THE EFFECTIVENESS OF SAFETY COUNTERMEASURES IN NEW YORK CITY

BY

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ABSTRACT

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The evaluation of the effectiveness of safety countermeasures is very important in urban transportation planning to build safe and livable communities for all residents. Over the last decade, New York City has achieved great reductions in traffic fatalities and crashes by installing safety countermeasures throughout the city. However, the effectiveness of many of the safety countermeasures remains unclear, which is, to a large extent, due to the lack of a rigorous study design and inadequate attention paid to built-environment factors. The objectives of this dissertation are: 1) to develop a safety framework for better understanding and implementing different safety countermeasures; 2) to develop and apply a rigorous study design and methodology in the evaluation of safety countermeasures; 3) to evaluate the safety countermeasures by controlling the effects of the build environment factors on traffic crashes; and 4) to make policy recommendations on the selection and implementation of various safety countermeasures to improve the safety of all road users. A rigorous quasi-experimental design, that is, a before-after analysis with a comparison group, followed by regression models using the Generalized Estimating Equations (GEE) methodology is used to evaluate the effectiveness of safety countermeasures for the safety of various road users, including motorists (e.g., left-turn signal phasing), bicyclists (e.g., bike lanes), and pedestrians (e.g., increasing cycle length, Barnes Dance, split phase timing, signal installation, and high visibility crosswalk). The study shows that: 1) the change of permissive left-turn signal phasing to protected/permissive or protected-only signal phasing does not result in a significant reduction in intersection crashes, and the reduction of left-turn crashes by the protect-only signal phasing is offset by a possible increase in over-taking crashes; 2) the installation of bike lanes does not result in an increase in crashes, despite a likely increase in the number of bicyclists after installation of bike lanes; and 3) the four signal-related countermeasures are found to be more effective in reducing crashes than high visibility crosswalks. Based on the safety framework and the evaluation results, recommendations are proposed for transportation planners and policy makers in the practice of improving traffic safety in large urban area.

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CHAPTER 1 Introduction

There is a global “crisis” in road traffic safety: it has been predicted that without effective actions and increased efforts, the number of road traffic deaths will increase to an estimated 1.9 million each year worldwide by 2020 and traffic crash will become the fifth leading cause of death in the world, resulting in an annual economic cost of over $500 billion (World Health Organization 2011). Taking actions to reduce road crashes and related fatalities and injuries is a “public health priority” (Sharma 2008). Many road safety countermeasures have been designed to solve traffic safety problems and the effectiveness of the safety countermeasures needs to be studied so that planners, engineers, and policy makers can make sound decisions to improve the safety for all users on the roads.

1.1 Background

In order to prevent traffic crashes, traffic safety professionals have been trying to understand what causes them (Rothe 2002) and various theories have been proposed to identify the causes of the crashes on the road (Elvik and Vaa 2004). In early 1900s crashes were treated as purely random events and Poisson model was used to describe the random process leading to crashes. Greenwood and Yule (1920) proposed accident proneness theory and used statistical models such as Negative Binomial model to describe the observed distributions of crashes. This theory was predominant from 1920s until about 1950s. In 1940s a causal theory was developed to find the causes of crashes by looking at the events that lead to the crashes (Cresswell and Froggatt 1963). The focus of this theory is on human errors and thus, modifying human behavior has been viewed as the most effective measure to prevent crashes. During 1960s and 1970s, systems theory was proposed to explain the total number of crashes in a system and it sought to find the solution by modifying the components of the road transportation system (Evans 1991). The improvements that have been made to the road system and motor vehicle design have dramatically reduced the crash rate. Behavioral theories have also been proposed in 1980s, one of which is the risk homeostasis theory and the idea is that the number of crashes is dependent on individual road user's behavior adaption to the safety measures (Wilde 1982, 2001). Each of these theories provides a partial explanation. For example, the randomness and proneness theories look for explanations of variations in the number of crashes, while the causal theory seeks to explain the causes of single crashes, and yet the systems theory attempts to explain the overall level of safety of a system. The theories being proposed so far have not resulted in a general theory of crash causation, which can be stated in terms of law-like propositions, such as those in physics, chemistry or biology (Elvik and Vaa 2004).

Since the 1940s and 1950s, there has been a rapid and widespread growth in automobile use in the United States, together with the increase in the number of crashes. In the search for the causes of traffic crashes, various measures to counteract traffic crashes have also been designed and studied by traffic engineers, safety professionals, planners and policy makers to improve safety on the roads. In general, the safety countermeasures can be classified as three kinds corresponding to the three components in the transportation system: change of users' behavior by the enforcement of traffic laws and education and training; vehicle related measures, such as seatbelt, airbag, and anti-lock braking that contribute to improved survivability post-crash and fewer injuries; and physical road infrastructure related measures. The effectiveness of traffic laws largely depends on enforcement and education, which require continuous efforts to make their effects lasting (Lu 2006). Safer vehicle designs are dependent on the vehicle-manufacturing industry and technology development. Infrastructure related measures may improve safety through self-explaining and forgiving road designs—for example, recognizable road layout that promote driving behavior in accordance with the traffic regulations and mitigate the consequence of crashes once they happen.

