury	1.4	(0.5, 2.3)	1.1	(0.9, 1.3)

[1] Serious injury refers to injuries need hospitalization. The definitions of the severity of collisions in this thesis are different and introduced in the next chapter.
[2] Slight injury refers to injuries need only medical treatment but not hospitalization.

Given the harm of speeding, it is meaningful to investigate factors that impact drivers' speeding behaviour. The normative influences (e.g., beliefs, attitude, and actions of important others) have been addressed by many studies (Conner et al., 2003; Elliot et al., 2005; Forward, 2009). A study was conducted based on a survey of 2,018 male drivers at the age of 18 and 28 (Møller & Haustein, 2014). The objective of the study was to investigate the role of peer influence on speeding behaviour. It was found that the perception of friends' speeding was the most important predictor of speeding behaviour for both age groups: drivers who thought their friends often drive too fast were more likely to commit speeding. The self-reported extents of personal and friends' speeding behaviours were compared between two groups. It was found that younger drivers were more likely to think themselves to be more prudent than their friends in driving. At the same time, their self-reported extents of their own and friends' speeding behaviours were lower than those of the older group. The authors believed that the younger drivers were socialized into increased speeding behaviour due to peer pressure, while the older drivers used peer pressure mainly to justify their speeding behaviour. In addition, the survey results indicated that the majority of people held a neutral attitude towards friends' speeding behaviour, different from the majority attitude of disagreement towards drinking and driving or driving under the influence of drugs. This result suggests that the risk of speeding was commonly underestimated among drivers.

However, drivers' propensity is not the only reason for speeding. They were also found to be influenced by the speed of vehicles around them and had the psychology of keeping up with the flow of traffic (Transport Canada, 2007; Zaldel, 1992; Fleiter et al., 2010). Connolly and Åberg (1993) proposed that the comparison between their own speed and the speed of nearby vehicles played an important role in drivers' behaviour and defined this phenomenon as the social contagion process. Their concerns stemmed from the possible self-amplifying social psychology through comparing speed. To illustrate the comparison effects with an analytical approach, a graph developed by Schelling (1971; 1978) was introduced. Figure 2-2(a) represents the distribution of the speeding threshold for a population of drivers. It can be seen that around 5% of the population will always commit speeding and another 5% of the population will never commit speeding. The rest of the drivers will commit speeding depending on the percentage of speeding drivers nearby. Figure 2-2(b) shows the cumulative curve of the distribution in Figure 2-2(a) and the curve has three intersections (B, C, and D) with the identity line. When the curve is below the identity line, the percentage of speeding drivers is larger than the percentage of drivers whose speeding thresholds are reached, and therefore, the percentage of speeding drivers will decrease, vice versa. Therefore, the percentage of speeding drivers is stable around points B and D, but becomes unstable around point C. If the percentage of speeding drivers exceeds that of point C, it will keep increasing to point D. Field observation data of pairs of vehicles were used to validate the contagion model. It was found that 49.8% of the speeds of following vehicles were within 5 km/h range of the speeds of leading vehicles, which was significantly distinct from the speed differences between randomly selected vehicles.

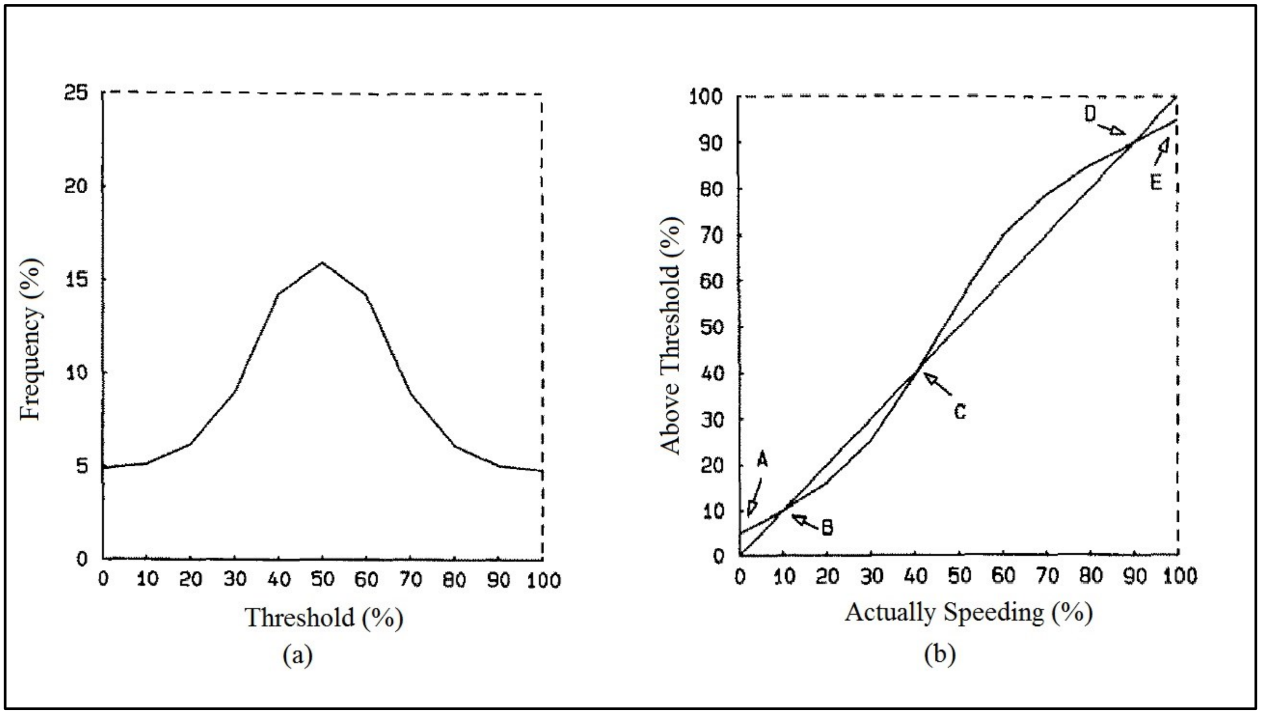

FIGURE 2-2 Distribution of Speeding Threshold (a) and Cumulative Curve (b) (Schelling, 1978)

This subsection attempts to explain why speeding is a serious issue and needs to be managed. First of all, speeding is a common problem in many countries and occurs on various types of roads. Secondly, the relationship between speeding and collisions has been proved from the perspectives of both driver group and road segment. It was found that the relationship can be described with exponential and power models, indicating that the risk will rise dramatically with excessive speed. Finally, speeding behaviour is found to be influenced not only by normative factors but also the speed of surrounding traffic.

2.1.2 Mechanisms of Enforcement

The mechanism of how traffic law enforcement increases compliance is illustrated in Figure 2-3 (Mäkinen, 2003). Legislation specifying the laws and regulations forms the foundation of enforcement operations and directly influences the behaviour of drivers who are willing to comply with the rules. The actual possibility of getting caught and punished due to the enforcement operation is the objective risk of speeding. The perceived possibility by drivers is the subjective risk of speeding, which varies with regards to personal experiences. At the same time, support measures, such as public campaigns, may enhance the subjective risk. It is the subjective risk that modifies drivers' behaviour and increases compliance to the speed limit.

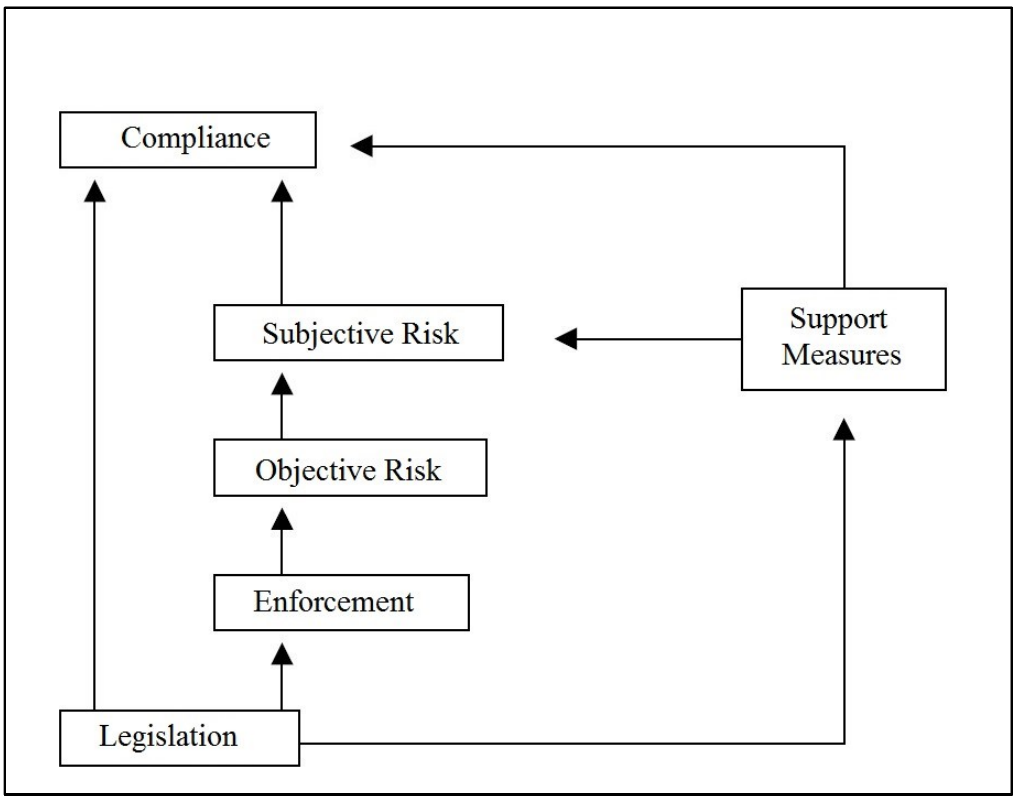

FIGURE 2-3 Enforcement Mechanism Model (revised from ESCAPE Consortium, 2003)

The subjective risk is conceived through two types of effects: general deterrence and specific deterrence. According to Stafford and Warr (1993), the conventional practice of distinguishing general and specific deterrence with regards to different populations was misleading, because drivers who were punished can also be influenced by general deterrence. Instead, they proposed the following:

> If deterrence is defined as the omission or curtailment of a criminal act out of fear of legal punishment (Gibbs, 1975), then general deterrence refers to the deterrent effect of indirect experience with punishment and punishment avoidance and specific deterrence refers to the deterrent effect of direct experience with punishment and punishment avoidance (Stafford and Warr, 1993).

The proposed concept has three improvements compared with the conventional one. Firstly, it recognizes the fact that any person or population may be influenced by a mix of general deterrence and specific deterrence. Secondly, it takes punishment avoidance into consideration when assessing the effects of deterrence. Punishment avoidance refers to the experiences of committing speeding without been punished. The subjective risk will be greatly diminished if punishment avoidance happens frequently. Finally, it is consistent with the contemporary learning theory. For speed enforcement, general deterrence can be roughly measured by the number of deployment hours, while specific deterrence can be measured by the number of issued tickets.

The mechanism of how subjective risk increases compliance can be explained from the perspective of economic theory, which relies on the assumption that the majority of drivers make rational decisions (Kenkel, 1993; Becker, 1968). Speeding is committed for the benefits of reduced travel time and excitement, but it also leads to some possible costs. Since speeding is an intentional behaviour under most circumstances, drivers have to make their decision whether to violate the speed limit or not by comparing the benefits with the possible costs. Suppose the benefits of speeding can be regarded as fixed or changing only slightly during a certain period of time. The decision is dictated mainly by the possible cost of speeding. Since safety and the other costs of speeding are difficult to estimate and often ignored by potential speeding drivers, the possible cost can be approximately calculated as the product of the speeding fine and the perceived possibility of being caught. This possibility is the subjective risk of enforcement and is influenced by both the objective risk and support measures. The link between subjective risk and objective risk is established through both general and specific deterrence.

In order to make drivers more likely to give up the idea of speeding, Kenkel (1993) suggested three methods to increase the possible cost of speeding: increasing the probability of violation detection, raising the cost of violation, and reducing the delay of the punishment.

Increasing the probability of violation detection (objective risk) can be realized through either spending more deployment hours or reducing the enforcement threshold (i.e., the minimum speed for drivers to get a ticket). As for the cost of violation, it should be noted that a speeding fine may not be the only source of monetary penalty. In some jurisdictions, major speed violation (e.g., exceeding the speed limit by 30 km/h or more) will lead to an increase in vehicle insurance premiums, which is more expensive than a speeding fine. Reducing the delay of punishment can reinforce specific deterrence effects and prevent drivers from speeding again during the time between violation and punishment.

Besides legal sanctions (e.g., demerit points and speeding fines), researchers proposed an extralegal sanction in the forms of self-imposed guilt and social disapproval, which were also found to have influences on deviant behaviours (Zimmerman, 2008), and therefore should be included as part of the cost of speeding. Although the extent of the extralegal sanction is difficult to measure and depends heavily on the personal norms and social status of drivers, it still reinforces the link between subjective risk and compliance to a certain extent. One example is that the adverse influences of being exposed for any violations will definitely cause many celebrities to be more cautious when driving.

This subsection attempts to explain why traffic enforcement can be effective as a means to reduce speed. The enforcement operations physically create the risk of being caught for speeding. This objective risk is conceived by drivers as the subjective risk through both general deterrence and specific deterrence. The mechanism of how subjective risk modifies drivers' behaviour can be explained with economic theory. It was suggested that a widespread and long-term implementation should be adopted in order to maximize the collision prevention function of traffic enforcement (Newstead et al., 2001). Leivesley (1987) interpreted the impacts of traffic enforcement from the perspectives of short-term effects and long-term effects. In the short term, enforcement can modify drivers' behaviour due to the fear of being caught and punished. In the long term, enforcement can gradually establish the social willingness to comply with traffic law.

Given the firm relationship between speeding and collisions, an increased compliance to speed limit due to enforcement will finally result in improved road safety. Thus, the theoretical link between traffic enforcement and road safety is established.

2.2 Safety Evaluation

Safety evaluations are conducted to examine the effectiveness of treatments. There are two types of evaluations: longitudinal evaluation, also known as before-and-after evaluation, and cross-sectional evaluation. The before-and-after evaluation needs the collision data in the periods before and after the implementation, while cross-sectional evaluation compares the collision data in only the after period between treated and untreated sites. Since most of the treatments were intentionally applied to "hot spots" (i.e., sites with high collision frequency) to maximize the safety effects, the significant difference in collision frequency between the treated sites and the untreated sites makes before-and-after evaluation a more favourable approach than cross-sectional evaluation for safety evaluation. There are three kinds of before-and-after evaluations: 1) naïve before-and-after evaluation; 2) before-and-after evaluation with a comparison group; and 3) before-and-after evaluation with the Empirical Bayes method.

2.2.1 Naïve Before-and-After Evaluation

In naïve before-and-after evaluation, the collision frequency in the before period is used to predict what would have been the collision frequency in the after period had the treatment not been implemented. This method simply assumes that the collision frequency will remain the same between the before period and the after period had there been no treatment. The assumption is subject to several issues and will result in erroneous conclusions.

The first issue is the regression-to-the-mean effect. This effect refers to the phenomenon that the collision frequency of one hot spot will decrease by itself, even without any treatment. The reduction witnessed at treated sites may be attributed to this effect, rather than the treatment, since these sites usually experience high collision frequency in the before period. Using a long before period is suggested in order to mitigate the possible impact of regression-to-the-mean effect.

The second issue is the general trend of collision frequency, which can be also called the maturation. The general trend is caused by gradual changes, such as traffic volume, economy, and road facility improvement. The continuous increase of traffic volume is likely to contribute to more collisions in many jurisdictions. On the other hand, the improvement of the overall road safety system can result in a general trend of decreasing collisions. Thus, the reduction in collision frequency at treated sites may be due to the general trend.

The last issue is external factors. Compared with the general trend mentioned above, external factors can be more temporary but also have remarkable influences on the treated sites. Some typical examples of external factors include the change of the police reporting threshold, the occurrence of other safety countermeasures, and extraordinary weather conditions during the evaluation period. Failing to take these factors into consideration will influence the reliability of evaluation results.

2.2.2 Before-and-After Evaluation with a Comparison Group

The method of before-and-after evaluation with a comparison group uses the data of a group of comparison sites to help estimate the collision frequency that would have occurred if the treatment had not been applied. A numerical example is provided here to illustrate. Suppose that the treated sites had 100 collisions during the before period and 60 collisions during the after period, while the untreated comparison sites had 80 collisions during the before period and 60 collisions during the after period. According to the naïve before-and-after method, the reduction would be 40 (100 minus 60) collisions or 40% (40 divided by 100). However, the data of comparison group indicated that the collision frequency decreased without the treatment. This decrease may be due to the general trend of safety improvement, or merely a rise in the police reporting threshold. Thus, by the comparison group method, the odds ratio is calculated as $(60/100)/(60/80) = 0.8$, which means the reduction percentage is "actually" 20%.

As can be seen, the preciseness of this method depends on the similarity between the treated site and comparison site. Collision frequency, traffic volume, road geometric characteristics, and geographic proximity can be adopted as the criteria when selecting comparison sites. According to Hauer (1997), there are two principle assumptions for this method. The first one is that various factors have changed in the same manner from the before period to the after period for both the treated group and the comparison group. The second one is that the extents to which these two groups are affected by the factors are identical. It is recommended that the collision count of the comparison group be sufficiently large. When pseudo odds ratios are calculated using different periods of before data, their mean should be close to 1 with small variance. Another issue in selecting the comparison sites is collision migration. The treatment implemented in one site may cause an increase of collisions in surrounding areas. For example, the road improvement made at one site may reduce drivers' caution and increase the risk at unimproved areas. Therefore, it is suggested to select comparison sites that are not likely to be influenced by the treatment.

Although the comparison group method is able to account for the influences of maturation and external factors, it still fails to address the regression-to-the-mean effect.

2.2.3 Before-and-After Evaluation with Empirical Bayes

The ultimate goal of any evaluation method is to estimate the expected number of collisions in the after period if the treatment had not been implemented. This task consists of two steps: 1) estimating the expected number of collisions in the before period and 2) predicting how this number will change as a result of maturation and external factors. As mentioned above, the naïve before-and-after method and comparison group method fail to account for the regression-to-the-mean effect for the treated sites, which means they are not able to estimate the unbiased expected number of collisions for the before period. This problem should not be neglected because the treated sites are very likely to suffer from the regression-to-the-mean effect. Hauer (1997) showed an example of how the number of collisions would change over time in his book. In total, 1,142 intersections in San Francisco with stop signs on minor approaches were grouped by the number of collisions in 1974. The average numbers of collisions of these groups were tracked during the following three years (1975-1977) and were plotted in Figure 2-4. The dash line in the figure represents the average number of collisions of all the intersections in 1974 and the numbers at the end of each line show the sample size of that group. It can be seen that all the lines move towards the average line regardless of the initial number of collisions in 1974.