Continued growth and decentralization throughout the United States have increased the number of cars on streets and highways. High traffic volumes and speeds, especially on residential streets, downgrade the quality of life for residents because of concerns on safety, noise, and pollution. In recent years there is a movement toward livable communities, where the use of public transportation and non-motorized modes such as walking and bicycling is
In addition to safety improvements for motor vehicles, many measures have been designed to improve the safety of non-motorized users such as pedestrians and bicyclists. Traditional engineering safety improvements focus on the roadway design and traffic controls, including the roadway geometry, roadside design, traffic signals, signs and markings, etc., for better accommodation of pedestrians and bicyclists on the roads. Over the last two decades, traffic

calming—“the combination of mainly physical[1] measures that reduce the negative effects of motor vehicle use, alter driver behavior, and improve conditions for non-motorized street users” (Ewing 1999)—are gaining more and more recognition in urban transportation planning and engineering in the U.S. and around the world. Traffic calming measures aim to improve street safety and residents’ quality of life, through reducing traffic speeds and volumes (Ewing, 1999). Due to the high proportion of vulnerable road users on the residential streets, traffic calming has been known as a good safety solution for such areas (Ewing 1999). Many large cities such as London, Paris, Copenhagen in Europe, Nagoya in Japan, and Melbourne in Australia have implemented area-wide traffic calming measures to slow down or reduce traffic and improve safety. In the U.S., there have been more than 150 communities with traffic calming programs, including New York City, one of the biggest cities in the U.S. (New York City Department of Transportation 2010a).

Over the last decades, various safety countermeasures have been implemented extensively in New York City to improve the safety for all road users, especially those vulnerable users—for example, pedestrians, bicyclists, older persons and schoolchildren. The improvements include both traditional engineering countermeasures (such as signal changes, geometric treatments, turning restriction, and signs and markings) and traffic calming measures

[1] Traffic calming measures are classified into two categories: nonphysical measures and physical measures (Ewing 1999). Nonphysical measures include psycho-perception measures (for example, restriping to visually narrow lanes, without physical changes), regulatory measures (such as stop signs and turn restriction that require enforcement), and signal timing for progression (to discourage drivers to speed). In traffic calming practice, more studies focus on the physical measures because nonphysical measures are usually not as effective as physical measures and sometimes nonphysical measures need to be combined with physical measures to have some effects. Physical measures, on the other hand, have proven effectiveness on reducing speed, volumes and collision. In the ITE’s definition, traffic calming measures are mainly physical measures.

(such as speed humps, neck-downs, and road diets). In an effort to improve the quality of life for residents and make communities safer and more livable, New York City has been working hard to promote transit use by installing bus lanes and improving access to bus stops and subway stations, to encourage the use of non-motorized modes by expanding its bicycle network and facilities, and to improve walking conditions for pedestrians of all ages. With the development of safety programs and aggressive implementation of various safety countermeasures (see the list in Appendix A) over the past 20 years, New York City has achieved vast reduction in fatalities (about 58% reduction from 1990 to 2009) and crashes, despite the increases in population (15% increase from 1990 to 2009), transit ridership and bicycle travel.

1.2 Research Questions and Objectives

Study of the effectiveness of safety countermeasures in reducing crashes and casualties is one of the most important tasks for transportation planners and engineers when evaluating a safety countermeasure and creating a better environment for all users of the roadway, so that the right safety countermeasures can be installed at the right place to achieve the most safety benefits. There are several limitations on the existing evaluation studies though.

Various methods have been used in practice to evaluate the impacts of road safety measures on crashes (more details are discussed in the following section in this chapter). They are mainly based on historical crash data, through before-after studies (comparing the crash counts or rates at the treated locations before the treatment versus after the treatment), cross-sectional analyses (comparing crash counts or crash rates at the treated locations versus those at the un-treated locations), or statistical models based on regression analysis (e.g., linear, Poisson, and negative binomial). The simple before-after analysis usually assumes that the safety countermeasures are the only reasons for the crash changes from before-period to the after-period and this method ignores the other factors that might contribute to the crash changes. Cross-sectional analysis considers the various factors that may affect crashes, such as the roadway geometry and traffic characteristics, in addition to the safety treatments, however, the trends of crashes over time are not accounted for in this method. The effectiveness of many safety countermeasures remains unclear or contradicting in literature (Elvik and Vaa 2004, Hauer 2004) partly due to the different methods being used and the lack of a rigorous study design to control various confounding factors that affect crashes.

As the measures are implemented in different types of the built environment, one needs to incorporate the characteristics of the built environment when studying the effectiveness of safety measures. There have been various studies on the relationship between the built environment and travel (travel behavior and travel demand) and traffic safety (crash frequency and severity). For example, the "4Ds" factors—density (for example, population, employment, and land use density), diversity (for example, different land use, ethnic group, and age group), design (for example, street network characteristics), and destination accessibility—have been studied in travel behavior area (Ewing and Dumbaugh 2009, Ewing and Cervero 2010).