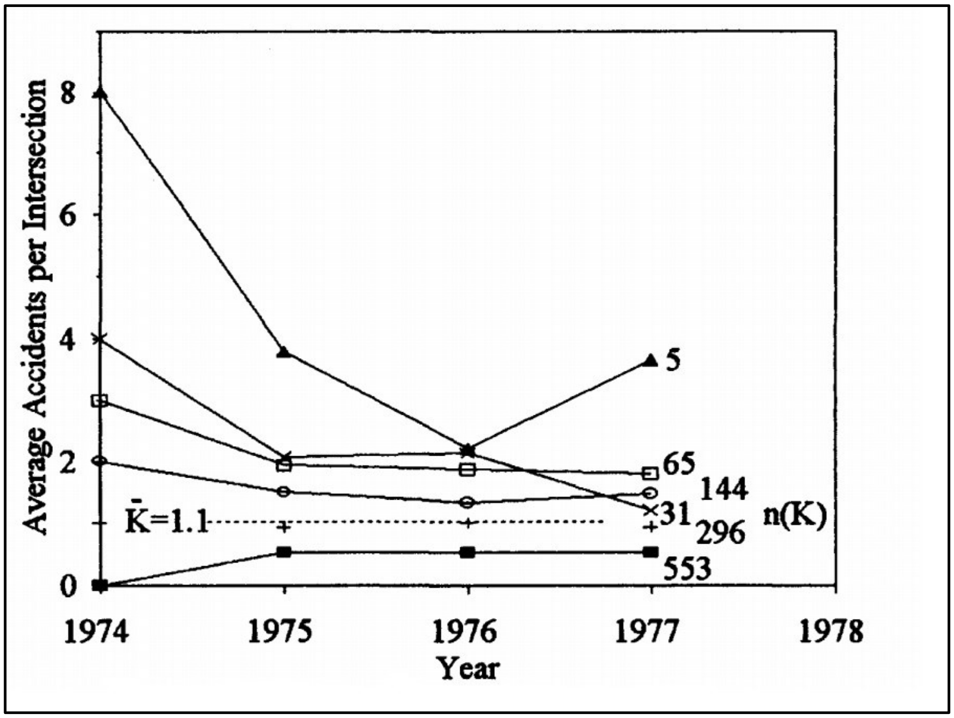

FIGURE 2-4 Regression-to-the-Mean Effect (Hauer, 1997)

It should be noted that the regression-to-the-mean effect should not be taken as an excuse for turning a blind eye to sites with high collision frequency. It shows how much the number of collisions can deviate from its expected value. Suppose the five intersections that had eight collisions in 1974 were chosen to be signalized and the average number of collisions decreased to three in 1975. If there were no influences of maturation and external factors, the actual reduction due to signal installation was only one collision, rather than five. Since it is quite common that the length of the before period with available data is limited, the estimation of the expected number of collisions in the before period is a very difficult task.

To solve this problem, the Empirical Bayes method proposes that two types of clues should be used together to estimate the expected number of collisions in the before period. The first clue is the collision data of the entity of interest (let Y denotes the number of collisions in the before period). The second clue is obtained from a group of other entities that have the similar traits as the entity of interest. This group is called the "reference population," which has a mean of $E\{\theta\}$ and a variance of $Var\{\theta\}$. Thus, the best estimate of θ for the entity of interest is $E\{\theta \mid Y\}$ with a variance of $Var\{\theta \mid Y\}$. Bayes' theorem for probability distributions is used to join the two clues together under two assumptions. The first assumption is that the distribution of $\theta's$ in the reference group follows a Gamma probability density function, which is the prior distribution. The second assumption is that the collision frequency Y is Poisson-distributed due to its rare, discrete, random, and non-negative characteristics. Thus, the posterior distribution $p(\theta \mid Y)$ also follows a Gamma distribution and is shown in Equation (2-2). The derivations of Equation (2-3) and (2-4) are presented in Appendix A.

$$p(\theta \mid Y) = \frac{p(Y \mid \theta) \times p(\theta)}{p(Y)} \tag{2-2}$$

Where, $p(Y)$ is the marginal distribution, and

$$E\{\theta \mid Y\} = w \cdot E\{\theta\} + (1 - w)Y \tag{2-3}$$

$$w = \frac{1}{1 + \frac{Var\{\theta\}}{E\{\theta\}}} \tag{2-4}$$

As shown in Equations (2-3) and (2-4), w is the weight of $E\{\theta\}$ in calculating $E\{\theta \mid Y\}$. If $Var\{\theta\}$ is very small, w will be close to 1 and $E\{\theta \mid Y\}$ is similar to $E\{\theta\}$. Conversely, if $Var\{\theta\}$ is much larger than $E\{\theta\}$, which means θ in the reference population is very diverse, $E\{\theta\}$ will have little influence on $E\{\theta \mid Y\}$ and the expected number of collisions is mainly determined by the observed number of collisions.

This section demonstrates that the Empirical Bayes method is more advanced than the other two methods in safety evaluation, due to its ability to account for the regression-to-the-mean effect. The calculations of the expected number of collisions during the after period will be introduced in the next chapter.

2.3 Previous Works on Automated Mobile Enforcement Evaluation

This section provides the safety evaluation results of automated mobile enforcement in the literature. The results are grouped into macroscopic effects and microscopic effects according to whether the evaluation targets include the unenforced sites. A summary of the results is provided in the last subsection.

2.3.1 Macroscopic Effects of Automated Mobile Enforcement

Carnis and Blais conducted an assessment of a French speed camera program (Carnis & Blais, 2013).The national enforcement program started in 2003. In total, 2,756 speed cameras, among which 933 were mobile ones, had been installed nation-wide on public roads and the highway network in 2010. The study adopted interrupted time-series analyses using autoregressive, integrated, moving average (ARIMA) intervention time-series models. The interrupted time-series analyses are considered suitable to examine the effects of an intervention on the behaviour of a time series (Biglan et al., 2000). The results showed that the introduction of the program was associated with significant reductions in both traffic fatalities and non-fatal injuries. Linear models with and without the enforcement variables were compared to estimate the reductions. A 21% reduction was found in the fatality rate per 100,000 vehicles, and it was proved to be immediate and permanent. The stable safety effect on fatal collisions was attributed to the intensity of the program and high detection capacity of the enforcement devices. However, the reduction percentage in non-fatal injuries decreased from 26.2% after the implementation in 2003 to 0.8% in 2010.

Chen et al. (2000) investigated the safety effects of a covert mobile photo radar program (PRP) in British Columbia, Canada. The PRP was initiated in March 1996 with a province-wide deployment of 30 covert mobile speed cameras and a public media campaign. Warning letters were first mailed to the owners of speeding vehicles. Violation tickets replaced warning letters in August 1996. Naïve before-and-after analysis revealed a 50% reduction in the percentage of speeding vehicles and a 75% reduction in the percentage of seriously speeding vehicles (16 km/h over the speed limit) at the enforced sites. A pooled cross-sectional time-series analysis of 19 monitoring sites across the province found a 2.4 km/h reduction in vehicles' mean speed. The monthly numbers of collisions, injuries, and fatalities were analyzed with the interrupted time-series method. Motor gasoline sale was incorporated in the models as a surrogate of vehicle kilometres travelled. The results showed 25%, 11%, and 17% reductions in the numbers of daytime speed-related collisions, daytime traffic collision victims carried by ambulances, and daytime traffic collision fatalities, respectively. The reason for using only the daytime collision data was to avoid the potential effects of impaired driving road checks conducted during the same period. However, the evaluation used only the first year of data after the implementation, and there was a possibility that the effects may have diminished as time went on.

The photo radar camera program was introduced to the city of Edmonton (Canada) in 1993 and has continued ever since. Tay (2010) conducted a study to validate the effectiveness of both the presence of enforcement vehicles and speed tickets on collision reduction. Monthly data for the number of severe collisions (injury and fatal), deployment hours, number of issued tickets, and social employment rate were collected. A Poisson generalized linear regression model was adopted to examine the relationship between the monthly collision frequency and the independent variables. In addition, a trend variable and monthly dummy variables were also included in the model to account for the general trend in safety and seasonal variation. It was found that the model fitted the data well and all the variables in the model were highly significant except for some monthly dummy variables. Both the number of deployment hours and number of issued tickets had positive effects on collision reduction. The marginal effects were estimated to be 70 reduced collisions per 1,000 deployment hours and 6 reduced collisions per 1,000 issued tickets. To further validate the effectiveness of issued tickets, the variable was removed from the model, which resulted in a 7.7 increase in the χ^2 statistic. Since the value is significantly larger than the critical value for one degree of freedom, the issued tickets were considered to have substantial effects on collision reduction. In addition, the increase of employment rate was also found to reduce the number of severe collisions. The possible explanation provided by the author was that the increased employment rate led to higher demand for safety and more revenue available for road maintenance, traffic enforcement, and public education.

2.3.2 Microscopic Effects of Automated Mobile Enforcement

Queensland, Australia, applied a randomized schedule method in its Random Road Watch (RRW) traffic-policing program. Instead of focusing only on high collision sites, each police division operated an individual program covering as many routes in the division's territory as possible.

The time-of-day and day-of-week of the enforcement schedule at each site was generated randomly, making the operation highly unpredictable (Leggett, 1997). Newstead et al. (2001) adopted a quasi-experimental design framework with Poisson regression models to evaluate the effects of the program on different severities of collisions. The models include constants, trend, and enforcement variables, which were further specified to represent the enforced/unenforced segments and enforced/unenforced time. Only the data that belong to the enforced segment and enforcement time (from 6:00 AM to midnight) were considered as part of the treatment group, while the rest was considered to be the control group. The models were aggregated by road type and police region through adding constraints on the enforcement variables to estimate the overall effects. The results revealed that the highest reduction occurred in fatal collisions at 31%, and the reductions decreased with severity level. Although the effect on fatal collisions remained stable, the effects on other severities of collisions increased with the time after the implementation. The estimated benefit cost ratio for the program reached 55:1. In addition, the study examined the relationship between collision reduction and enforcement output variables (i.e., program coverage, offences detected, and hours enforced). It was found that although all of the output variables had a positive relationship with collision reduction, only the program coverage variable was significant. One limitation of the study was that the model fit was not considered due to the hierarchical chain of models. As for the potential bias caused by the regression-to-the-mean effect, the influence was minimized due to the 3-year study period, as well as a large number of enforced segments.

Goldenbeld and Schagen evaluated a mobile enforcement program in one Dutch province (2005). The program started in 1998 and was intensified in 2001. The study examined both the speed and safety effects on 28 sections of rural roads with a speed limit of 80 km/h or 100 km/h. The mean speed and percentage of speeding vehicles were examined with repeated measures analyses. Significant reductions were found for each year from 1998 to 2002 compared with the preceding year, and the highest reductions were observed in the first year and the fourth year when the enforcement was intensified. The safety effects were examined using before-and-after analysis with a comparison group. The odd ratios for injury collisions and serious traffic casualties were both 0.79, indicating a 21% reduction. The comparison of the traffic volumes between the enforced roads and comparison roads showed a similar trend. However, there were several limitations of the study. The effects were estimated based on small numbers of casualties and collisions, and the effects of other engineering countermeasures cannot be ruled out from the analysis. More importantly, although the enforced roads were selected based on a relatively long period of historical data, the regression-to-the-mean effect could have still influenced the estimation results. The authors suggested that the Empirical Bayes method as proposed by Hauer (1997) would be a solution to the problem.

Speed cameras were introduced to New Zealand in 1993 and overtly operated on roads with speed-related collisions. A trial of covert enforcement was conducted in one of the police regions on open roads with a speed limit of 100 km/h in 1997. Keall et al. (2001) compared the effects of the two types of enforcement on speed and safety. The study used an interrupted time-series design with open roads in the other police regions as the control area. Significant net reductions of 2.3 km/h and 2.9 km/h were found for mean speed and 85th percentile speed, respectively. A logit model was used to examine the safety effects. Dummy variables for the enforcement and season, as well as a trend variable, were included in the model. The reduction in the number of collisions was estimated to be 22% (P=0.054) and 29% (P=0.066) in the number of casualties. Significant reductions in speed and collisions were also found when the analysis targets were expanded to include all roads in police region, indicating the covert enforcement had more general effects. In addition, the net change in speed was found to diminish with time, while the safety effect remained stable. It should be noted the reduction may have resulted from a huge increase in the number of issued speed tickets, from about 1% to 5% of the traffic.

2.3.3 Summary of the Effects of Automated Mobile Enforcement

A summary of the literature is presented in Table 2-3 with a brief description of the enforcement program, method, data, and major findings. In addition to the studies mentioned in the previous subsections, several other relevant works are also included.

TABLE 2-3 Summary of Automated Mobile Enforcement Studies

Study	Effect	Method	Data and Study Period	Program Description	Major Findings
Carnis and Blais (2013)	Macro	Interrupted time-series analyses with ARIMA models.	Monthly non-fatal injuries and fatalities per 100,000 registered vehicles. Before period=4 years, after period=7 years.	1,823 fixed devices and 933 mobile devices on public roads and highway.	Nation-wide: Fatalities: -20.7% [-11.3; -30.3] (95% CI); Non-fatal injuries: overall -7.3% [+1.8; -16.5] (95% CI, diminishes from 26.2% to 0.79%).
Chen, Wilson, Meckle, and Cooper(2000)	Macro	Simple before-and-after; time-series cross-sectional analysis; interrupted time-series analysis.	Monthly provincial data of daytime speed-related collisions, injuries, and fatalities. Before period=5 years, after period=1 year.	30 mobile covert speed cameras with public media campaign. 30,000 hours of deployment and 250,000 violation tickets in the first year.	Province-wide: 25% reduction in the number of daytime speed-related collisions; 11% reduction in daytime traffic collision victims carried by BC ambulances; 17% reduction in daytime traffic collision fatalities.
Tay (2010)	Macro	Poisson generalized linear model.	Monthly severe collision (includes injury collisions and severe collisions). Evaluated the on-going program with a study period of 4 years.	5 mobile enforcement vehicles; 1,560 deployment hours and 12,534 violation tickets per month on average.	Both deployment hours and violation tickets variables were significant in the model. The marginal effects of increasing 1,000 hours of deployment and 1,000 issued tickets were estimated to be reductions of 70 and 6 collisions, respectively.
Camero, Cavallo, and Gilbert (1992)	Macro	Time-series analysis with ARIMA models; multivariate regression model.	Monthly numbers of casualty collisions by severity. Before period=7 years, after period=2 years.	54 covert speed cameras in Victoria state (mainly on arterial roads) with mass media public campaign; the enforcement had different targets in Melbourne metropolitan area and rural areas.	20.9% [13.3, 27.9] (95% CI) reduction in casualty collisions in Victoria; 21.1% [12.4, 28.9] (95% CI) reduction in casualty collisions in Melbourne; 19.5% [10.7, 27.5] (95% CI) reduction in casualty collisions in Victoria rural areas.
Christie, Lyons, Dunstan, Jones (2003)	Macro	Before-and-after analysis with comparison group.	Number of injury collisions. Study period from 1996 to 2000 (different sites had different initial date).	101 mobile speed camera sites on different types of road in South Wales region. The intervention year ranged from 1996 to 2000.	Different lengths of routes that extended from the enforcement site were examined. The longest distance reached 500 metres with a significant reduction of 41%; No significant change with time in collision reduction during the first two years since the enforcement.

Table 2-3 Continued

Study	Effect	Method	Data and Study Period	Program Description	Major Findings
Newstead, Cameron, and Leggett (2001)	Micro	Quasi-experimental evaluation; Poisson regression model; multivariate regression analysis.	Monthly collision data by different types of severity. Study period from January 1986 to June 1997 (different region had different initial date).	Each of the police divisions (279) selected some 40 enforcement sites. A randomized schedule was generated with a series of sites and time of day for enforcement.	31% reduction in fatal collisions on enforced segments during the enforcement time; 11% reduction in total collisions in areas outside metropolitan Brisbane; the benefit cost ratio for the program was estimated to be 55:1.
Goldenbeld, and Schagen (2005)	Micro	Before-and-after analysis with comparison group.	Number of serious traffic casualties and injury collisions. Before period=8 years, after period=5 years.	The enforcement was conducted on rural roads with 80 km/h or 100 km/h speed limit. The enforcement vehicles were covert but there were warning signs along the enforced roads. Public campaign accompanied the program.	21% reduction in both the number of injury collisions and serious traffic casualties.
Keall, Povey, and Frith (2001)	Micro	Time-series analysis with linear regression logit model.	Monthly number of police-reported collisions and casualties. Before period=4 years, after period=1 year.	A covert enforcement trial was conducted in one of the four police regions in New Zealand while the original overt enforcement was still on. Public campaign accompanied the program.	22% (P=0.054) reduction in collisions, 29% (P=0.066) reduction in casualties, and 9% (P=0.006) reduction in the casualty-per-collision rate.
Chen, Meckle, and Wilson (2002)	Micro	Empirical Bayes method with comparison group.	Police-reported collisions in the before and after period. Before period=2 years, after period=2 years.	12 enforcement locations (not active at the same time) on a 22 km highway. The total enforcement time is 1,313 hours in the 2-year after period.	14%±11% reduction in collisions at enforcement locations; 19%±10% reduction in collisions at non-enforcement locations; 16%±7% reduction in collisions along the highway as a whole.

All the studies mentioned above confirmed the effects of automated mobile enforcement on traffic safety. The estimated collision reductions were usually between 10% and 30%. More reductions were observed for fatal and severe injury collisions than property-damage-only collisions (Carnis & Blais, 2013; Newstead et al., 2001). The comparison between covert and overt enforcement revealed that covert enforcement was able to achieve a larger reduction in collisions (Keall et al., 2001). The macro effect evaluations usually adopted an interrupted time-series analysis to examine the effects of the introduction of intervention measures (Chen et al., 2000, Carnis & Blais, 2013; Cameron et al., 1992), while the micro evaluation adopted a wide range of methods. Thomas et al. (2008) summarized several issues that need to be addressed when conducting evaluations. Ignoring any one of them may impact the reliability of the evaluation results:

- Possible time trend effects (e.g., general trends in collisions);
- Possible confounding factors such as concurrent treatments or enforcement, changes in data measure, and other factors;
- Changes in the traffic volumes between the before and after period; and
- Regression-to-the-mean effect.

The first two issues can be accounted for by using a comparison group. However, this method is unable to address the last two issues. The Empirical Bayes (EB) method as proposed by Hauer (1997) is considered to be the standard of professional practice to deal with the regression-to-the-mean effect and the change in traffic volumes (Goldenbeld & Schagen, 2005; Thomas et al., 2008). However, EB method requires a sufficient number of reference sites with the same characteristics as the enforced sites to develop safety performance functions, which limits its application in many studies. The regression-to-the-mean effect is not likely to have strong impacts on macroscopic evaluation as long as the number of collisions is large enough.

The phenomenon that unenforced roads are also influenced by enforcement activities is called the spillover effect, which can either increase or reduce collisions. The macroscopic collision reduction due to enforcement can be partly attributed to the spillover effect. Christie et al. (2003) found that the spillover effect of one mobile enforcement site can be as long as 500 meters along the route extended in both directions. However, the spillover effect can also have an adverse impact on safety for two reasons. Firstly, although more often for fixed enforcement, drivers were found to slow down near the enforcement site and then speed up after they passed the cameras. This is the so-called "kangaroo effect," which will increase collisions at areas downstream of the enforcement site (Elvik, 1997). Secondly, some drivers might adjust their travel routes to avoid enforcement, which increases the traffic volume on alternative routes and causes more collisions. Thus, it is very important to exclude roads that may be influenced by the spillover effect from the comparison group or reference population.

As mentioned in the first chapter, the objectives of this thesis are to evaluate the safety effects of automated mobile enforcement at the segment-based level and city-wide level. For segment-based evaluation, before-and-after evaluation with the Empirical Bayes method and yearly calibration factors were proposed to account for the issues discussed above. In addition, this thesis also examined the issues of continuous versus discontinuous enforcement effects and the spillover effects on nearby segments, which were rarely discussed in previous studies. For the city-wide evaluation, the generalized linear model was adopted to investigate the relationship between the monthly number of collisions and the enforcement variables. The interrupted time-series analysis is not suitable here due to the early implementation date of the program.

3 SEGMENT-BASED EVALUATION

This chapter evaluates the segment-based safety effects of automated mobile enforcement. There are three objectives of the evaluation. The first objective is to examine the safety effects of enforcement on urban arterial roads. The second one is to compare the effects of continuous and discontinuous enforcement. The third one is to investigate the spillover effects of enforcement. The work from this chapter is currently under review as R. Li, K. El-Basyouny, A. Kim, "A Before-and-After Empirical Bayes Evaluation of Automated Mobile Speed Enforcement on Urban Arterial Roads".

3.1 Data Description

This evaluation covered the time period between January 2005 and December 2012. The enforced segment is defined as one approach of the roadway that had the same direction as the enforcement operation. Yearly data on deployment, traffic counts, collisions by severity/type, and road geometry were collected from different databases for the City of Edmonton, Alberta, Canada. The following severities and types of collisions were included:

- Severe Collisions (sum of fatal and injury collisions);
- Property Damage Only (PDO) Collisions;
- Total Collisions (sum of Severe and PDO collisions);
- Speed-Related PDO Collisions; and
- Speed-Related Collisions.

Only mid-block collisions were considered in this analysis. This is due to the fact that intersection collisions have distinct characteristics and may not be directly influenced by speed enforcement. A statistical summary of the evaluated segments data is shown in Table 3-1.

TABLE 3-1 Summary Statistics of the Evaluated Segments Dataset

	Average	Standard Deviation	Minimum	Maximum
Average Yearly* Deployment Hours	37.2	53.4	1.0	279.6
Segment Length (metres)	962	508	184	3233
Median (0: no, 1: yes)	0.5	0.5	0	1
Unsignalized Intersection Density (/km)	4.2	3.1	0	15.8
Average Yearly AADT	9781	5094	2079	22960
Average Yearly Severe Collisions	0.6	0.7	0.0	3.1
Average Yearly PDO Collisions	3.1	3.7	0.3	23.9
Average Yearly Total Collisions	3.8	4.3	0.3	27.0
Average Yearly Speed-Related PDO Collisions	1.8	1.8	0.1	11.3
Average Yearly Speed-Related Collisions	2.4	2.4	0.2	14.4

* Average Yearly means the average of the yearly data during the study period

3.2 Methodology

3.2.1 Safety Performance Function

Safety performance functions (SPF) are regression models that are used to estimate the predicted average collision frequency for a specific type of road segment or intersection. In this evaluation, the generalized linear model (GLM) was adopted to examine the relationship between the number of collisions and explanatory variables. A negative binomial (NB) error structure was used to describe the collision distribution. Previous research has shown that NB distribution is able to better describe overdispersed collision data than Poisson distribution, which limits the mean to be equal to the variance (Lu et al., 2014; Chen & Persaud, 2014). The specifications of the NB model are presented below (El-basyouny & Sayed, 2010).

Let Y_i denote the number of collisions at site $i\,(i = 1,2,3,...,n)$ with a mean of θ_i. It is assumed that the numbers of collisions at each site are independent and follow that

$$Y_i \mid \theta_i \sim \text{Poisson}\,(\theta_i) \tag{3-1}$$

To address overdispersion for unobserved/unmeasured heterogeneity, it is assumed that

$$\theta_i = \mu_i \exp\,(u_i) \tag{3-2}$$

where μ_i is determined by a set of covariates representing site-specific characteristics multiplied by a corresponding set of regression parameters to be estimated. The term $\exp(u_i)$ represents a multiplicative random effect. The negative binomial model is obtained by the assumption

$$\exp(u_i) \mid \kappa \sim \text{Gamma}(\kappa, \kappa) \tag{3-3}$$

$$E(\theta_i) = \mu_i \cdot E(e^{u_i}) = \mu \cdot \frac{\kappa}{\kappa} = \mu \tag{3-4}$$

$$Var(\theta_i) = \mu_i^{\,2} \cdot Var(e^{u_i}) = \mu^2 \cdot \frac{\kappa}{\kappa^2} = \frac{\mu^2}{\kappa} \tag{3-5}$$

where κ is the inverse dispersion parameter. The probability function, mean, and variance of the negative binomial distribution are given by

$$P(Y_i = y_i \mid \mu_i, \kappa) = \frac{\Gamma(y_i + \kappa)}{y_i!\Gamma(\kappa)} \left(\frac{\kappa}{\kappa + \mu_i} \right)^{\kappa} \left(\frac{\mu_i}{\kappa + \mu_i} \right)^{y_i} \tag{3-6}$$

$$E(Y_i) = \mu_i \tag{3-7}$$

$$Var(Y_i) = \mu_i + \frac{\mu_i^2}{\kappa} \tag{3-8}$$

where y_i is the number of observed collisions. A standard SPF model form for road segments was selected. In the model, the predicted yearly average number of collisions is the dependent variable, while traffic volume and road geometric characteristics are the independent variables. The model form is shown in Equation (3-9).

$$\ln(\mu) = \beta_0 + \beta_1 \ln(V) + \beta_2 \ln(L) + \beta_3 UNSD + \beta_4 Median \tag{3-9}$$

Where:

μ	=	predicted yearly average number of collisions
V	=	annual average daily traffic
L	=	length of segment (km)
$UNSD$	=	density of unsignalized intersections (/km)
$Median$	=	dummy variable for the presence of median
$\beta_0 - \beta_4$	=	regression parameters

The goal of developing local SPFs is to obtain an average number of collisions given the traffic volume and geometric characteristics of a particular road segment. This number serves as a "baseline" in the local environment. Thus, the quality of the reference segments population is crucial to the accuracy of prediction. A sufficient sample size is also important to strengthen the statistical power of the models. To this end, a thorough selection of reference segments was conducted within the scope of the whole city. The criteria for the selection are listed below:

- Arterial road segment;
- Similar traffic volume;
- Similar collision frequency;
- No enforcement; and
- Not upstream/downstream of or adjacent to enforced segments.

In total, 266 arterial segments were selected to develop the local SPFs. The parameters were estimated in SAS through the GENMOD procedure (SAS Institute Inc., 2012), which uses maximum likelihood estimation with the Newton-Raphson algorithm. The goodness of fit of the models was measured by scaled deviance (SD) and Pearson χ^2, which are widely used for NB models. Both SD and Pearson χ^2 are asymptotically χ^2 distributed with $n-p$ degrees of freedom, where n is the number of observations and p is the number of regression parameters (Aitkin et al., 1989). The calculations for SD and Pearson χ^2 are shown in Equations (3-10) and (3-11).

$$SD = 2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{y_i}{\mu_i}\right) - (y_i + \kappa)\ln\left(\frac{y_i + \kappa}{\mu_i + \kappa}\right)\right] \tag{3-10}$$

$$Pearson\chi^2 = \sum_{i=1}^{n}\frac{[y_i - \mu_i]^2}{Var(Y_i)} \tag{3-11}$$

3.2.2 Yearly Calibration Factor

The SPFs contain only traffic volume and road geometric variables and are calibrated with aggregated data during the study period. Thus, they are not able to capture the annual fluctuation in collision frequency caused by confounding factors, such as weather condition, roadway improvement, and general trends in traffic safety (Ye et al., 2013). The yearly calibration factor is calculated as the ratio between the sum of the observed number of collisions and the sum of the number of collisions predicted by SPFs in the same year, using the reference segments data, as shown in Equation (3-12). The assumption made here is that the impacts of confounding factors on collision frequency are similar between the reference segments and the enforced segments. The predicted number of collisions by SPF will be adjusted through multiplying the corresponding yearly calibration factor to obtain a more accurate prediction.

$$C_{ij} = \frac{\sum_{Allsites} N_{ij}}{\sum_{Allsites} \mu_{ij}} \tag{3-12}$$

Where:

C = yearly calibration factor

N = observed number of collisions

μ = predicted number of collisions

i = collision severity/type

j = year

3.2.3 Before-and-After Evaluation with Empirical Bayes Method

The regression-to-the-mean (RTM) effect reflects the random variation of collision frequency in the absence of any external factors. In other words, the high collision frequency at one site will decrease after a period of time even if no countermeasure is implemented. Since most jurisdictions give more priority to sites with high collision frequency for enforcement, significant reduction obtained using conventional evaluation methods may be biased due to ignorance of the RTM effect. The Empirical Bayes (EB) method proposed by Hauer (1997) explicitly addressed this issue by incorporating the collision information of reference sites into the evaluation. The EB method is also able to account for changes in traffic volume and length of the before and after periods. The evaluation procedure is described below.

The first step is to calculate the expected number of collisions for the before period of each site. The expected number of collisions is the sum of the weighted observed number of collisions and the predicted number of collisions adjusted by the yearly calibration factors. The calculations for the expected number of collisions are shown in Equations (3-13) and (3-14). In this evaluation, the minimum length of the before period was two years, and the minimum length of the after period was one year.

$$E_B = w \cdot \mu_B + (1-w) \cdot N_B \tag{3-13}$$

$$w = \frac{1}{1+\mu_B/\kappa} \tag{3-14}$$

Where:

w = weight used in calculating the expected number of collisions

E_B = sum of the expected number of collisions for the entire before period

μ_B = sum of the predicted number of collisions for the entire before period

N_B = sum of the observed number of collisions for the entire before period

κ = inverse dispersion parameter of SPF

The second step is to calculate the expected number of collisions for the after period. A multiplier is developed to account for the differences in the period length and traffic volume between the before and the after period. This multiplier is the ratio between the predicted collisions for the after period and the predicted collisions for the before period. The expected number of collisions for the after period can be calculated by applying this multiplier to the expected number of collisions for the before period, as shown in Equation (3-15).

$$E_A = \left(\frac{\mu_A}{\mu_B}\right) E_B \tag{3-15}$$

Where:

E_A = sum of the expected number of collisions for the entire after period

μ_A = sum of the predicted number of collisions for the entire after period

The third step is to calculate the overall odds ratio of collision reduction (δ) and its standard error, shown in Equations (3-16), (3-17), and (3-18).

$$\delta = \frac{\sum_{Allsites} N_A \Big/ \sum_{Allsites} E_A}{1 + Var(\sum_{Allsites} E_A) \Big/ (\sum_{Allsites} E_A)^2} \tag{3-16}$$

$$Var(\sum_{Allsites} E_A) = \sum_{Allsites} [(\mu_A / \mu_B)^2 \times E_B \times (1-w)] \tag{3-17}$$

$$SE(\delta) = \sqrt{\frac{(\sum_{Allsites} N_A \Big/ \sum_{Allsites} E_A)^2 [\frac{1}{\sum_{Allsites} N_A} + Var(\sum_{Allsites} E_A) \Big/ (\sum_{Allsites} E_A)^2]}{[1 + Var(\sum_{Allsites} E_A) \Big/ (\sum_{Allsites} E_A)^2]}} \tag{3-18}$$

Where:

N_A = sum of the observed number of collisions for the entire after period

The last step is to assess the statistical significance of the estimated collision reduction percentage, which is calculated as $100 \cdot (1-\delta)$ with a standard error of $100 \cdot SE(\delta)$. The ratio between the reduction percentage and its standard error is compared with the critical values for significance. If the value of the ratio is greater than 1.97, the collision reduction percentage is significant at the 95% confidence level. If the value of the ratio is greater than 1.65, the collision reduction percentage is significant at the 90% confidence level; otherwise, it is not significant at the 90% confidence level.

3.3 Results and Discussions

3.3.1 SPFs and Yearly Calibration Factors

The local SPFs were developed using the data and methodology described above. The models' goodness of fit was measured by two statistics: scaled deviance and Pearson χ^2, shown in Table 3-2. As demonstrated in the table, all the statistics are smaller than the critical value of χ^2 distribution, indicating that the models fit the data relatively well. The estimation results for the regression parameters are shown in Table 3-3. All the parameters are highly significant, except for the median parameter in the speed-related PDO collision model. The signs of the parameters are intuitive. The collision frequency increases with traffic volume, segment length, and unsignalized intersection density, while it decreases when there is a median present. All the shape parameters were highly significant, which validates the overdispersion of the data. The yearly calibration factors by year and by collision severity/type are shown in Table 3-4.

TABLE 3-2 SPFs Model Goodness of Fit

	Severe Collision	PDO Collision	Total Collision	Speed-related PDO Collision	Speed-related Collision
Scaled Deviance	294.01	281.19	279.93	282.08	279.94
Pearson χ^2	269.84	286.41	288.19	294.99	289.37
Degrees of freedom	261	261	261	261	261
$\chi^2_{.05}$	299.68	299.68	299.68	299.68	299.68

TABLE 3-3 SPFs Estimates Results

	Severe Collision	PDO Collision	Total Collision	Speed-related PDO Collision	Speed-related Collision
Intercept	-10.25*	-5.87*	-6.00*	-6.48*	-6.73*
AADT	1.05*	0.74*	0.78*	0.75*	0.81*
Length	0.44*	0.36*	0.38*	0.40*	0.41*
UNSD	0.06*	0.07*	0.07*	0.07*	0.06*
Median	-0.28*	-0.32*	-0.31*	-0.15	-0.18**
Dispersion Parameter	0.38*	0.34*	0.34*	0.34*	0.34*

* Significant at 99% level ** Significant at 95% level

TABLE 3-4 Yearly Calibration Factors

Year	Severe Collision	PDO Collision	Total Collision	Speed-related PDO Collision	Speed-related Collision
2005	1.19	0.81	0.88	0.86	0.95
2006	1.43	0.95	1.03	0.99	1.11
2007	1.20	1.00	1.03	0.99	1.05
2008	0.98	1.11	1.09	1.12	1.09
2009	0.74	1.19	1.12	1.22	1.10
2010	0.80	1.10	1.05	1.11	1.03
2011	0.72	0.91	0.88	0.81	0.79
2012	0.90	0.98	0.97	0.92	0.92

3.3.2 Overall Before-and-After Evaluation

In total, 93 enforced arterial road segments were evaluated with the before-and-after EB method, following the procedure described in the methodology section. For each site, the adjusted yearly average predicted number of collisions was calculated using the corresponding traffic volume data and calibration factor of that year. Finally, the overall collision reduction percentages and their statistical test ratios by collision severity/type are shown in Table 3-5. The results suggest that there were significant reductions in all severities/types of collisions. The highest reduction occurred in severe collisions at 20.1%. The results are consistent with those of previous studies: Newstead et al. (2001) found a 31% reduction in fatal collisions and an 11% reduction in total collisions in the Queensland Random Road Watch program; Goldenbeld and Schagen (2005) estimated a 21% reduction in injury collisions; the covert enforcement program in New Zealand led to a 22% reduction for the police reported collisions (Keall et al., 2001). In addition, the results here also indicate that enforcement had greater impacts on severe and speed-related collisions, in comparison to the others listed in Table 3-5.

TABLE 3-5 Overall Before-and-After Evaluation Results

	Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
Collision Reduction (%)	20.1	14.3	14.5	17.9	18.5
Statistical Test Ratio	2.3*	3.29*	3.64*	3.3*	3.91*

* Significant at 95% level

For enforcement programs, sites were usually selected based on historical data and the expertise of authorities. However, jurisdictions that somehow lack a comprehensive dataset or experience in automated mobile enforcement may find it useful to have certain criteria and thresholds for site selection. Thus, the 93 segments were classified into groups based on the site selection criteria in the literature to examine the potential thresholds for effective enforcement (Ko et al., 2013):

- The average number of collisions per year during the before period;
- The average AADT during the before period; and
- The average collision rate during the before period (average number of collisions per million vehicle kilometres travelled per day).

For each criterion and collision severity/type, the 93 enforced segments were divided into three groups according to pre-specified thresholds. After the classification, the safety evaluation was conducted within each group, and the results are shown in Table 3-6.

In general, greater reductions were achieved for the segments that had a high collision frequency or high collision rate in the before period. For example, a 20% significant reduction is expected to be achieved if the segment has more than three speed-related collisions per year or more than one speed-related collision per million vehicle kilometres travelled per day. The evaluation results based on the AADT criterion revealed that segments with an average AADT between 7,000 and 12,000 experienced the highest reductions ranging from 26% to 31%.

It should be noted that the magnitude of reduction is the outcome of both the characteristics of enforced segments (e.g., collision frequency, AADT, and collision rate) and the assigned enforcement resources. Thus, the 93 segments were reclassified by deployment hours (both total and average yearly) to examine their effects on collision reduction. The evaluation results are shown in Table 3-7. It can be observed that there were significant reductions, regardless of the collision severity/type, for the segments that had total deployment hours above 70 or average yearly deployment hours above 30. However, the average values of the total and average yearly deployment hours of these segments were actually 310 and 96 respectively, which are much higher than the thresholds. Nevertheless, the results do indicate that longer deployment hours can lead to greater collision reduction.