When it comes to the study of the effectiveness of safety countermeasures, however, the characteristics of the built environment, especially at the broader level of neighborhood or are not controlled adequately. The factors that are under investigation are usually the roadway geometry design—such as road width, on-street parking, number of lanes for roadway segment or control type, number of approach for intersections, and traffic characteristics—such as the vehicle and pedestrian volumes. However, the important differences among individual regions or neighborhoods, such as demographic characteristics, land use, transportation systems infrastructure and operation and road safety related attitudes and behaviors will also affect the difference in crashes at different locations and during different time periods (Ewing and Dumbaugh 2009). These factors are usually ignored in previous studies.

Despite the city-wide reduction in fatalities and crashes, the effectiveness of each different safety countermeasure in New York City needs to be systematically and rigorously studied. The effectiveness of safety countermeasures that has been studied in other cities may not be appropriate for New York City, which differs in many ways from other large U.S. cities. The transportation in New York City is characterized by high congestion, high percentage of taxis and buses, large number of pedestrians and bicyclists, older and narrower streets, and numerous public transit stations. Furthermore, the large density and diversity of population and land use in New York City adds to conflicts in roadways, as people from different countries and cultures may behave differently in driving, bicycling or walking. The complexity in traffic and travel behavior may result in higher possibility of crashes in New York City.

To further the study of the effectiveness of safety countermeasures with respect to the issues discussed—unclear effectiveness of some safety countermeasures, lack of a rigorous study design, and inadequate attention to the built environment factors—in this dissertation I investigate the effectiveness of a range of safety countermeasures in New York City by applying a rigorous study design (before-after analysis with comparison group), incorporating the built environment factors in the evaluation, followed by regression models using generalized estimating equations (GEE) method. This dissertation aims to answer the following questions:

(1) What's the effectiveness of the selected safety countermeasures in New York City—including both traditional engineering measures (such as installation of new signals, signal phase changes, and crosswalks) and traffic calming measures (such speed humps and road diets), and measures that aim at improving the safety of different road users (motorists, bicyclists, and pedestrians)—in reducing crashes?
(2) What built environment factors and what effects of the built environment factors will have on crashes and what the effectiveness of safety countermeasures will be by controlling those built environment factors?
(3) What lessons can traffic engineers, safety professionals, planner and policy makers learn from New York City's experience in improving traffic safety?

By answering these questions, it is anticipated that the results of the study will help transportation planners and engineers in selecting the appropriate safety countermeasures and applying at appropriate locations. The objectives of this research are:

(1) To develop a safety framework that can be used to help understand and make decision on selecting and implementing different safety countermeasure to reduce crashes and improve safety of a transportation system;

(2) To develop and apply a rigorous study design and methodology in the evaluation of safety countermeasures;

(3) To study the effects of the build environment factors on traffic crashes; and

(4) To make policy recommendations on the selection and implementation of various safety countermeasures to improve the safety of all road users.

1.3 Overview of the Evaluation Methodology

In the study of the effectiveness of safety countermeasures, it is important to note that the change in crash frequency at a specific location (for example, an intersection or a roadway segment) may be attributed to different causal factors, including not only the effect from the implementation of a specific safety improvement measure, but also many other confounding factors such as the trend effects that are due to driver composition (in terms of behavior, age, etc.), weather conditions, enforcement, etc., in the area in different periods of time, or the change in exposures (traffic volume and pattern), or even random effect such as the regression-to-the-mean bias—a location with high crash count is likely to experience crash reduction, even if no improvement has been implemented. The evaluation of the effectiveness of safety countermeasures must employ proper study designs that seek to minimize or account for these effects other than the safety countermeasures.

Road safety studies are usually observational studies (Hauer 1997) instead of randomized experiments—lack of random assignment is almost universally true for transportation improvement measures, as countermeasures are often installed based on a citywide transportation improvement plan and at hot-spot locations (with a high number of crashes). The commonly used study design for the evaluation of traffic safety countermeasures is quasi-experimental design (Shadish *et al.* 2002), which is similar to the experimental design but lacks the element of random assignment. The quasi-experimental design has four approaches: one-group pretest-posttest design (naïve before-after study); posttest only design with a comparison group (cross-section study); a pretest-posttest design with a comparison group; and the empirical Bayesian approach.

- **One-group pretest-posttest design (naïve before-after study)**

This study design (Shadish *et al.* 2002) compares the observed crashes at the treated locations before and after the implementation of the safety countermeasures. It is also the "naïve before-after study" in Hauer (1997). In this study design, the change in the observed crash counts at treated locations from the before to the after period is considered the treatment effect. However, there may be many other reasons leading to the different observed crashes in the periods before and after the implementation of road safety countermeasures. Because this research design lacks a control for any confounding factors and may overestimate the effect of safety countermeasures (Elvik 2002), it is classified as "weak" quasi-experimental designs and not recommended in real world safety evaluation projects (Shadish *et al.* 2002, Institute of Transportation Engineers 2009).

- **Posttest only design with a comparison group (cross-section study)**

This study design is essentially the cross-section design, in which a comparison group (a group of untreated locations sharing some common features, such as roadway geometry characteristics, with the treatment group) is selected and the crash counts (or crash rates) in the period after the implementation of the safety countermeasure are compared between the treatment group and comparison group. It is assumed that crash statistics at comparison sites reflected general safety trends, and that differences in crash rates at treated sites were attributable to the implementation of safety countermeasures. However, this too is a "weak" design as "…the possibility of pretest group differences makes it very hard to separate treatment from selection effects" (Shadish *et al.* 2002, p. 116) and there may be many other confounding influences that distinguish the treatment group from any comparison group.

- **Pretest-posttest design with a comparison group**

This research design compares the difference in crash changes between pre-test and post-test for the treatment group and the comparison group. Whether the treatment group has experienced greater reductions in crashes from pre-test to post-test than has the comparison group can then be determined. If the differences are statistically significant, this is relatively strong evidence of a treatment effect. The pretest-posttest design with a comparison group is a more robust design. The immediate effect of the safety countermeasure can be captured by the comparison of post-test and pre-test crashes and the trend in the area can be accounted for by the comparison with untreated streets (Shadish *et al.* 2002).

By this research design, there are different approaches can be used to evaluate the effectiveness of safety countermeasures, with different methods of comparison group selection.

1) *Before-after evaluation with one-to-one matched comparison and difference-of-means tests*

The first approach is the before-after evaluation with one-to-one matched comparison, also called yoked comparison (Griffin and Flowers 1997, Harwood *et al.* 2002, Institute of Transportation Engineers 2009). In this approach a group of similar locations are selected by one-to-one matching between the treated sites and the untreated sites (comparison sites). That is, a comparison site is selected to be similar to the corresponding treatment site, in terms of area type (urban or rural), location type (intersection or roadway segment), roadway geometry characteristics, such as number of legs and traffic control types (for example, signalized, stop-control, etc.) for intersections, or one-way or two-way, divided or not, number of travel lanes and parking lanes for roadway segments. The assumption of this approach is that the confounding factors (except for the safety treatment) affect the number of crashes in the same manner for the treatment site and the matched comparison site, thus, the crash change from the before period to the after period would be similar for the treatment site (had there been no treatment in the treated site) and the matched comparison site.

The paired samples difference-of-means tests (t-tests) can be used to evaluate the effectiveness of safety countermeasures with the data consisting of the one-to-one matched treatment sites and comparison sites (Ewing *et al.* 2011). The difference in crash frequency in the after period relative to the before period for the treated sites, less the equivalent difference for sites can be calculated. A one-sample t-test can then be conducted. If the computed value (the relative change in crashes) is significantly less than zero, then the null hypothesis of no treatment effect can be rejected and concluded that the treatment effect is significant. By using a well-chosen comparison group so that the crash frequencies in the before period are similar for treatment sites and comparison sites, the selection bias and regression-to-the-mean may be minimized.

There are several issues with this approach. First, because one treated site has only one comparison site, it is possible to have different estimates when other comparison sites are used, and thus the findings based on this approach may be variable (Institute of Transportation Engineers 2009). The other issue is that this method is lack of control of potentially confounding variables, such as the change in traffic volumes (Elvik 2002).

2) Before-after evaluation with comparison group and regression models

The second approach is the before-after evaluation with comparison group, in which a larger comparison group is selected without the need for a one-to-one matching between the comparison sites and the treatment sites. This approach resolves the first issue, that is, variable findings, associated with the before-and-after evaluation using the one-to-one matched comparison, considering that the larger the comparison group, the better the assessment (Harwood *et al.* 2002, Institute of Transportation Engineers 2009).

One method is the Comparison Group Analysis (Hauer 1997), which calculates the expected crashes in treatment group in the after period had there been no treatment by applying the ratio of crash changes from before period to after period in the comparison group to the crashes in the treatment group in the before period. The expected crashes are then compared with the observed crashes in the treatment group in the after period to find the treatment effect. However, this method cannot control the regression-to-the-mean bias and many other confounding factors that are not used in comparison group selection.

The other possible way is to use regression models to compare the changes in crashes from the pre-treatment period to the post-treatment period for the two groups, by incorporating dummy variables representing the periods and groups to capture how the crash changes from before period to after period in different groups. The benefits of using regression model is that the effects of various factors that affect crashes, such as site features and neighborhood built environment can also be controlled and found in the regression model, and the regression-to-the-means effects—the high crash counts in the treatment group—can also be controlled by dummy variable in the models.