TABLE 3-6 Evaluation Results by Site Selection Criteria

Criterion		Collision			AADT			Collision Rate		
Severe Collision	Threshold	< 0.3	[0.3, 1)	≥ 1	< 7000	[7000, 12000)	≥ 12000	< 0.2	[0.2, 0.4)	≥ 0.4
	Reduction (%)	15.1	27.1**	19.1	12.7	26.2**	19.2	14.1	25	22.4**
	Group Size	30	36	27	31	33	29	43	23	27
	Average Total Hours [a]	85.6	151.4	98.3	44.9	111.4	193.3	149.9	82	86.7
	Average Yearly Hours [b]	26.5	46.6	36.4	14.4	36.3	62.4	43.1	28.8	34.8
PDO Collision	Threshold	< 1.5	[1.5, 3)	≥ 3	< 7000	[7000, 12000)	≥ 12000	< 0.6	[0.6, 1.1)	≥ 1.1
	Reduction (%)	8.3	13.6	16.6*	16.7**	27.4*	5.5	-3.5	20.5*	17.4*
	Group Size	31	34	28	31	33	29	29	31	33
	Average Total Hours	130.2	96.7	119.6	44.9	111.4	193.3	165.9	97.2	86.3
	Average Yearly Hours	33.4	34.6	44.4	14.4	36.3	62.4	45.5	33.8	32.9
Total Collision	Threshold	< 1.5	[1.5, 3.5)	≥ 3.5	< 7000	[7000, 12000)	≥ 12000	< 0.8	[0.8, 1.5)	≥ 1.5
	Reduction (%)	2.9	7.1	19.4*	16.3**	26.5*	6.4	-1.8	22.9*	17.4*
	Group Size	28	32	33	31	33	29	33	29	31
	Average Total Hours	148.8	86	113.8	44.9	111.4	193.3	193.4	52.2	89.5
	Average Yearly Hours	39.5	31.4	40.7	14.4	36.3	62.4	55	20.4	33.9
Speed-Related PDO Collision	Threshold	< 1	[1, 2)	≥ 2	< 7000	[7000, 12000)	≥ 12000	< 0.4	[0.4, 0.8)	≥ 0.8
	Reduction (%)	28.8*	6.1	20.2*	24.7*	30.5*	7.6	6.9	19.4**	22.7*
	Test Ratio	33	32	28	31	33	29	30	31	32
	Average Total Hours	127.2	102.3	114.4	44.9	111.4	193.3	160.6	98.5	87.5
	Average Yearly Hours	35.1	34.7	42.3	14.4	36.3	62.4	42.4	37.1	32.3
Speed-Related Collision	Threshold	< 1.3	[1.3, 2.8)	≥ 2.8	< 7000	[7000, 12000)	≥ 12000	< 0.5	[0.5, 1)	≥ 1
	Reduction (%)	16.7	13.5	21.5*	22.6*	30.1*	9.5	4.5	23.1*	22*
	Group Size	33	31	29	31	33	29	28	31	34
	Average Total Hours	124	125.3	92.9	44.9	111.4	193.3	186.4	84.2	83.7
	Average Yearly Hours	33.3	43.6	34.6	14.4	36.3	62.4	50	31.6	31.6

* Significant at 95% level

** Significant at 90% level

[a] Average total deployment hours per site

[b] Average yearly deployment hours per site (Total deployment hours divided by the number of enforcement years)

TABLE 3-7 Evaluation Results by Deployment Hours

	Criterion	Total Deployment Hours			Average Yearly Deployment Hours		
	Threshold	< 15	[15, 70)	≥ 70	< 9	[9, 30)	≥ 30
Severe Collision	Reduction (%)	6.2	22.9	27.3*	17.2	11.2	29.1*
	Group Size	31	31	31	33	31	29
	Average Collisions [a]	0.7	0.8	0.8	0.6	0.9	0.9
	Average AADT [b]	8599	9388	11597	8335	9618	11858
	Average Collision Rate [c]	0.3	0.3	0.2	0.2	0.3	0.2
PDO Collision	Reduction (%)	14.4**	6.8	18.5*	14.9**	10	16.8*
	Group Size	31	31	31	33	31	29
	Average Collisions	3.2	3.2	3.4	2.6	3.1	4.1
	Average AADT	8599	9388	11597	8335	9618	11858
	Average Collision Rate	1.4	1	1.1	1.1	1.2	1.2
Total Collision	Reduction (%)	13**	8.5	18.9*	13.8**	9.6	18.3*
	Group Size	31	31	31	33	31	29
	Average Collisions	3.9	4	4.1	3.2	4	5
	Average AADT	8599	9388	11597	8335	9618	11858
	Average Collision Rate	1.7	1.3	1.3	1.3	1.5	1.4
Speed-Related PDO Collision	Reduction (%)	10.7	15.3	23.7*	10.7	20.6*	21.4*
	Group Size	31	31	31	33	31	29
	Average Collisions	1.8	1.9	2	1.5	2	2.3
	Average AADT	8599	9388	11597	8335	9618	11858
	Average Collision Rate	0.7	0.6	0.7	0.6	0.7	0.7
Speed-Related Collision	Reduction (%)	11.7	15.6**	24.1*	11.6	18.1*	23.4*
	Group Size	31	31	31	33	31	29
	Average Collisions	2.5	2.7	2.8	2.1	2.9	3.2
	Average AADT	8599	9388	11597	8335	9618	11858
	Average Collision Rate	1	0.9	0.9	0.9	1.1	0.9

* Significant at 95% level

** Significant at 90% level

[a] Average yearly collisions in the before period per site

[b] Average AADT in the before period per site

[c] Average collision rate in the before period per site

3.3.3 Continuous versus Discontinuous Enforcement Evaluation

Among all the enforced segments, some were enforced each year during the after period, while others were not, due to limited enforcement resources. In this subsection, the safety effects on the continuously enforced segments were compared with those on the discontinuously enforced segments using the same methodology. The purpose is to determine which enforcement strategy is more effective in reducing collisions. Before conducting the evaluation, it was critical to control for both site characteristics and the number of deployment hours, since they were found to be related to safety effects. As shown in Table 3-8, enforced segments were selected to ensure that both groups had similar collision data, traffic volume, and deployment hours. The evaluation results are provided in Table 3-9. It can be observed that the continuously enforced segments had larger reductions for all severities/types of collisions compared to the segments that were discontinuously enforced. The implication of the results is that continuous enforcement is a preferred strategy leading to greater collision reduction than discontinuous enforcement.

TABLE 3-8 Continuously Enforced versus Discontinuously Enforced Segment Data

	Group Size	Collisions [a]	AADT [a]	Collision Rate [a]	Deployment Hours [b]
Continuously Enforced	23	3.2	9272	1.4	55.4
Discontinuous Enforced	23	3.1	8683	1.2	58.5

[a] Average value per site in the before period

[b] Average value per site in the after period

TABLE 3-9 Continuous versus Discontinuous Enforcement Evaluation Results

	Severe Collision	PDO Collision	Total Collision	Speed-related PDO Collision	Speed-related Collision
Continuous					
Collision Reduction (%)	32.1	28.7	27.7	27.3	26.7
Statistical Test Ratio	1.74**	3.22*	3.35*	2.38*	2.64*
Discontinuous					
Collision Reduction (%)	17.9	8.5	8.6	15.0	13.4
Statistical Test Ratio	1.01	0.91	0.99	1.37	1.36

* Significant at 95% level ** Significant at 90% level

3.3.4 Spillover Effects

The spillover effect refers to the phenomenon of nearby enforcement operations influencing collisions on unenforced areas. It should be noted that although the analysis targets of this evaluation are road segments, the enforcement was conducted only at a specific site within each segment. Since significant collision reductions have been found on the enforced segments, the range of the spillover effect of the enforcement should be comparable to the length of the enforced segments, of which the average is around 1,000 meters. This coincides with the results estimated by Christie at el. (2003) that the spillover effect can extend to 500 meters along the route in both directions from the enforcement locations.

Additional evaluations were conducted to further investigate the spillover effect. Firstly, unenforced segments upstream/downstream of the enforced segments were evaluated. Secondly, unenforced segments that were the adjacent approach (i.e., in opposite directions) of the enforced segments were evaluated. In total, there were 75 upstream/downstream segments (39 upstream and 36 downstream). A statistical summary of the upstream/downstream segments data is shown in Table 3-10, and the evaluation results are shown in Table 3-11.

TABLE 3-10 Summary Statistics of the Upstream/Downstream Segments

	Average	Standard Deviation	Minimum	Maximum
Segment Length (metres)	534	341	123	1653
Median (0: no, 1: yes)	0.6	0.5	0	1
Unsignalized Intersection Density (/km)	3.9	2.9	0	11.6
Average Yearly AADT	11549	5214	1811	29328
Average Yearly Severe Collisions	0.5	0.5	0	2.9
Average Yearly PDO Collisions	2.5	2.3	0.8	12.6
Average Yearly Total Collisions	3.0	2.7	1.0	15.5
Average Yearly Speed-related PDO Collisions	1.4	1.2	0.3	6.9
Average Yearly Speed-related Collisions	1.9	1.6	0.6	8.7

* Average Yearly means the average of the yearly data during the study period

TABLE 3-11 Upstream/Downstream Segments Evaluation Results

	Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
Overall					
Collision Reduction (%)	-3	-10.8	-11.3	-1.5	-3.3
Statistical Test Ratio	-0.21	-1.58	-1.78**	-0.18	-0.44
Upstream					
Collision Reduction (%)	-15.2	-8.3	-11.3	1.1	-4.6
Statistical Test Ratio	-0.74	-0.86	-1.25	0.09	-0.43
Downstream					
Collision Reduction (%)	12.6	-13.5	-11	-4.3	-1.5
Statistical Test Ratio	0.67	-1.38	-1.24	-0.34	-0.14

** Significant at 90% level

The results showed that there were increases in the number of collisions for all severities/types of collisions. However, the increases were not significant at the 90% level except for the total collisions. The magnitudes of the increases were larger for the PDO and total collisions than for the other collisions. The results were similar for the separate evaluations for the upstream and downstream segments, except for the severe collisions: a decrease on the downstream segments and an increase on the upstream segments. All the effects were not significant at the 90% level. Considering the evaluation results of the upstream/downstream segments, it is safe to conclude that the segments used to calibrate the SPFs were not significantly affected by the enforcement.

Next, 39 enforced segments that did not have enforcement on their adjacent approaches were selected. A comparison of the enforced and unenforced segments' statistics is provided in Table 3-12, and the evaluation results are shown in Table 3-13. The results show that for the enforced segments, only severe and speed-related collisions were significantly reduced, while for the unenforced segments, only the PDO collisions, total collisions, and speed-related PDO collisions were significantly reduced. One possible explanation for this phenomenon might be the different effects of general and specific deterrence. Although the enforcement operations were planned to be covert, some drivers were able to recognize the enforcement vehicles. It may be easier for drivers on the adjacent approach to observe the enforcement vehicle and therefore slow down, resulting in reduced PDO and total collisions. Severe and speed-related collisions on the enforced segments were reduced because of the specific deterrence to the aggressive violators that refuse to slow down until punished. Once again, the results confirm that enforcement is capable of improving safety.

TABLE 3-12 Summary Statistics of the Enforced and Unenforced Segments

	Average	Standard Deviation	Minimum	Maximum
Segment Length (metres)	983	670	184	3233
Median (0: no, 1: yes)	0.5	0.5	0	1
Unsignalized Intersection Density (/km)	4.5	2.9	0	10.3
Average Yearly AADT	10350	4351	2278	21891
Enforced Segments				
Average Yearly Severe Collisions	0.7	0.9	0	3.1
Average Yearly PDO Collisions	3.8	4.9	0.4	23.9
Average Yearly Total Collisions	4.5	5.7	0.5	27.0
Average Yearly Speed-Related PDO Collisions	2.0	2.3	0.1	11.3
Average Yearly Speed-Related Collisions	2.7	3.1	0.3	14.4
Unenforced Segments				
Average Yearly Severe Collisions	0.5	0.7	0	2.8
Average Yearly PDO Collisions	2.3	2.3	0.1	10.1
Average Yearly Total Collisions	2.8	2.9	0.1	12.6
Average Yearly Speed-Related PDO Collisions	1.4	1.4	0	6.0
Average Yearly Speed-Related Collisions	1.9	2.0	0	8.8

* Average Yearly means the average of the yearly data during the study period

TABLE 3-13 Enforced versus Unenforced Segments Evaluation Results

	Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
Enforced					
Collision Reduction (%)	26.1	1.8	4.5	9.2	14
Statistical Test Ratio	2.17*	0.27	0.75	1.1	1.98*
Unenforced					
Collision Reduction (%)	2.5	14.6	14.1	15.4	11.1
Statistical Test Ratio	0.16	2.02*	2.15*	1.73**	1.38

* Significant at 95% level ** Significant at 90% level

4 CITY-WIDE EVALUATION

This chapter evaluates the city-wide safety effects of automated mobile enforcement. The first objective is to examine the relationship between monthly enforcement statistics and city-wide collisions. The marginal safety effects of 1,000 deployment hours and 10,000 issued speed tickets are estimated in terms of collision reduction. The second objective is to investigate the threshold of deployment hours that can generate significant collision reduction.

4.1 Data Description

The same study period as the segment-based evaluation (January 2005 to December 2012) was used in this evaluation. The monthly number of collisions and enforcement statistics were collected and aggregated for the city-wide level. The severities/types of collisions are listed below:

- Severe Collisions (sum of fatal and injury collisions);
- Property Damage Only (PDO) Collisions;
- Total Collisions;
- Speed-Related PDO Collisions; and
- Speed-Related Collisions.

In the previous chapter, only midblock collisions were considered. The hypothesis was that the effects of enforcement should be mainly reflected by the midblock collisions, rather than the intersection collisions. Since this chapter evaluates the macroscopic effects of enforcement, both midblock collisions and all collisions (midblock plus intersection collisions) are examined.

The enforcement statistics are the monthly deployment hours and number of issued tickets. The monthly deployment hours include all the enforcement hours of the program in one month. It should be noted that the number of issued tickets is an approximation of the number of violations during the enforcement. Some violations were not converted to speed tickets due to difficulties in validation and verification (e.g., multiple vehicles in one photo, unrecognizable vehicle plate number). However, the number of issued tickets accurately represents the number of drivers who were affected by specific deterrence. Usually, drivers receive speed tickets around one week post-violation, which makes the number of issued tickets reasonably examinable on a monthly basis.

In addition, the employment rate was collected to account for socio-economic factors. According to Tay (2010), the employment rate had an inverse relationship with the number of severe collisions, which may be due to the increase of revenue for road facility improvement and citizens' demand for safety.

In total, there are 96 monthly data entries. Summary statistics of the monthly data are provided in Table 4-1. It was found that the midblock collisions make up around 40% of all collisions, with the lowest 30% for severe collisions and the highest 46% for speed-related PDO collisions. Data series are plotted in Figures 4-1 to 4-5 to better illustrate their monthly trends and variations. For the collision data, only severe, total, and speed-related collisions are plotted to avoid duplications.

TABLE 4-1 Summary Statistics of the Dataset

	Average	Standard Deviation	Minimum	Maximum
Average Monthly Deployment Hours	2003	855	654	3608
Average Monthly Number of Issued Tickets	13258	5553	3481	27369
Average Employment Rate (%)	68.6	1.5	65.9	71.7
Midblock Collisions				
Average Monthly Severe Collisions	116	35	55	185
Average Monthly PDO Collisions	752	230	405	1584
Average Monthly Total Collisions	868	237	537	1742
Average Monthly Speed-Related PDO Collisions	501	157	277	1108
Average Monthly Speed-Related Collisions	617	167	375	1266
All Collisions				
Average Monthly Severe Collisions	384	96	215	611
Average Monthly PDO Collisions	1806	520	1106	3308
Average Monthly Total Collisions	2190	528	1450	3720
Average Monthly Speed-Related PDO Collisions	1094	323	665	2095
Average Monthly Speed-Related Collisions	1479	336	949	2507