- **Empirical Bayes method**

The Empirical Bayes method has been developed to account for the regression-to-the-mean effects (Hauer 1997). It is a statistical approach in which the crash frequency at treated sites in the after period if the treatment had not been implemented is predicted using some crash prediction models or safety performance functions (SPFs) developed from a reference group (a group of untreated sites that are similar to the treatment group) and the observed crashes in the before period. SPFs are regression models that explain the relationship between crash frequency and some explanatory variables such as traffic volume on the roadway. The treatment effect can be found by comparing the predicted crash frequency and the observed crash frequency at treated sites in the after period.

This method is relatively complicated and the data needs can be quite extensive—for example, the annual traffic volume data of many years pre-treatment for all the locations in the treatment group and the reference group. It is quite possible that the traffic volume data are unavailable for many of the treatment sites and comparison sites. New York City, for example, have implemented various safety countermeasures during the last decades, however, most of the treated streets lack the traffic volume data.

In this dissertation, the pretest-posttest design with a comparison group, one of the stronger of the quasi-experimental design, is selected to evaluate the effectiveness of safety countermeasures in New York City. A set of untreated locations is selected as the comparison group and crashes during pre and post-treatment periods are collected for both the treated and untreated groups. The changes in crashes from the pre-treatment period to the post-treatment period for the two groups are then compared. If the treatment group experienced a greater reduction in crashes from pre-treatment to post-treatment than the comparison group did, it points to the effectiveness of the countermeasure. After applying the comparison group analysis (Hauer 1997), regression models are developed to test the effectiveness of safety countermeasures by controlling the various confounding factors and the regression-to-the-mean bias.

1.4 Structure of the Dissertation

This dissertation is comprised of six chapters (including the Introduction). Chapter 2 contains the review of New York City's efforts in safety improvements and a preliminary evaluation of thirteen safety countermeasures in New York City. In Chapter 2, I also discuss the lessons transportation engineers and planner can learn from New York City's experience in improving safety.

In the following three chapters, a more rigorous quasi-experimental design, followed by regression models incorporating built environment factors is applied to evaluate safety countermeasures that aim at improving safety for various road users, including motorists, bicyclists, and pedestrians. In Chapter 3, I evaluate the safety impacts of installing left-turn signal phases for motor vehicle safety at intersections. In Chapter 4, the effectiveness of bike lanes in improving bicycling safety in New York City is studied. Chapter 5 contains the comparison of five pedestrian safety countermeasures, including increasing cycle length for pedestrian crossing, Barnes Dance, split phase timing, signal installation, and high visibility crosswalk, in reducing pedestrian crashes at intersections.

Chapter 6 contains a summary of the study results, discussion of the policy recommendations, the limitations, and future research areas.

CHAPTER 2

Safety Countermeasures and Crash Reduction in New York City —Experience and Lessons Learned

New York City is a traffic safety model in the United States as it has a much lower traffic fatality rate than the national average (3.3 vs. 13.7 per 100,000 persons in 2007) and many other large American cities. The number of fatalities continues to decline over the last ten years, reaching the record-low of 258 fatalities in 2009. How did New York City achieve this feat in traffic safety? And how experience and lessons of New York City can be learned? In this chapter, I seek to answer these questions.

2.1 Introduction

Road traffic fatalities and injuries constitute a major global public health problem—each year nearly 1.2 million people die from road collisions and as high as 50 million are injured on roads worldwide (Peden *et al.* 2004). Almost half of those deaths or injuries in road traffic crashes are vulnerable road users—pedestrians, cyclists and motorcyclists (World Health Organization 2009). In the United States, more than 30,000 fatal crashes and 800,000 injuries occur each year (Fatality Analysis Reporting System & the General Estimate System). Road traffic crashes are among the top 10 causes of death of all ages in the U.S. and for the life lost before age 65, traffic crashes ranked third in 2007, following only cancer and heart diseases (Centers for Disease Control and Prevention 2010). Despite a continuing trend of declining crashes over the last decade (National Highway Traffic Safety Administration 2010b), U.S. lags behind many other developed countries, such as England, Australia, and Europe, in traffic safety, whether it is measured in terms of traffic fatalities per capita or per vehicle miles traveled (Peden *et al.* 2004).

Among the major cities in the U.S. with a population exceeding 250,000, New York City (NYC) stands out as a traffic safety model in the nation. New York City has a lower traffic fatality rate than the national average and other large American cities—with 3.30 traffic fatalities per 100,000 persons in 2007, it is a quarter of the national rate and less than half of those of other big cities such as Chicago (6.85), Los Angeles (7.74), Philadelphia (7.18), and Houston (9.37) (New York City Department of Transportation 2008b). New York City also maintained a low pedestrian fatality rate: for example, its pedestrian fatality rate is 1.6 per 100,000 persons in 2007, compared to 1.8 in Chicago. This is despite a high percentage of trips involving walking—nearly 57% of the commuters in New York City used non-motorized modes or public transportation, versus 16% in Chicago (New York City Department of Transportation 2008a).

Between 1990 and 2009, the traffic fatality rate in New York City declined much faster than the national rate (see Figure 2.1). Fatalities reached a record-low of 258 fatalities in 2009, the lowest number since 1910, when the records were first kept, and crashes of all kinds, including total crashes, injurious crashes, vehicle crashes, pedestrian crashes, and bicyclist crashes, have also been decreasing (see Figure 2.2). During the same 20 year period, the population in New York City has increased by about 15% (U.S. Census Bureau 2009), accompanied by increases in total transit ridership, subway ridership, and bus ridership (The City of New York 2011).

How did New York City achieve this feat in traffic safety? What experience and lessons of New York City can be learned? In this paper, I seek to answer these questions. I first describe the unique features that characterize New York City's transportation system and its road users. This is followed by a presentation of a safety framework under which I evaluated thirteen safety countermeasures implemented in the city during the past two decades. Drawing upon the safety framework and the results on the effectiveness of these thirteen countermeasures, I discuss the experience and the lessons that can be learned.

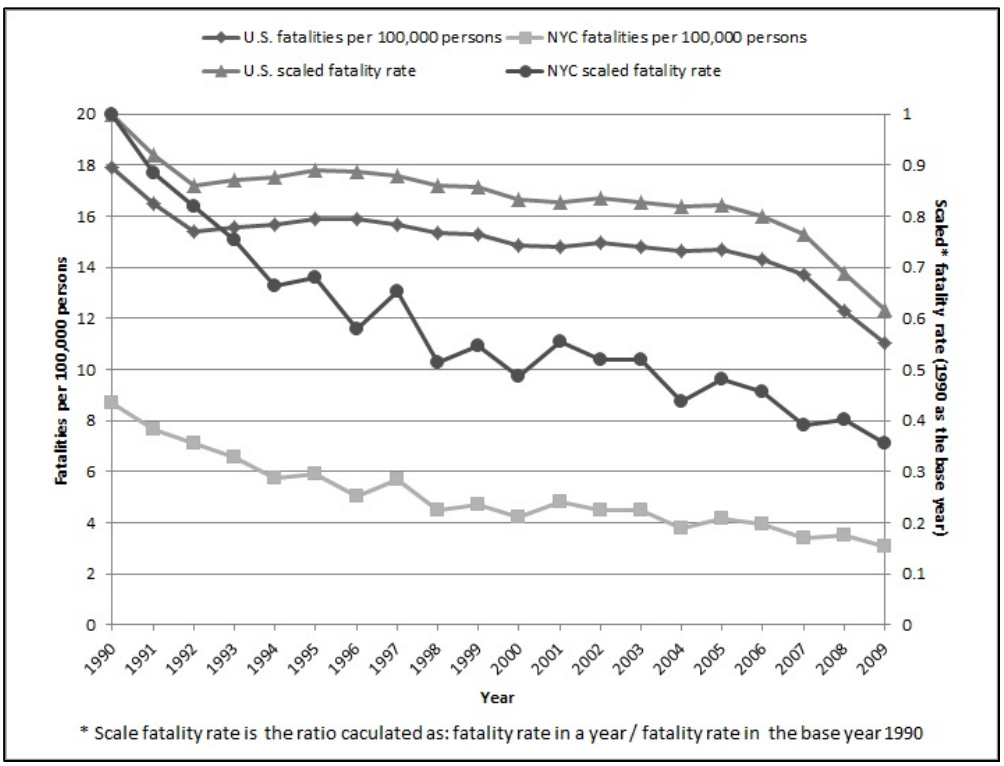

Figure 2.1 Fatality Rates in the U.S. and NYC between 1990 and 2009

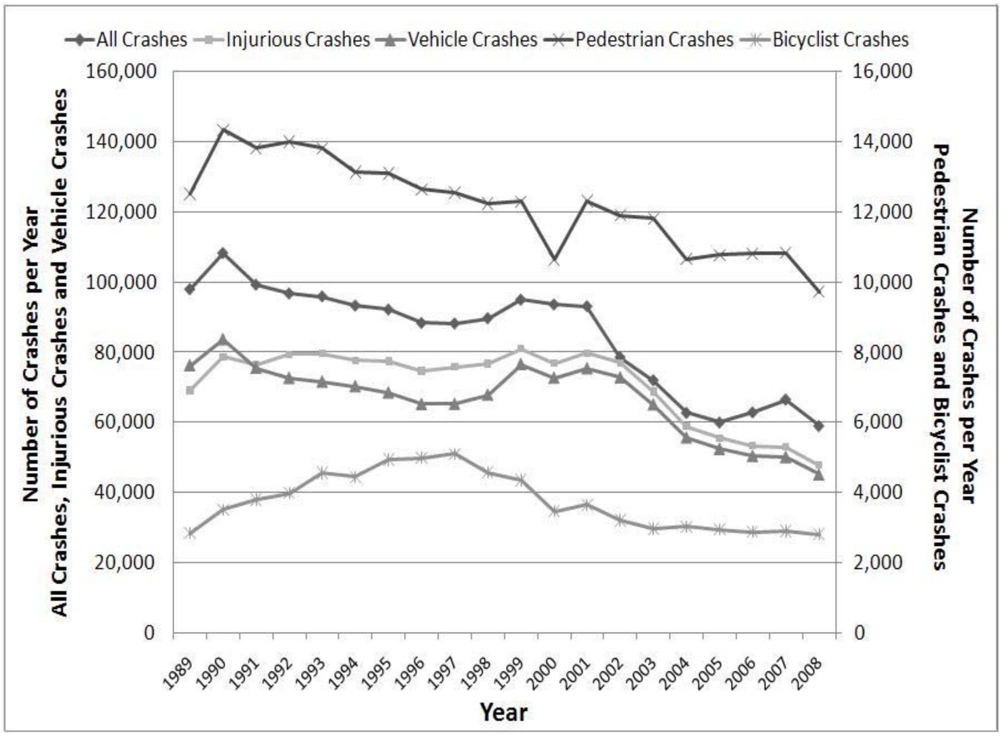

Figure 2.2 New York City Traffic Crashes between 1989 and 2008

2.2 New York City's Experience in Road Crash Reduction

2.2.1 Multi-Modal Transportation System in New York City

Four of five counties (boroughs) in New York City have been rated the most compact of 954 counties in the United States, the exception being Staten Island (Ewing *et al.* 2003a). These counties are more compact than the central counties of San Francisco, Philadelphia, Chicago, and all other metropolitan areas. Sprawl and its antithesis, compactness, are defined for counties in terms of various density measures and street connectivity measures. Compactness has been linked to travel, health, and other positive outcomes in many studies (Ewing *et al.* 2003b, Cho *et al.* 2006, Doyle *et al.* 2006, Ewing *et al.* 2006, Plantinga and Bernell 2007, Ewing and Rong

2008, Ewing *et al.* 2008, Joshu *et al.* 2008, Stone 2008, Trowbridge and McDonald 2008, Fan and Song 2009, Lee 2009, Trowbridge *et al.* 2009, Stone *et al.* 2010).