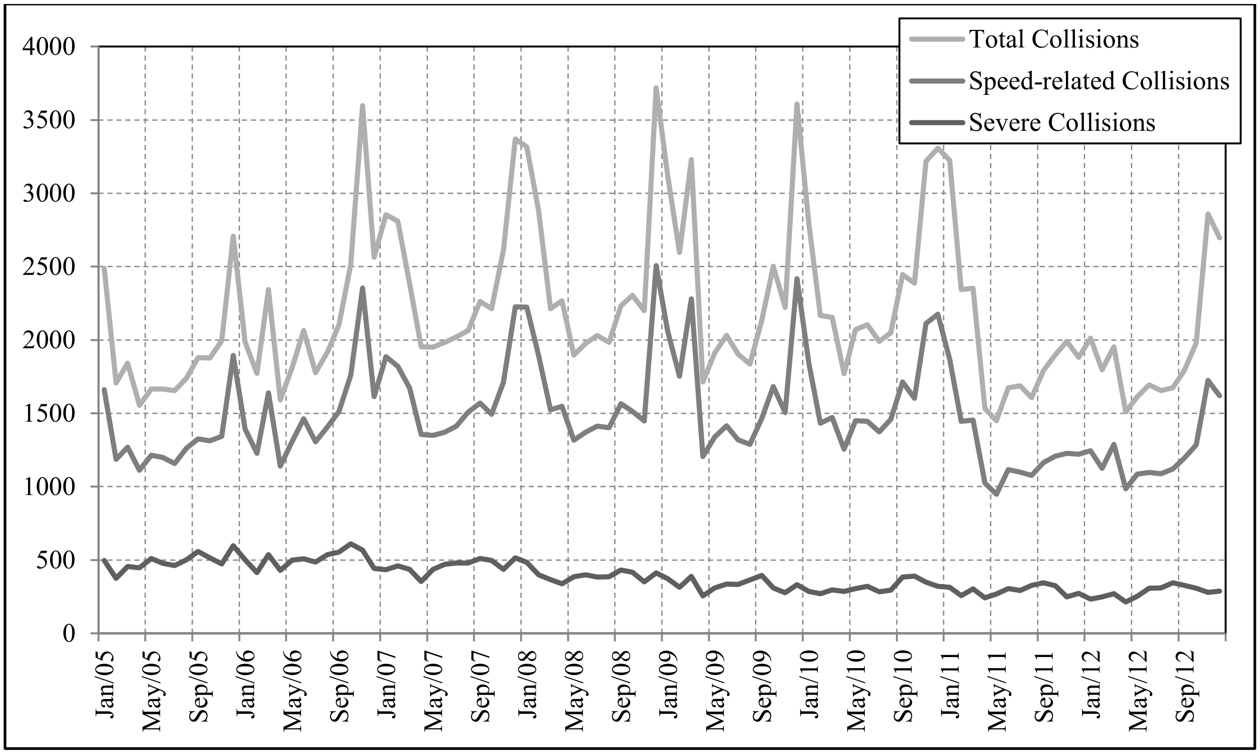

FIGURE 4-1 Monthly Trend of All Collisions

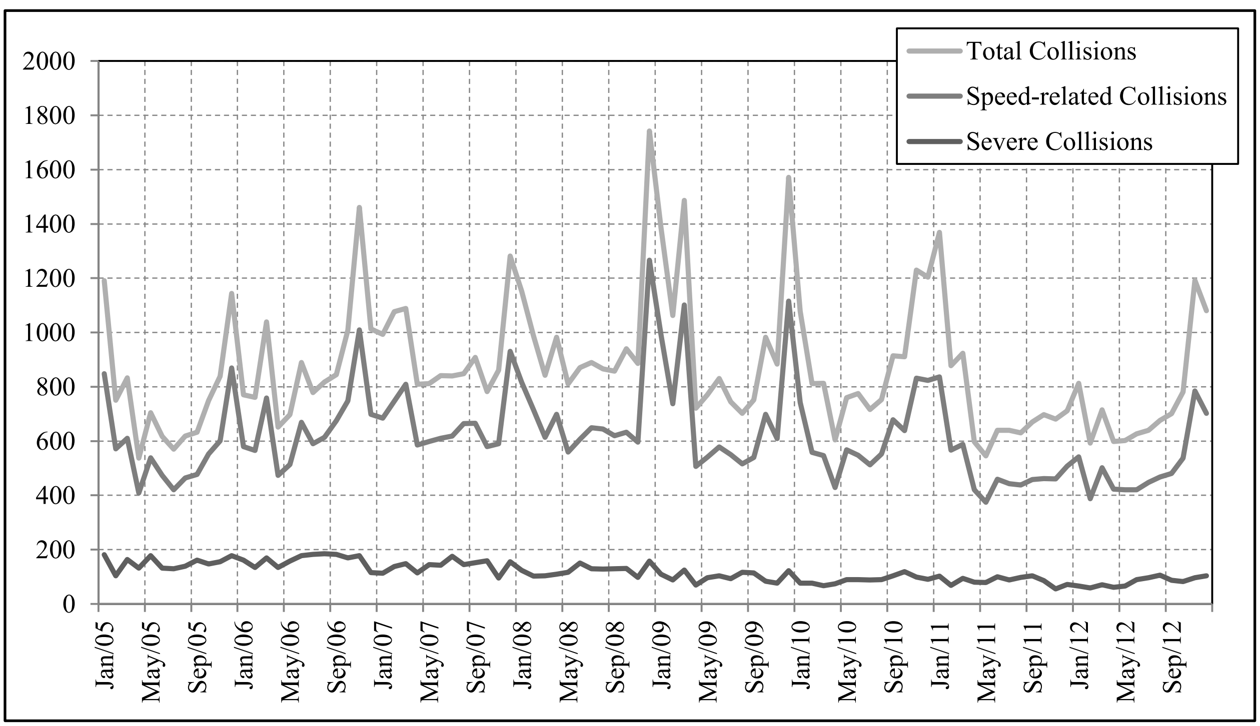

FIGURE 4-2 Monthly Trend of Midblock Collisions

FIGURE 4-3 Monthly Trend of Deployment Hours

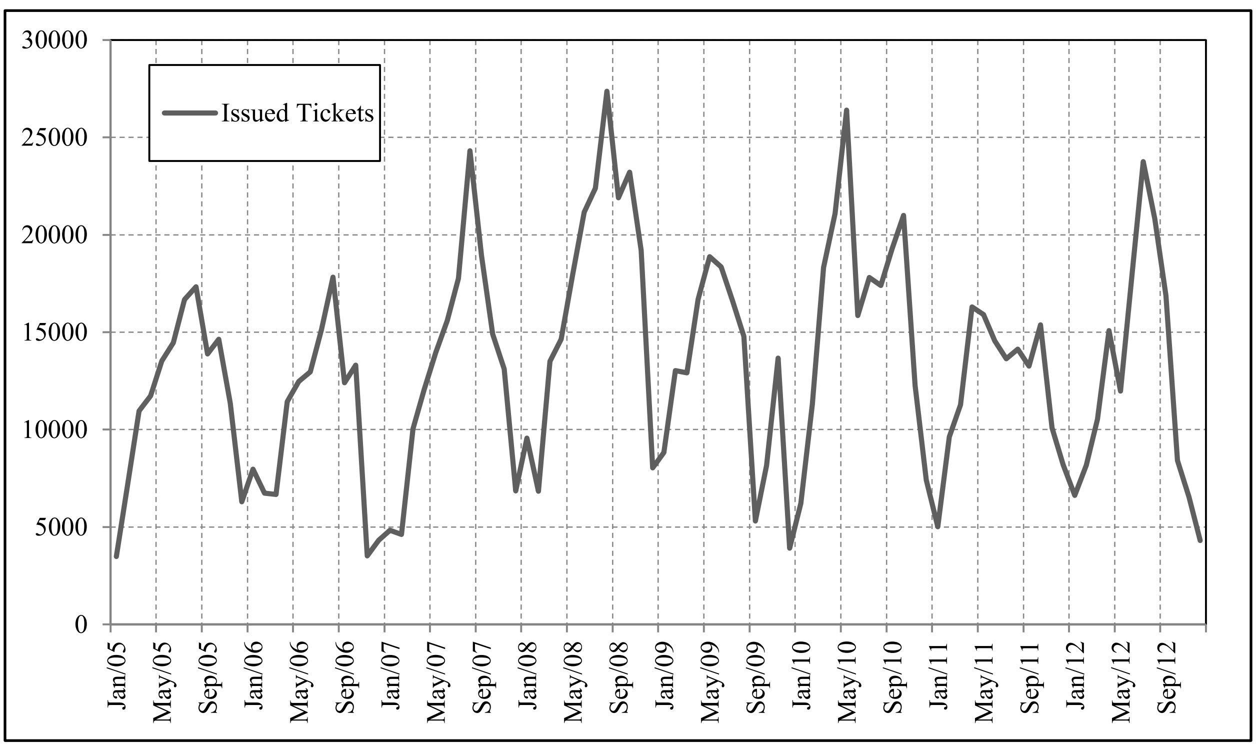

FIGURE 4-4 Monthly Trend of Issued Tickets

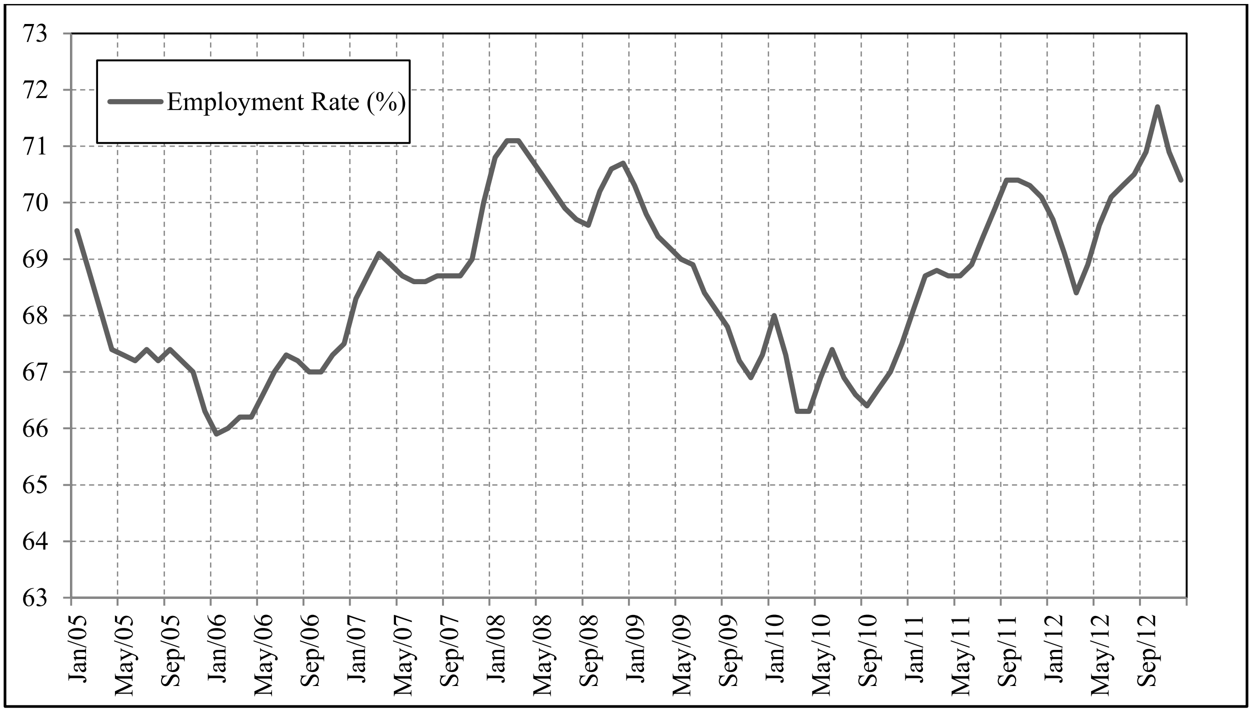

FIGURE 4-5 Monthly Trend of Employment Rate

The variations of the monthly collision data show clear seasonal patterns. More total and speed-related collisions occurred during the winter months, due to poor road conditions caused by snow and ice. However, the pattern is the opposite for severe collisions: less severe collisions occurred during the winter months. The explanation is likely to be that the slower speed during the winter months decreases the severity of collisions. The trends of the midblock collisions are very similar to those of all collisions, and the percentage of speed-related collisions among total collisions is slightly higher for the midblock collisions. The monthly deployment hours experienced a substantial increase at the end of 2009, rising from around 1,500 hours to around 3,000 hours. The monthly number of issued tickets shows a clear seasonal pattern with more tickets issued during the summer months, which validates the higher speed of traffic during that time. Finally, the employment rate seems to fluctuate with a cycle of four years.

4.2 Methodology

The generalized linear model (GLM) is adopted to examine the relationship between the monthly number of collisions and explanatory variables. The most commonly used collision distributions are Poisson and negative binomial (NB) distributions (Ye et al., 2013; El-basyouny & Sayed, 2013). Although some studies used Poisson distribution in GLM models for system-wide collisions (Newstead et al., 2001; Tay, 2010), it can be observed from Table 4-1 that the variance of the data is larger than the mean, indicating the possibility of overdispersion in the data. The NB distribution was found to be able to better describe the overdispersed data than Poisson distribution (Lu et al, 2014; Chen & Persaud, 2014). According to Miao (1994), although model parameters estimated under Poisson distribution are close to the true values, the variances of them tend to be underestimated, leading to an overstated significance level. To address these concerns, this research compares both distributions to determine which distribution is more suitable for the city-wide collision data. The NB distribution has been introduced in the previous chapter. Thus, only Poisson distribution is described below.

$$p(Y_i = y_i) = p(y_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!} \qquad i = 1,\ 2,\ 3,\ \ldots,\ n \tag{4-1}$$

$$E(Y_i) = Var(Y_i) = \mu_i = e^{\sum_{j=1}^{k} x_{ij}\beta_j} \tag{4-2}$$

Y_i denotes the number of collisions in month $i\ (i = 1,\ 2,\ 3,\ \ldots,\ n)$ and y_i is the observed number of collisions in that month, which is assumed to follow Poisson distribution with mean μ_i. The μ_i is calculated as shown in Equation (4-2), where x_{ij} are a set of independent variables and β_j are the regression parameters to be estimated. In the model, the monthly deployment hours, number of issued tickets, and employment rate were the independent variables. It should be noted that since deployment hours and the number of issued tickets were generated from the same event, it is impossible for them to be absolutely independent of each other (e.g., increased deployment hours may be associated with increased number of issued tickets). However, the correlation coefficient between these two variables was only 0.13. As can be observed in Figure 4-3 and Figure 4-4, the deployment hours do not show clear seasonal variation and increased greatly during the study period, while the number of tickets shows an obvious seasonal pattern. Thus, it is acceptable to keep them together in the models.

Monthly dummies, employment rate, and trend variables are added to the model to account for monthly change factors, socio-economic factors, and the general trend, respectively. In addition, another dummy variable is included to account for the increase of the PDO collisions reporting threshold since 2011. The model form is shown in Equation (4-3). The parameters were estimated in SAS through the GENMOD procedure (SAS Institute Inc., 2012), which uses maximum likelihood estimation with the Newton-Raphson algorithm.

$$\begin{aligned}\ln(\mu) = {} & \beta_0 + \beta_1 \text{ Hour} + \beta_2 \text{ Tickets} + \beta_3 \text{ Employment} + \beta_4 \text{ Trend} + \beta_5 \text{ Threshold} \\ & + \beta_{6-16} \text{ MonthlyDummies}\end{aligned} \tag{4-3}$$

Where:

μ	=	predicted monthly collision frequency
Hour	=	monthly deployment hour
Tickets	=	monthly number of issued tickets
Employment	=	employment rate (%)
Trend	=	trend variable
Threshold	=	dummy variable (0 before 2011, 1 after)
$\beta_0 - \beta_{16}$	=	regression parameters

The marginal effect of one variable can be estimated by taking the partial differential of Equation (4-2). For the generalized linear model with the log link function, the marginal effect is the product of the predicted value of the dependent variable and the corresponding coefficient of the variable, as shown in Equation (4-4). The predicted number of collisions can be replaced with the data mean to obtain an overall marginal effect.

$$\frac{\partial E(y \mid x_j)}{\partial x_j} = \mu \cdot \beta_j \tag{4-4}$$

The goodness of fit of the model is measured by scaled deviance (SD) and the Pearson χ^2, which are widely used statistics for the NB and Poisson model (Ye et al., 2013). Both SD and Pearson χ^2 are asymptotically χ^2 distributed with $n-p$ degrees of freedom, where n is the number of observations and p is the number of regression parameters (Aitkin et al., 1989). The calculations of SD and Pearson χ^2 for the NB model are introduced in the previous chapter. The calculations for the Poisson model are shown in Equations (4-5) and (4-6).

$$SD = 2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{y_i}{\mu_i}\right) - \left(y_i - \mu_i\right)\right] \tag{4-5}$$

$$Pearson\chi^2 = \sum_{i=1}^{n}\frac{\left[y_i - \mu_i\right]^2}{\mu_i} \tag{4-6}$$

It has been found that these statistics may be not valid to assess the fit of the model when the mean of the data is low, which is often referred to as low sample mean problem (Wood, 2002). For example, the SD is usually too small, suggesting the goodness of fit is too good to be true, when the sample mean is low and the sample size is big. However, there is a gap in the literature on the properness of these statistics if the sample mean is very high (e.g., city-wide data). As can be observed in Equation (4-6), compared with the calculation of Pearson χ^2 for the NB model, the variance is replaced with the mean in the denominator, which is the property of Poisson distribution. However, the summary statistics of the data suggest that the variance of the data is much larger than the mean. This will result in a larger value of Pearson χ^2 for the Poisson model, which may underestimate the fit of the model.

4.3 Results and Discussions

4.3.1 Poisson versus NB Models

The SD and Pearson χ^2 of the models are shown in Table 4-2. The number of observations is 96, and the number of regression parameters is 16 for severe collision models and 17 for other models. This is because the severe collision models do not need to include the threshold variable, which is set only for models containing PDO collisions. Therefore, the degree of freedom is 80 for severe collision models and 79 for the other models. The critical values for χ^2 distribution with degrees of freedom of 80 and 79 are 101.88 and 100.75, respectively. Thus, if SD and Pearson χ^2 are smaller than these critical values, the models fit the data well. It can be seen that all the statistics of NB models are smaller than the critical values. However, the statistics of Poisson models are much larger than the critical values.

TABLE 4-2 Models' Goodness of Fit

		Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
	Degrees of freedom	80	79	79	79	79
	$\chi^2_{.05}$	101.88	100.75	100.75	100.75	100.75
All Collisions						
Poisson	Pearson χ^2	318.24	3044.40	2961.87	1870.09	1807.33
	Scaled Deviance	318.13	2970.73	2909.29	1830.57	1783.65
NB	Pearson χ^2	94.55	99.60	98.59	98.84	97.67
	Scaled Deviance	94.63	95.79	95.83	95.59	95.65
Midblock Collisions						
Poisson	Pearson χ^2	231.99	1864.03	1910.40	1278.58	1323.64
	Scaled Deviance	236.15	1811.91	1863.65	1249.88	1298.99
NB	Pearson χ^2	92.36	99.61	99.29	98.53	98.20
	Scaled Deviance	95.10	95.67	95.73	95.46	95.53

The estimation results for the regression parameters of models using all collisions and midblock collisions only are shown in Table 4-3 and Table 4-4, respectively. For the models using all collisions, most of the monthly dummies are significant (at least 90% level), except for January and November in NB models. This is reasonable because December is chosen as the baseline and these two months are close to December. Some summer and fall monthly dummies have positive signs for severe collisions, indicating more severe collisions occurred during those months. The situation is the opposite for other types of collisions. This is consistent with the data trends described in the data section.

The deployment hour variable is significant only in Poisson models, not including the severe collision model. The number of issued tickets variable is significant in Poisson models and NB models except for the severe collision model. Both of the enforcement variables have negative signs in the models, suggesting that enforcement reduced collisions, regardless of the severity and type.

The employment rate variable is significant with a positive sign in all the models except for the NB severe collision model. This means the increase in employment rate will lead to more collisions, which may be due to the increased traffic volume. The trend variable is significant in all the models, with a negative sign for severe collision models and a positive sign for the other models, which means that the number of severe collisions has a decreasing trend while that of PDO collisions has an increasing trend. The police reporting threshold variable is found to be highly significant in all the models, which is intuitive because the raised threshold should have an immediate impact on the number of recorded collisions.

The estimation results of the models using midblock collisions only are very similar to those of the models using all collisions. The November dummy variable becomes significant in all the models, indicating the midblock collisions are less sensitive to the adverse effects of snow and ice than intersection collisions (i.e., the number of midblock collisions is still significantly less in November than in December). The number of issued tickets variable is significant in all the models except for the NB severe collision model. However, the deployment hour variable is still not significant in either the NB model or the Poisson severe collision model.

TABLE 4-3 Parameter Estimates Results for Models Using All Collisions

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Hour	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	5.835	-0.107	-0.225	-0.097	-0.253	-0.097	-0.037	-0.055	0.022	0.098	0.067	-0.057	-0.001	-0.027	0.008	-0.008	NA	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.001	0.217	0.076	0.493	0.001	0.017	0.033	0.896	0.077	0.050	0.000	NA	NA
	NB	Estimate	5.631	-0.106	-0.215	-0.092	-0.253	-0.102	-0.032	-0.051	0.026	0.104	0.068	-0.057	0.009	-0.023	0.011	-0.008	NA	0.006
		P Value	0.000	0.023	0.000	0.060	0.000	0.061	0.553	0.365	0.662	0.045	0.188	0.237	0.667	0.393	0.143	0.000	NA	0.000
PDO Collision	Poisson	Estimate	5.751	-0.032	-0.210	-0.155	-0.428	-0.408	-0.365	-0.384	-0.375	-0.316	-0.241	-0.079	-0.027	-0.124	0.029	0.007	-0.449	NA
		P Value	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.039	-0.019	-0.209	-0.159	-0.440	-0.421	-0.376	-0.398	-0.387	-0.322	-0.248	-0.084	-0.037	-0.103	0.024	0.007	-0.428	0.015
		P Value	0.000	0.766	0.001	0.020	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.197	0.319	0.016	0.052	0.000	0.000	0.000
Total Collision	Poisson	Estimate	6.335	-0.050	-0.219	-0.154	-0.407	-0.359	-0.313	-0.331	-0.308	-0.247	-0.193	-0.079	-0.020	-0.107	0.024	0.004	-0.364	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.596	-0.039	-0.217	-0.156	-0.415	-0.369	-0.321	-0.341	-0.318	-0.251	-0.198	-0.083	-0.028	-0.090	0.020	0.004	-0.343	0.012
		P Value	0.000	0.497	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.159	0.409	0.019	0.078	0.000	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	5.146	-0.042	-0.213	-0.122	-0.390	-0.379	-0.353	-0.370	-0.337	-0.306	-0.258	-0.103	-0.025	-0.122	0.030	0.008	-0.570	NA
		P Value	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.567	-0.025	-0.207	-0.124	-0.397	-0.388	-0.357	-0.378	-0.343	-0.308	-0.260	-0.104	-0.040	-0.103	0.023	0.008	-0.542	0.015
		P Value	0.000	0.694	0.002	0.074	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.116	0.299	0.017	0.066	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	6.050	-0.065	-0.225	-0.127	-0.367	-0.316	-0.278	-0.296	-0.249	-0.206	-0.182	-0.097	-0.015	-0.097	0.022	0.004	-0.417	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.044	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.350	-0.054	-0.220	-0.126	-0.370	-0.320	-0.281	-0.300	-0.254	-0.207	-0.183	-0.098	-0.024	-0.084	0.018	0.004	-0.394	0.011
		P Value	0.000	0.325	0.000	0.033	0.000	0.000	0.000	0.000	0.001	0.001	0.004	0.083	0.458	0.022	0.101	0.000	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

TABLE 4-4 Parameter Estimates Results for Models Using Midblock Collisions Only

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Hour	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	4.117	-0.167	-0.341	-0.104	-0.269	-0.071	-0.002	0.014	0.058	0.065	0.020	-0.132	-0.011	-0.059	0.018	-0.009	NA	NA
		P Value	0.000	0.000	0.000	0.030	0.000	0.188	0.970	0.806	0.322	0.203	0.704	0.007	0.577	0.034	0.025	0.000	NA	NA
	NB	Estimate	3.975	-0.178	-0.344	-0.117	-0.276	-0.088	-0.002	0.010	0.058	0.062	0.015	-0.141	-0.001	-0.057	0.020	-0.009	NA	0.013
		P Value	0.000	0.015	0.000	0.129	0.001	0.303	0.980	0.914	0.532	0.448	0.857	0.065	0.970	0.182	0.104	0.000	NA	0.000
PDO Collision	Poisson	Estimate	4.438	-0.064	-0.285	-0.131	-0.460	-0.435	-0.381	-0.421	-0.391	-0.385	-0.279	-0.127	-0.049	-0.115	0.037	0.006	-0.411	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.606	-0.043	-0.278	-0.134	-0.475	-0.448	-0.394	-0.438	-0.405	-0.389	-0.285	-0.130	-0.059	-0.091	0.034	0.006	-0.394	0.022
		P Value	0.000	0.576	0.000	0.105	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.099	0.198	0.076	0.024	0.000	0.000	0.000
Total Collision	Poisson	Estimate	4.888	-0.081	-0.297	-0.134	-0.442	-0.391	-0.335	-0.365	-0.333	-0.328	-0.244	-0.130	-0.043	-0.107	0.033	0.004	-0.349	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.085	-0.061	-0.292	-0.136	-0.453	-0.402	-0.346	-0.379	-0.345	-0.330	-0.249	-0.132	-0.053	-0.086	0.030	0.004	-0.329	0.019
		P Value	0.000	0.402	0.000	0.082	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.078	0.223	0.078	0.037	0.001	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	3.878	-0.101	-0.305	-0.131	-0.464	-0.443	-0.398	-0.423	-0.373	-0.376	-0.299	-0.170	-0.046	-0.120	0.040	0.005	-0.480	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.183	-0.079	-0.297	-0.136	-0.475	-0.453	-0.407	-0.438	-0.386	-0.377	-0.304	-0.171	-0.056	-0.097	0.035	0.006	-0.457	0.022
		P Value	0.000	0.306	0.000	0.106	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.034	0.230	0.064	0.024	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	4.531	-0.118	-0.318	-0.135	-0.438	-0.379	-0.329	-0.345	-0.296	-0.298	-0.247	-0.168	-0.038	-0.107	0.034	0.003	-0.382	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.810	-0.098	-0.312	-0.138	-0.443	-0.386	-0.336	-0.354	-0.306	-0.297	-0.250	-0.167	-0.048	-0.089	0.030	0.003	-0.358	0.019
		P Value	0.000	0.169	0.000	0.076	0.000	0.000	0.000	0.000	0.002	0.001	0.003	0.025	0.269	0.066	0.037	0.017	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

So far, the following can be concluded (PDO collisions are used to generally represent all the severities/types of collisions except for severe collisions):

- More severe collisions occur in summer months, while more PDO collisions occur in winter months;
- There is an increasing trend for PDO collisions and a decreasing trend for severe collisions;
- The number of issued tickets has an inverse relationship with the number of PDO collisions; and
- The employment rate has a positive relationship with the number of PDO collisions.

The question here is whether the number of deployment hours can influence the number of collisions or not. Although the estimates of the Poisson and NB models are close to each other, the deployment hour variable is highly significant in Poisson models but insignificant in NB models. It has been found that the highly significant parameters in the Poisson model may be caused by the underestimated variance, which is also the reason for the huge differences in goodness of fit statistics between the two models.

The R^2 is chosen as a supplementary index to compare the goodness of fit of the two models. One of the merits of using R^2 is that the calculation is not related to the distribution of models as shown in Equation (4-7). Models with higher R^2 value are considered to be able to better describe the data.

$$R^2 = 1 - \frac{\sum (y_i - \mu_i)^2}{\sum (y_i - \bar{y})^2} \tag{4-7}$$

where y_i is the observed number of collisions in month i; μ_i is the predicted number of collisions in that month; and $\bar{y}$ is the average of the observed numbers of collisions in the study period. The values of R^2 are presented in Table 4-5.

TABLE 4-5 Comparison of R^2 between Poisson and NB Models

	Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
All Collisions					
Poisson	0.850	0.762	0.732	0.770	0.728
NB	0.847	0.759	0.729	0.766	0.725
Midblock Collisions					
Poisson	0.749	0.665	0.640	0.686	0.636
NB	0.742	0.679	0.638	0.668	0.619

It can be observed that the R^2 of the models using all collisions are better than the models using midblock collisions only. As for the type of collisions, severe collision models have the highest R^2. This may be due to less variation in severe collisions than other types of collisions. The value of R^2 is likely to be related to the homogeneity of the data, which explains why R^2 of the total collision models are lower than either severe collision models or PDO collision models.

The differences in R^2 between Poisson and NB models are marginal. Poisson models have slightly higher R^2 than NB models, except for the PDO collision model using midblock collisions only. The results indicate that both models have similar and satisfying goodness of fit. To better illustrate the preciseness of the models, the models with the highest R^2 value (the Poisson severe collision model using all collisions) and the lowest R^2 value (NB speed-related collision model using midblock collisions only) are plotted against the observed data in Figure 4-6 and Figure 4-7, respectively.

Since R^2 values suggest both models can describe the data relatively well, it is clear that the unreasonably high values of the goodness of fit statistics of Poisson models are caused by the specifications of formulas. Although the significance of the deployment hour variable is not determined, it can be interpreted that the number of deployment hours does have some influences on collision reduction, but it is not as significant as that of the issued tickets.

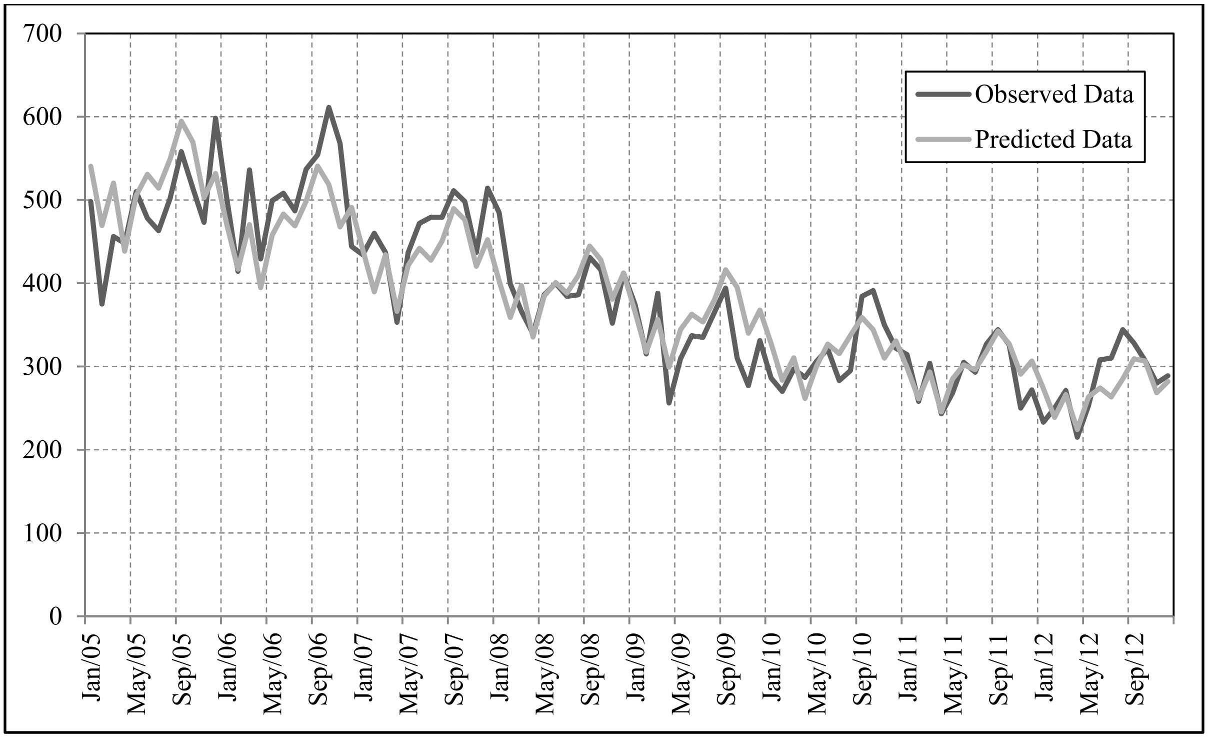

FIGURE 4-6 Poisson Severe Collision Model Using All Collisions

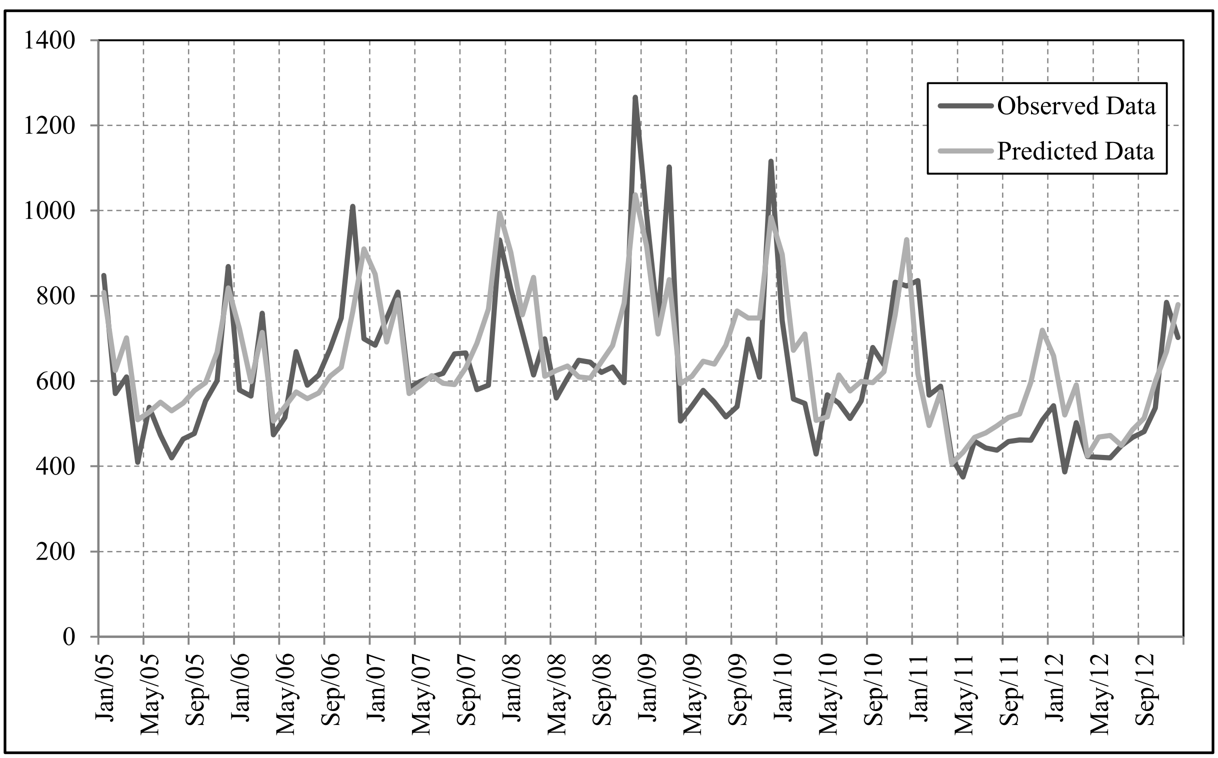

FIGURE 4-7 NB Speed-Related Collision Model Using Midblock Collisions Only

4.3.2 Marginal Effects of Enforcement Variables

The marginal effect is the expected change of the dependent variable (number of collisions) as a function of the change in a certain explanatory variable while keeping all the other variables constant. As described in the methodology section, the marginal effect of one variable in the model with the Log-link function can be calculated as the product of the predicted number of collisions and the estimated parameter of that variable. Thus, the magnitude of the parameter can be regarded as the reduction ratio. Usually, the mean of the observed numbers of collisions is used to replace the predicted number of collisions to obtain the overall marginal effect of one variable. Since the estimation results for parameters of the Poisson and NB models are close to each other, the calculations are based on the estimation results for Poisson models. The marginal effects of increasing 1,000 deployment hours and 10,000 issued tickets are shown in Table 4-6.

TABLE 4-6 Marginal Effects of Enforcement Variables

	Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
All Collisions					
1,000 Hour	-1	-49	-44	-27	-22
10,000 Tickets	-10	-223	-234	-133	-144
Midblock Collisions					
1,000 Hour	-1	-37	-37	-23	-23
10,000 Tickets	-7	-86	-93	-60	-66

4.3.3 Threshold for Deployment Hours

In the previous subsection, the deployment hour variable is found to be significant in Poisson models (except for the severe collision model) but insignificant in NB models. Thus, the deployment hour variable is not as significant as the number of issued tickets, employment rate, trend, and threshold variables. The deployment hour variable represents the general deterrence of the enforcement program. Compared with specific deterrence generated by issuing speed tickets, the general deterrence is believed to be more temporary and has less spillover effect. If a driver only witnessed enforcement at a specific site but has never been issued any tickets, he or she may commit speeding when there is no enforcement in sight or speed up after passing the site. However, if the driver was issued a ticket, especially when being unaware of the enforcement, he or she is very likely to recall the unpleasant experience each time at the same location for a period of time. The fear of being punished again makes the driver control his or her speed.

The scenarios above explain why speed tickets are more significant than the presence of enforcement itself in reducing city-wide collisions. However, there should be a considerable amount of more self-disciplined drivers who are willing to modify their behaviours as long as the general deterrence is sufficiently strong. Although the threshold for general deterrence to modify behaviour varies among different individuals, it is assumed that there exists a certain threshold for deployment hours to have a significant impact on city-wide collisions. The threshold assumption can be proved with logical extremes: no significant effects when deployment hours approach none but highly significant effects when enforcement is everywhere at any time.

The deployment hour variable is replaced with a deployment dummy variable to indicate whether deployment hours in one month reached a certain value of deployment hours or not. Although a higher value is more likely to result in significant estimation, it is hoped that the value can be as close to the actual threshold as possible to serve as a minimum requirement for deployment. The median of monthly deployment hour data is chosen as the value. According to the data, the median is around 1,500 hours and several months before the huge increase at the end of 2009 reached this value.

It was found that the goodness of fit statistics for all the models except for the NB severe collision models reduced. This means that, in general, the replacement of the deployment hour variable with the deployment dummy variable increases the goodness of fit of the models. The exact reduction values are shown in Table 4-7.

TABLE 4-7 Reduction of Models' Goodness of Fit Statistics

		Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
All Collisions						
Poisson	Pearson χ^2	12.35	126.68	117.97	82.35	74.96
	Scaled Deviance	11.05	102.32	97.03	67.32	62.39
NB	Pearson χ^2	-0.20	1.16	1.07	1.19	1.10
	Scaled Deviance	-0.68	0.01	0.01	0.03	0.03
Midblock Collisions						
Poisson	Pearson χ^2	0.84	40.79	35.39	39.50	32.92
	Scaled Deviance	0.77	31.76	27.42	32.75	27.14
NB	Pearson χ^2	-0.29	0.81	0.72	0.91	0.75
	Scaled Deviance	-0.28	0.04	0.03	0.10	0.07

The estimation results for the regression parameters of models using all collisions and midblock collisions only are shown in Table 4-8 and Table 4-9, respectively. It can be observed that the deployment dummy variable is significant in all the models except for severe collision models. Although the employment rate variable became insignificant in NB models using all collisions, it remained significant in most of the models using midblock collisions only. In general, the estimation of each parameter does not change much due to the replacement.

Next, the threshold value was changed to 1,400 hours and 1,600 hours (please see Appendix B for the estimation results). Their models' goodness of fit statistics and parameters' significance were compared with those of the 1,500 hour models. In the 1,400 hour models, most of the goodness of fit statistics increased, and the deployment dummy variable is insignificant in NB models. In the 1,600 hour models, most of the goodness of fit statistics also increased, and the deployment dummy variable was significant in Poisson models and NB models using midblock collisions only. In addition, the deployment dummy variable became highly significant in severe collision models. The results indicate 1,500 hours is the closest value to the actual threshold. This is because a lower or higher than actual value will either include "ineffective" months or exclude "effective" months, thus diminishing the models' goodness of fit and parameters' significance. However, the significant deployment dummy variable in severe collision models when the value is 1,600 hours may suggest that more deployment hours are needed in order to have a significant impact on severe collision reductions.