New York City's transportation system is truly multi-modal, comprising a large road network of different functional classes (expressways, arterials, collectors and local streets), bridges and tunnels, an extensive public transportation network of subway, commuter rail, bus and ferry, and an ever-expanding bicycle network and facilities (bike lanes, bike paths, bike racks and other bicycle facilities). Travel in New York City is characterized by the highest shares of public transit, taxi, and non-motorized modes—more than 50% of the commuting trips are made by public transit (in which walking is necessary for transit riders to access the transit stations), walking or bicycling (see Table 2.1). Manhattan, with the highest population density (more than 70 thousand per square mile) in the country, also has the highest non-auto mode share. Many of the streets in New York City are older and narrower than those of cities that were developed later, and are highly congested with a mixed traffic of private automobiles, taxis, trucks, buses, and emergency vehicles. Furthermore, the large density and the high diversity of population and land use in New York City add to complexity in roadways, as people from different cultures may behave differently in driving, bicycling or walking (Lawson and Edwards 1991, Haworth *et al.* 2000, Dobson *et al.* 2004, Chen *et al.* 2012). In addition to many residents, New York City also attracts more than millions of foreign and American tourists each year, up to 48.8 million in 2010 (nycgo.com 2011). The tourists bring with them their own travel habits, as drivers, transit riders, pedestrians, and bicyclists. The complex transportation network, coupled with density and diversity in road users and their modes of travel may result in more crashes in New York City.

Table 2.1 Share of Different Travel Modes in the Five Boroughs in New York City

Borough	Population Density (1000/sq. mi)	Commuting Travel Mode Share (%)				
		Car	Public Transit	Bicycling	Walking	Other
Manhattan	66.8	11.0	59.6	0.9	21.9	6.6
Bronx	31.7	36.4	53.7	0.2	7.2	2.5
Brooklyn	34.7	30.4	57.4	0.5	8.8	2.8
Queens	20.5	44.5	47.4	0.3	5.7	2.2
Staten Island	7.7	66.4	28.4	0.2	2.9	2.1
New York City	26.4	32.9	52.8	0.5	10.4	3.5

Note: The population and commuting travel mode share data is based on Census 2000.

2.2.2 Traffic Safety Framework

A safety framework is one that has systematically combines a set of safety strategies together for the purpose of crash reduction. An effective safety framework needs to be grounded in safety theory and consider the unique characteristics of the local area. In the context of this study, New York City is characterized by its complex and extensive multi-modal networks, its dense population and diverse land uses, its aging and narrow streets, and the many cultures brought with its many immigrants. I propose a safety framework that is based on three principal dimensions of crash: why, who, and where (Figure 2.3).