TABLE 4-8 Parameter Estimates Results for Models Using All Collisions (Dummy Deployment Variable)

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Deployment	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	6.276	-0.090	-0.225	-0.084	-0.250	-0.102	-0.041	-0.052	0.037	0.100	0.069	-0.049	-0.048	-0.026	0.002	-0.008	NA	NA
		P Value	0.000	0.001	0.000	0.002	0.000	0.001	0.165	0.092	0.249	0.000	0.014	0.064	0.000	0.085	0.674	0.000	NA	NA
	NB	Estimate	6.087	-0.093	-0.216	-0.082	-0.250	-0.102	-0.033	-0.048	0.039	0.106	0.071	-0.052	-0.039	-0.023	0.005	-0.008	NA	0.006
		P Value	0.000	0.045	0.000	0.089	0.000	0.055	0.533	0.386	0.503	0.039	0.164	0.275	0.123	0.382	0.565	0.000	NA	0.000
PDO Collision	Poisson	Estimate	6.411	-0.017	-0.214	-0.153	-0.439	-0.430	-0.385	-0.397	-0.373	-0.327	-0.254	-0.076	-0.083	-0.117	0.019	0.007	-0.425	NA
		P Value	0.000	0.095	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.499	-0.005	-0.212	-0.154	-0.448	-0.442	-0.394	-0.406	-0.379	-0.329	-0.258	-0.080	-0.081	-0.098	0.017	0.007	-0.414	0.015
		P Value	0.000	0.935	0.001	0.021	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.211	0.040	0.015	0.159	0.000	0.000	0.000
Total Collision	Poisson	Estimate	6.934	-0.036	-0.224	-0.152	-0.417	-0.380	-0.332	-0.344	-0.306	-0.257	-0.205	-0.076	-0.071	-0.099	0.015	0.004	-0.339	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	7.063	-0.027	-0.221	-0.153	-0.423	-0.389	-0.338	-0.351	-0.312	-0.259	-0.209	-0.080	-0.071	-0.085	0.013	0.004	-0.326	0.012
		P Value	0.000	0.634	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.166	0.048	0.020	0.245	0.000	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	5.875	-0.027	-0.219	-0.121	-0.403	-0.405	-0.375	-0.386	-0.337	-0.319	-0.273	-0.101	-0.086	-0.113	0.019	0.008	-0.542	NA
		P Value	0.000	0.042	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.102	-0.010	-0.211	-0.120	-0.406	-0.412	-0.378	-0.389	-0.335	-0.317	-0.273	-0.100	-0.090	-0.097	0.015	0.008	-0.525	0.015
		P Value	0.000	0.875	0.001	0.076	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.123	0.025	0.017	0.220	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	6.682	-0.052	-0.231	-0.126	-0.378	-0.338	-0.298	-0.310	-0.250	-0.218	-0.194	-0.096	-0.067	-0.088	0.013	0.004	-0.388	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.872	-0.042	-0.225	-0.124	-0.379	-0.341	-0.299	-0.310	-0.250	-0.216	-0.194	-0.096	-0.070	-0.078	0.010	0.004	-0.373	0.011
		P Value	0.000	0.437	0.000	0.031	0.000	0.000	0.000	0.000	0.001	0.001	0.002	0.084	0.039	0.026	0.348	0.000	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

TABLE 4-9 Parameter Estimates Results for Models Using Midblock Collisions Only (Dummy Deployment Variable)

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Deployment	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	4.350	-0.156	-0.342	-0.096	-0.268	-0.076	-0.007	0.015	0.068	0.067	0.020	-0.127	-0.036	-0.059	0.014	-0.009	NA	NA
		P Value	0.000	0.001	0.000	0.048	0.000	0.155	0.900	0.790	0.248	0.193	0.701	0.010	0.131	0.035	0.082	0.000	NA	NA
	NB	Estimate	4.205	-0.170	-0.344	-0.111	-0.275	-0.091	-0.004	0.010	0.065	0.062	0.015	-0.138	-0.025	-0.057	0.016	-0.009	NA	0.012
		P Value	0.000	0.022	0.000	0.149	0.001	0.287	0.959	0.909	0.484	0.445	0.854	0.071	0.525	0.182	0.195	0.000	NA	0.000
PDO Collision	Poisson	Estimate	4.812	-0.047	-0.285	-0.123	-0.462	-0.451	-0.393	-0.424	-0.378	-0.386	-0.285	-0.118	-0.086	-0.117	0.031	0.005	-0.414	NA
		P Value	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.903	-0.026	-0.280	-0.125	-0.478	-0.468	-0.410	-0.443	-0.390	-0.393	-0.294	-0.122	-0.094	-0.092	0.029	0.005	-0.399	0.021
		P Value	0.000	0.733	0.000	0.124	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.117	0.051	0.062	0.049	0.000	0.000	0.000
Total Collision	Poisson	Estimate	5.191	-0.065	-0.297	-0.126	-0.443	-0.404	-0.345	-0.367	-0.320	-0.327	-0.249	-0.122	-0.074	-0.108	0.028	0.003	-0.352	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.342	-0.046	-0.293	-0.128	-0.455	-0.419	-0.360	-0.383	-0.332	-0.333	-0.258	-0.124	-0.083	-0.087	0.026	0.003	-0.334	0.019
		P Value	0.000	0.527	0.000	0.096	0.000	0.000	0.000	0.000	0.001	0.000	0.002	0.093	0.068	0.063	0.067	0.001	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	4.435	-0.082	-0.308	-0.124	-0.471	-0.464	-0.416	-0.431	-0.362	-0.381	-0.309	-0.163	-0.096	-0.118	0.031	0.005	-0.471	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.689	-0.060	-0.301	-0.128	-0.482	-0.479	-0.429	-0.448	-0.373	-0.387	-0.317	-0.163	-0.108	-0.094	0.027	0.005	-0.449	0.021
		P Value	0.000	0.435	0.000	0.118	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.039	0.027	0.060	0.073	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	4.960	-0.101	-0.320	-0.128	-0.442	-0.396	-0.344	-0.350	-0.286	-0.301	-0.254	-0.161	-0.078	-0.106	0.027	0.002	-0.375	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.213	-0.082	-0.316	-0.131	-0.449	-0.408	-0.354	-0.363	-0.294	-0.304	-0.261	-0.160	-0.089	-0.087	0.023	0.002	-0.353	0.018
		P Value	0.000	0.247	0.000	0.084	0.000	0.000	0.000	0.000	0.002	0.000	0.001	0.029	0.048	0.060	0.094	0.011	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

5 CONCLUSIONS AND FUTURE RESEARCH

5.1 Concluding Remarks

In the segment-based analysis, a before-and-after evaluation with the Empirical Bayes method was used to examine the safety effects of automated mobile speed enforcement on urban arterial road segments. Local safety performance functions and yearly calibration factors for different severities/types of collisions were developed to increase the accuracy of the predicted number of collisions. Significant reductions were found for all severities/types of collisions with the highest reduction occurring in severe collisions, followed by speed-related collisions. The reductions ranged from 14% to 20%, which is consistent with previous research findings. The evaluation based on site selection criteria and deployment hours suggests that segments with higher collision frequencies/rates and longer deployment hours are likely to experience greater collision reductions. The comparison between continuously and discontinuously enforced segments revealed that the former experienced larger reductions in all severities/types of collisions. Finally, there were no spillover effects upstream or downstream of the enforced segments. However, there was a spillover effect on adjacent unenforced segments. Adjacent unenforced segments showed statistically significant reductions for PDO, total, and speed-related PDO collisions.

In the city-wide analysis, the relationship between enforcement variables and monthly collisions is examined using the generalized linear models, while accounting for seasonal and socio-economic factors, general trend, and changes in the police reporting threshold. Poisson and negative binomial (NB) models were compared, and it was found that the number of issued tickets variable is significant in both models, while the deployment hour variable is significant only in Poisson models. Although the estimation results are similar for the two models, the goodness of fit statistics of Poisson models are much larger than those of NB models, which is due to the underestimation of variance in Poisson models. The R^2 of the models are calculated to be within the range of 0.62 and 0.85, indicating that all the models fit the data relatively well. The marginal effects of increasing 1,000 deployment hours and 10,000 issued tickets in terms of reduced total collisions were estimated to be 44 and 234, respectively. The deployment dummy variable was found to be significant when 1,500 hours was selected as the minimum monthly deployment length.

To compare the safety effects of enforcement at these two levels, average monthly collisions, deployment hours and issued tickets are used to estimate the overall city-wide collision reduction percentages (please see Appendix C, Table C-1). It is found that the range of the city-wide midblock collision reductions is from 10% to 25%, which is comparable to that of the segment-based midblock collisions reductions. However, the city-wide severe collision reduction is much smaller than the segment-based one, which is similar to the results of the spillover effects on unenforced adjacent segments. In fact, the city-wide reductions can be seen as the outcomes of the mixed impacts of enforcement and its spillover effects. It can be concluded that the spillover effect of severe collision is much lower than other severities/types of collisions.

The effects of general deterrence and specific deterrence, as the fundamentals of the enforcement mechanism, deserve to be reviewed at this point. As mentioned in the spillover effect evaluation (Subsection 3.3.4), the reductions in severe collisions and speed-related collisions are likely to be caused by the specific deterrence while the reduction in PDO collisions is likely to be caused by the general deterrence. When the unit of analysis is an enforced segment, the specific and general deterrence can be simply represented by the issued tickets and presence of enforcement, respectively. However, when the analysis target is a city, the general deterrence, which refers to the deterrent effect with indirect experiences, can also be expressed as the number of issued tickets. This is because people share their experience of being punished with others, which may modify other peoples' behaviours. The marginal effects of the deployment hours and issued tickets shed light on their percentages in reducing collisions (please see Appendix C, Figures C-1 and C-2). It is found that more than 60% of the city-wide midblock collisions and more than 75% of the city-wide all collisions were reduced due to the issued tickets. Although the spillover effect of severe collisions is low among other severities/types of collisions, more than 80% percent of reduced city-wide severe collisions were due to the issued ticket. Once again, this confirms the effectiveness of issuing speed tickets on severe collision reduction.

The enforcement mechanism model in Subsection 2.1.2 illustrates how enforcement can improve drivers' compliance to traffic law. The results from this research confirm the model yet bring more clues on the links between the enforcement variables, deterrence effects, and collision reductions. Thus, a modified enforcement model is shown in Figure 5-1.There are two types of links in the figure. The solid lines represent the links that are substantial at both city-wide level and segment level. The dash lines represent the links that are weak at segment level. The link between issued tickets and general deterrence is weak because that the possibility for someone to hear others were punished on specific road segments he/she usually drives on is low. The link between general deterrence and enforced segments is weak due to the fact that it is difficult for drivers to observe enforcement vehicles on enforced segments. The link between specific deterrence and unenforced segments is complex since the effects on different severities/types of collisions are inconsistent and may need further investigation.

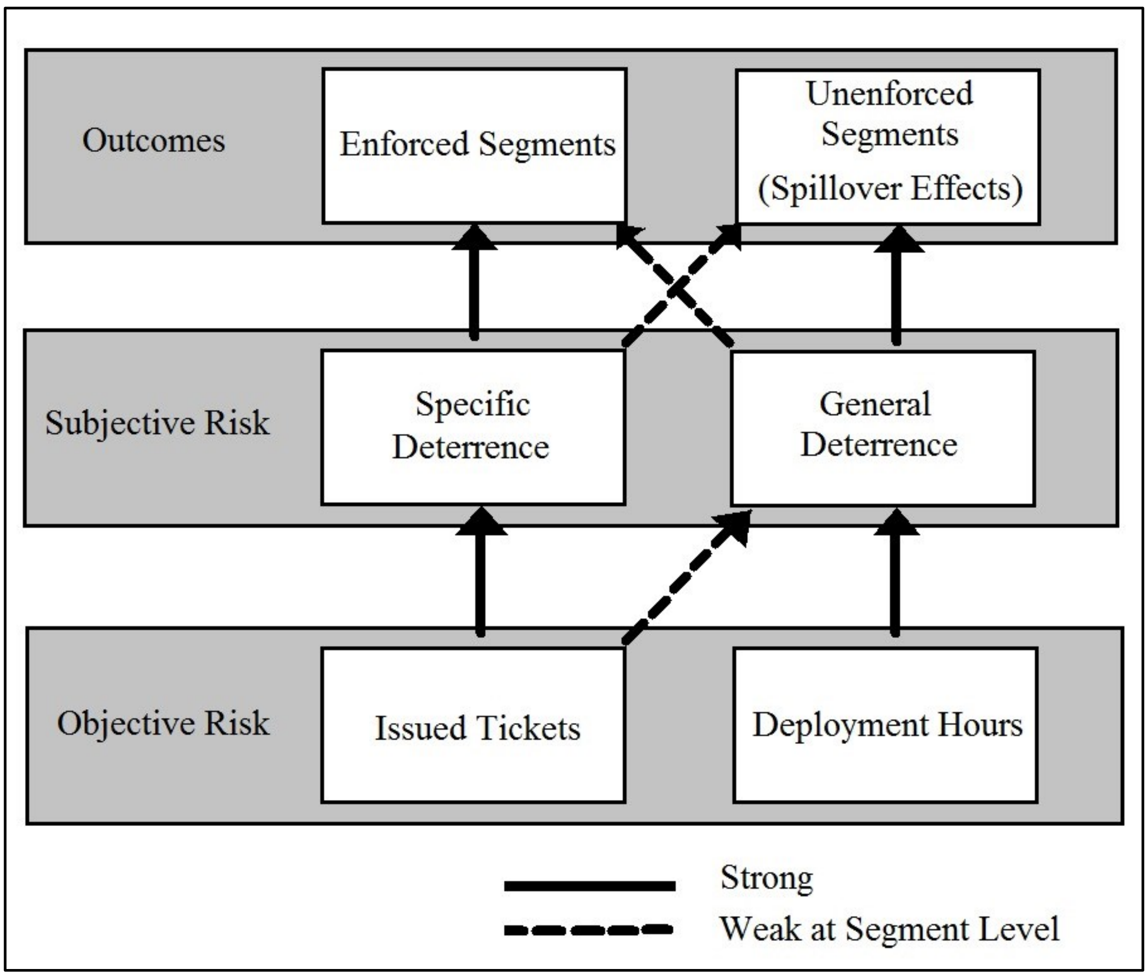

FIGURE 5-1 Modified Enforcement Model

In summary, the primary findings in this thesis are listed below:

- There is a 20% reduction in midblock severe collisions and a 15% reduction in midblock total collisions on enforced segments;
- The spillover effects of enforcement are validated on adjacent unenforced segments with a 15% reduction in midblock PDO collisions;
- The minimum deployment hours to make significant reduction effects on city-wide collisions is estimated to be around 1,500 hours; and
- Issued speed tickets are estimated to be responsible for 78% of total collision reduction and 87% of severe collision reduction at city-wide level.

Finally, there are several limitations in this research. One limitation of the segment-based evaluation is that the deployment data before January 2005 is not available. Therefore, it is not possible to be absolutely certain that the evaluated segments had never been enforced prior to the study period. However, the possibility for one segment to have a two-year gap between enforcement periods is low. More importantly, the evaluation results would have been underestimated if there had been any enforcement prior to the study period. The evaluation also excludes the segments that were enforced throughout the entire study period or had a before period of only one year. Thus, the estimated reductions may not be able to represent all enforced segments. As for the city-wide evaluation, although the models are developed to account for as many factors that may influence collision frequency as possible, they are not able to take other enforcement programs and engineering treatments (if there were any) into considerations. However, the effects of these events should be much less than this program at the city-wide level.

5.2 Future Research

This thesis validates the safety effects of automated mobile enforcement at both the segment level and city-wide level. Further research may focus on the following topics:

- Speed effects of enforcement and their relationship with safety effects;
- Safety effects of enforcement on collector roads and local roads;
- Establishing enforcement effectiveness models to explain the relationship between the magnitude of collision reduction and site characteristics;

- Investigating the relationship between other deployment variables (e.g., number of enforcement trips, number of enforced sites) and city-wide collisions; and
- Drivers' attitude towards automated mobile speed enforcement with regards to their demographic characteristics.

All these topics add to the knowledge of automated mobile speed enforcement and will improve the effectiveness and efficiency of future enforcement programs.

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APPENDIX A: Posterior Distribution Derivation Using Collision Frequency

The Poisson distribution of Y given θ is

$$p(Y \mid \theta) = \theta^{Y} e^{-\theta} / Y! \tag{A-1}$$

The prior gamma distribution of θ is

$$p(\theta) = e^{-\theta\beta}\theta^{\alpha-1}\beta^{\alpha} / \Gamma(\alpha) \tag{A-2}$$

Where α is the shape parameter and β is the reciprocal of the scale parameter. $E\{\theta\} = \dfrac{\alpha}{\beta}$,

$Var\{\theta\} = \dfrac{\alpha}{\beta^2}$. The joint distribution of Y and θ is

$$p(Y,\theta) = p(Y \mid \theta)p(\theta) = \frac{\theta^{Y} e^{-\theta}}{Y!}\frac{e^{-\theta\beta}\theta^{\alpha-1}\beta^{\alpha}}{\Gamma(\alpha)} = \frac{e^{-\theta(\beta+1)}\theta^{\alpha+Y-1}\beta^{\alpha}}{Y!\Gamma(\alpha)} \tag{A-3}$$

The marginal distribution of Y is

$$p(Y) = \int_0^\infty p(Y,\theta)d\theta = \frac{\beta^{\alpha}}{Y!\Gamma(\alpha)}\int_0^\infty e^{-\theta(\beta+1)}\theta^{\alpha+Y-1}d\theta = \frac{\beta^{\alpha}}{Y!\Gamma(\alpha)}\frac{\Gamma(\alpha+Y)}{(\beta+1)^{\alpha+Y}} \tag{A-4}$$

Which is a negative binomial distribution. The posterior distribution of θ given Y is

$$p(\theta \mid Y) = \frac{p(Y \mid \theta)p(\theta)}{p(Y)} = \frac{p(Y,\theta)}{\int_0^\infty p(Y,\theta)d\theta} = \frac{e^{-\theta(\beta+1)}\theta^{\alpha+Y-1}\beta^{\alpha}}{Y!\Gamma(\alpha)} \Bigg/ \frac{\beta^{\alpha}\Gamma(Y+\alpha)}{Y!\Gamma(\alpha)(\beta+1)^{Y+\alpha}} = \frac{e^{-\theta(\beta+1)}\theta^{\alpha+Y-1}(\beta+1)^{Y+\alpha}}{\Gamma(Y+\alpha)} \tag{A-5}$$

Which is a gamma distribution where $(\alpha+Y)$ is the shape parameter and $(\beta+1)$ is the reciprocal of the scale parameter. The Empirical Bayes (EB) estimate is the posterior mean

$$EB = (\alpha+Y)/(\beta+1) = \frac{\beta}{(\beta+1)}(\alpha/\beta) + \frac{1}{(\beta+1)}(Y) \tag{A-6}$$

Which is a weighted average of the prior mean (α/β) and the observed number of collisions Y.

Estimation of parameters α and β:

Maximum Likelihood Estimators (MLEs) obtained using PROC GENMOD in SAS.

APPENDIX B: Estimation Results for Deployment Dummy Variable Models

TABLE B-1 Parameter Estimates Results for Models Using All Collisions (1,400 Hours)

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Deployment	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	6.097	-0.099	-0.232	-0.098	-0.261	-0.093	-0.037	-0.057	0.019	0.093	0.067	-0.056	-0.030	-0.021	0.005	-0.008	NA	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.002	0.208	0.068	0.552	0.001	0.017	0.035	0.017	0.171	0.291	0.000	NA	NA
	NB	Estimate	5.943	-0.099	-0.221	-0.092	-0.258	-0.097	-0.031	-0.051	0.026	0.101	0.070	-0.056	-0.025	-0.019	0.007	-0.008	NA	0.006
		P Value	0.000	0.033	0.000	0.058	0.000	0.073	0.564	0.362	0.660	0.051	0.174	0.239	0.292	0.479	0.382	0.000	NA	0.000
PDO Collision	Poisson	Estimate	6.075	-0.021	-0.223	-0.167	-0.452	-0.412	-0.375	-0.396	-0.392	-0.330	-0.250	-0.079	-0.062	-0.109	0.024	0.007	-0.440	NA
		P Value	0.000	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.132	-0.012	-0.219	-0.166	-0.457	-0.421	-0.380	-0.403	-0.397	-0.331	-0.252	-0.085	-0.055	-0.095	0.023	0.007	-0.433	0.015
		P Value	0.000	0.853	0.001	0.015	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.193	0.140	0.024	0.052	0.000	0.000	0.000
Total Collision	Poisson	Estimate	6.603	-0.041	-0.230	-0.163	-0.426	-0.363	-0.321	-0.341	-0.321	-0.259	-0.201	-0.080	-0.048	-0.095	0.020	0.004	-0.355	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.708	-0.033	-0.226	-0.162	-0.430	-0.370	-0.325	-0.346	-0.326	-0.259	-0.202	-0.084	-0.045	-0.084	0.018	0.004	-0.345	0.012
		P Value	0.000	0.562	0.000	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.155	0.184	0.029	0.086	0.000	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	5.437	-0.032	-0.226	-0.133	-0.412	-0.383	-0.361	-0.381	-0.353	-0.318	-0.267	-0.103	-0.057	-0.109	0.025	0.008	-0.563	NA
		P Value	0.000	0.017	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.597	-0.018	-0.216	-0.131	-0.412	-0.388	-0.359	-0.381	-0.351	-0.315	-0.264	-0.104	-0.052	-0.098	0.023	0.008	-0.552	0.015
		P Value	0.000	0.773	0.001	0.060	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.115	0.171	0.023	0.057	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	6.289	-0.058	-0.235	-0.135	-0.383	-0.319	-0.285	-0.305	-0.261	-0.216	-0.188	-0.098	-0.039	-0.087	0.019	0.003	-0.408	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	6.447	-0.049	-0.228	-0.132	-0.382	-0.321	-0.284	-0.304	-0.261	-0.214	-0.187	-0.098	-0.038	-0.079	0.016	0.003	-0.396	0.011
		P Value	0.000	0.370	0.000	0.026	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.080	0.236	0.032	0.110	0.000	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

TABLE B-2 Parameter Estimates Results for Models Using Midblock Collisions Only (1,400 Hours)

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Deployment	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	4.087	-0.167	-0.344	-0.107	-0.273	-0.072	-0.004	0.012	0.055	0.063	0.018	-0.132	-0.009	-0.058	0.018	-0.009	NA	NA
		P Value	0.000	0.000	0.000	0.027	0.000	0.181	0.947	0.829	0.345	0.216	0.726	0.007	0.714	0.041	0.025	0.000	NA	NA
	NB	Estimate	3.975	-0.177	-0.344	-0.117	-0.277	-0.088	-0.002	0.009	0.057	0.062	0.015	-0.141	-0.001	-0.057	0.020	-0.009	NA	0.013
		P Value	0.000	0.016	0.000	0.127	0.001	0.301	0.978	0.915	0.534	0.451	0.859	0.065	0.973	0.188	0.110	0.000	NA	0.000
PDO Collision	Poisson	Estimate	4.013	-0.057	-0.281	-0.125	-0.454	-0.422	-0.369	-0.407	-0.380	-0.372	-0.271	-0.118	-0.024	-0.126	0.042	0.005	-0.459	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.089	-0.037	-0.276	-0.130	-0.471	-0.438	-0.384	-0.425	-0.396	-0.381	-0.279	-0.123	-0.029	-0.102	0.041	0.005	-0.445	0.022
		P Value	0.000	0.627	0.001	0.121	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.120	0.530	0.049	0.004	0.000	0.000	0.000
Total Collision	Poisson	Estimate	4.436	-0.075	-0.291	-0.128	-0.433	-0.378	-0.322	-0.350	-0.320	-0.314	-0.235	-0.121	-0.014	-0.119	0.039	0.003	-0.396	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.161	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.562	-0.056	-0.287	-0.131	-0.446	-0.391	-0.334	-0.365	-0.334	-0.320	-0.243	-0.125	-0.021	-0.098	0.037	0.003	-0.379	0.020
		P Value	0.000	0.441	0.000	0.099	0.000	0.000	0.000	0.000	0.001	0.000	0.004	0.097	0.635	0.046	0.006	0.002	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	3.573	-0.093	-0.304	-0.128	-0.463	-0.432	-0.390	-0.412	-0.365	-0.367	-0.293	-0.162	-0.030	-0.127	0.044	0.005	-0.518	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.023	0.000	0.000	0.000	0.000	NA
	NB	Estimate	3.828	-0.073	-0.299	-0.136	-0.477	-0.446	-0.400	-0.429	-0.382	-0.375	-0.301	-0.166	-0.039	-0.103	0.040	0.005	-0.497	0.022
		P Value	0.000	0.351	0.000	0.110	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.039	0.398	0.050	0.007	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	4.178	-0.113	-0.315	-0.131	-0.432	-0.368	-0.319	-0.333	-0.286	-0.287	-0.240	-0.161	-0.017	-0.117	0.039	0.002	-0.420	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.157	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.424	-0.094	-0.311	-0.135	-0.441	-0.378	-0.328	-0.344	-0.299	-0.292	-0.246	-0.161	-0.026	-0.098	0.035	0.002	-0.398	0.019
		P Value	0.000	0.195	0.000	0.085	0.000	0.000	0.000	0.000	0.002	0.001	0.003	0.030	0.541	0.045	0.009	0.034	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

TABLE B-3 Parameter Estimates Results for Models Using All Collisions (1,600 Hours)

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Deployment	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	**Poisson**	**Estimate**	6.404	-0.103	-0.223	-0.098	-0.257	-0.101	-0.041	-0.049	0.027	0.102	0.071	-0.045	-0.071	-0.026	0.000	-0.007	NA	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.001	0.164	0.114	0.409	0.000	0.012	0.090	0.000	0.081	0.971	0.000	NA	NA
	NB	**Estimate**	6.235	-0.101	-0.214	-0.092	-0.255	-0.103	-0.034	-0.046	0.030	0.107	0.072	-0.049	-0.062	-0.023	0.002	-0.007	NA	0.005
		P Value	0.000	0.025	0.000	0.052	0.000	0.052	0.522	0.402	0.593	0.034	0.152	0.303	0.030	0.372	0.778	0.000	NA	0.000
PDO Collision	**Poisson**	**Estimate**	6.020	-0.031	-0.208	-0.160	-0.435	-0.416	-0.372	-0.385	-0.380	-0.317	-0.245	-0.073	-0.060	-0.124	0.024	0.007	-0.451	NA
		P Value	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	**Estimate**	6.137	-0.019	-0.206	-0.163	-0.444	-0.428	-0.381	-0.395	-0.388	-0.320	-0.250	-0.078	-0.059	-0.106	0.022	0.007	-0.438	0.015
		P Value	0.000	0.767	0.001	0.017	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.232	0.205	0.009	0.075	0.000	0.000	0.000
Total Collision	**Poisson**	**Estimate**	6.604	-0.049	-0.218	-0.159	-0.414	-0.368	-0.320	-0.334	-0.313	-0.249	-0.198	-0.074	-0.052	-0.106	0.020	0.004	-0.361	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	**Estimate**	6.758	-0.039	-0.216	-0.161	-0.420	-0.377	-0.327	-0.341	-0.320	-0.251	-0.201	-0.078	-0.052	-0.091	0.017	0.004	-0.346	0.012
		P Value	0.000	0.494	0.000	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.183	0.210	0.013	0.129	0.000	0.000	0.000
Speed-Related PDO Collision	**Poisson**	**Estimate**	5.488	-0.041	-0.212	-0.129	-0.399	-0.390	-0.362	-0.374	-0.344	-0.309	-0.264	-0.098	-0.065	-0.121	0.024	0.008	-0.568	NA
		P Value	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	**Estimate**	5.739	-0.025	-0.205	-0.130	-0.403	-0.398	-0.364	-0.377	-0.346	-0.307	-0.264	-0.097	-0.069	-0.105	0.020	0.008	-0.550	0.015
		P Value	0.000	0.691	0.002	0.060	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.139	0.145	0.011	0.110	0.000	0.000	0.000
Speed-Related Collision	**Poisson**	**Estimate**	6.382	-0.065	-0.226	-0.134	-0.376	-0.326	-0.288	-0.300	-0.256	-0.210	-0.188	-0.094	-0.051	-0.094	0.017	0.004	-0.408	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	**Estimate**	6.594	-0.054	-0.220	-0.133	-0.377	-0.330	-0.289	-0.301	-0.258	-0.208	-0.187	-0.094	-0.055	-0.084	0.014	0.004	-0.392	0.011
		P Value	0.000	0.318	0.000	0.025	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.095	0.171	0.018	0.198	0.000	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

TABLE B-4 Parameter Estimates Results for Models Using Midblock Collisions Only (1,600 Hours)

Parameter			Intercept	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Deployment	Tickets	Employment	Trend	Threshold	Dispersion
Severe Collision	Poisson	Estimate	4.937	-0.162	-0.338	-0.108	-0.277	-0.080	-0.010	0.023	0.064	0.071	0.024	-0.114	-0.114	-0.058	0.005	-0.008	NA	NA
		P Value	0.000	0.000	0.000	0.024	0.000	0.137	0.845	0.684	0.273	0.161	0.636	0.020	0.000	0.035	0.517	0.000	NA	NA
	NB	Estimate	4.814	-0.172	-0.342	-0.119	-0.281	-0.093	-0.008	0.015	0.061	0.066	0.019	-0.125	-0.102	-0.058	0.007	-0.008	NA	0.011
		P Value	0.000	0.015	0.000	0.109	0.001	0.260	0.924	0.859	0.492	0.405	0.815	0.091	0.023	0.165	0.563	0.000	NA	0.000
PDO Collision	Poisson	Estimate	5.008	-0.062	-0.283	-0.142	-0.474	-0.454	-0.397	-0.425	-0.401	-0.388	-0.288	-0.116	-0.118	-0.114	0.028	0.006	-0.411	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.189	-0.045	-0.279	-0.151	-0.494	-0.473	-0.415	-0.445	-0.419	-0.395	-0.296	-0.119	-0.132	-0.089	0.025	0.006	-0.388	0.021
		P Value	0.000	0.550	0.000	0.064	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.123	0.018	0.067	0.100	0.000	0.000	0.000
Total Collision	Poisson	Estimate	5.451	-0.079	-0.296	-0.146	-0.456	-0.409	-0.350	-0.370	-0.343	-0.331	-0.253	-0.120	-0.110	-0.105	0.024	0.004	-0.343	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.671	-0.063	-0.293	-0.153	-0.471	-0.425	-0.366	-0.386	-0.359	-0.336	-0.260	-0.122	-0.125	-0.083	0.020	0.004	-0.320	0.019
		P Value	0.000	0.376	0.000	0.048	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.097	0.018	0.072	0.147	0.000	0.000	0.000
Speed-Related PDO Collision	Poisson	Estimate	4.585	-0.099	-0.305	-0.145	-0.482	-0.465	-0.418	-0.431	-0.387	-0.382	-0.311	-0.160	-0.127	-0.117	0.028	0.006	-0.470	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	4.919	-0.082	-0.299	-0.156	-0.497	-0.481	-0.431	-0.448	-0.403	-0.387	-0.317	-0.160	-0.143	-0.093	0.023	0.006	-0.442	0.021
		P Value	0.000	0.281	0.000	0.059	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.041	0.012	0.062	0.129	0.000	0.000	0.000
Speed-Related Collision	Poisson	Estimate	5.213	-0.117	-0.319	-0.149	-0.456	-0.401	-0.349	-0.353	-0.310	-0.304	-0.258	-0.159	-0.115	-0.102	0.023	0.003	-0.366	NA
		P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	NB	Estimate	5.523	-0.101	-0.315	-0.157	-0.464	-0.413	-0.360	-0.365	-0.322	-0.306	-0.263	-0.157	-0.130	-0.084	0.018	0.003	-0.341	0.018
		P Value	0.000	0.149	0.000	0.040	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.030	0.013	0.066	0.187	0.002	0.000	0.000

Parameters significant at 90% and higher level are marked with grey fill colour.

APPENDIX C: Supplementary Tables and Figures

TABLE C-1 Comparison between Segment-Based and City-Wide Collision Reductions

	Severe Collision	PDO Collision	Total Collision	Speed-Related PDO Collision	Speed-Related Collision
Segment-Based Midblock Collision Reduction (%)	20.1	14.3	14.5	17.9	18.5
City-Wide Midblock Collision Reduction (%)	9.7	25.0	22.7	25.1	21.6
City-Wide All Collision Reduction (%)	4.0	21.8	18.2	21.1	15.9

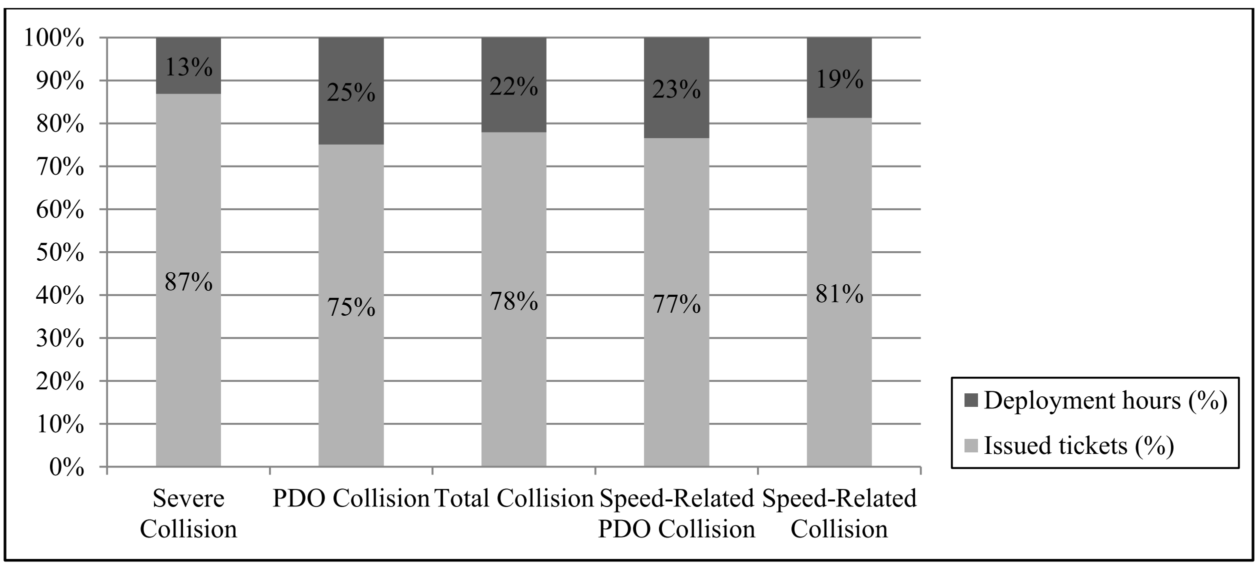

FIGURE C-1 Percentages of Reduced City-Wide All Collisions

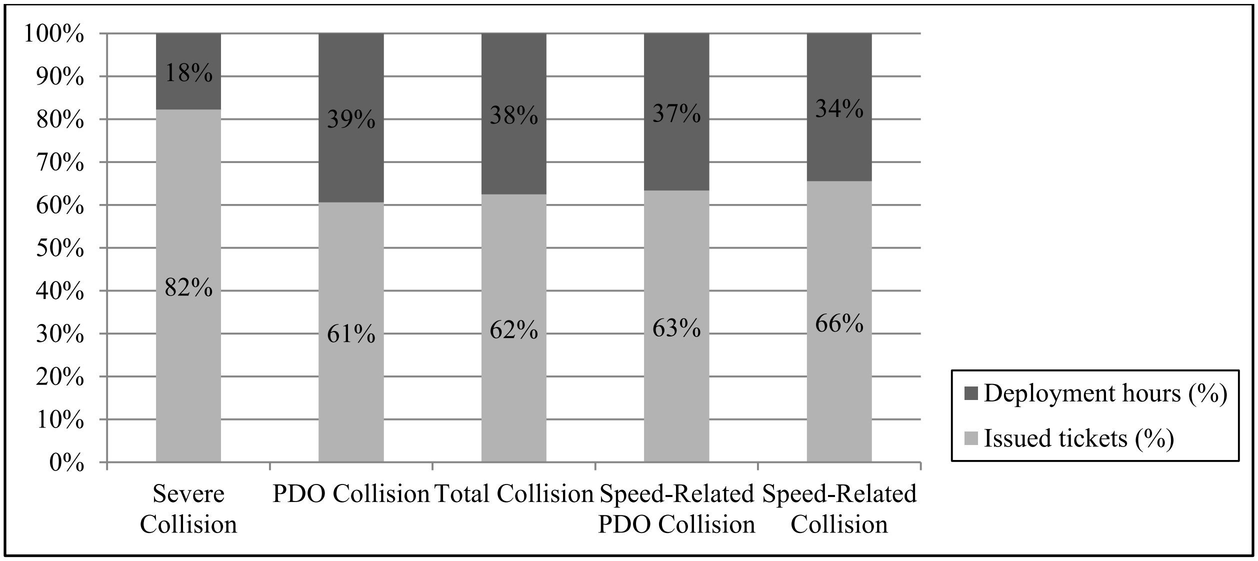

FIGURE C-2 Percentages of Reduced City-Wide Midblock Collisions