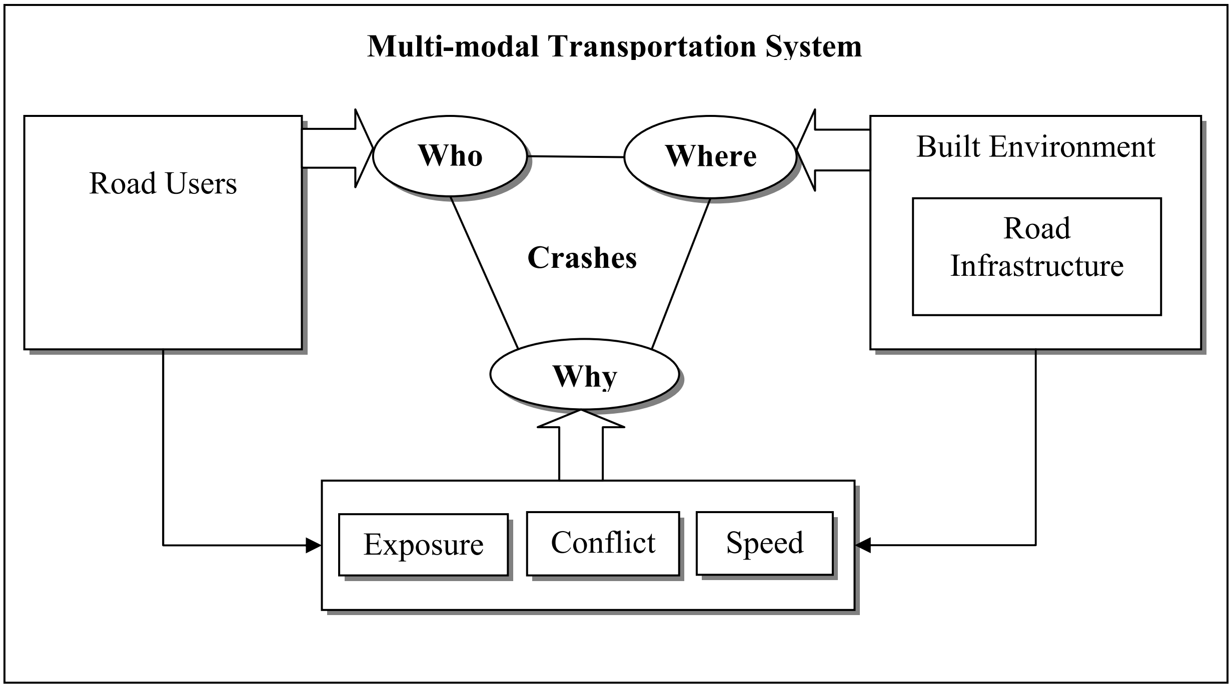

Figure 2.3 Traffic Safety Framework

The "why" dimension of crash is well established in the field—exposure, speed (Zegeer *et al.* 2002, Garder 2004), and conflict are the three pivotal forces that affect crashes (Ewing and Dumbaugh 2009). I further argue that a successful safety framework needs also to consider the "who" and the "where" dimension (Table 2.2). The former refers to the many road users of different modes—motorists, pedestrians, and bicyclists etc. and their unique characteristics, for example, age, race, and ethnicity of different groups—Asians from different countries such as Chinese, Japanese, and Indian, or Hispanic such as Puerto Rican, Peruvian, Mexican, etc., may have different road-use habits in their origin countries; the latter broadly refers to the surrounding built environment—not only the attributes associated with a particular site (those associated with an intersection or a road segment), but also the context in which the site is set, for example, the density of the population, diversity of land uses, and safety culture (Chen *et al.* 2012).

Table 2.2 Road Users and Road Infrastructure in Multi-Modal Transportation System

Who: Road Users	
Travel Modes	Motor vehicles (drivers and passengers)
	Pedestrians (including transit riders)
	Bicyclists
	Motorcyclists
Age Groups	Schoolchildren
	Senior
	Others
Ethnic Groups	Asian (such as Chinese, Japanese, and Indian)
	Black
	Hispanic (such as Puerto Rican, Peruvian, Mexican)
	White
	Others
Where: Built Environment	
Road Infrastructure (site-level)	
Travel Modes	Roadway Network
	Pedestrian facility (crosswalk, sidewalk, etc.)
	Transit Network (bus route, bus stops, subway entrances, etc.)
	Bicycle network
Location Types	Segments
	Intersections
Context (neighborhood-level)	
Neighborhood Characteristics	Density of population
	Density of land use
	Safety culture
	Others

2.2.3 Safety Countermeasures in New York City

Three categories of safety countermeasures (Figure 2.4) are designed to prevent crashes and/or alleviate injuries through three mediating factors: exposure, conflict, and speed. Signal-related countermeasures are usually designed to improve safety by reducing conflicts between multiple vehicles or between vehicles and other road users. For example, left-turn signal phasing is designed to reduce conflicts between multiple vehicles; leading pedestrian interval (LPI) and Barnes Dance (pedestrian scrambles) are designed to reduce conflicts between pedestrians and vehicles at the intersections; and the installation of new signals are for the safety of all road users including motor vehicles, pedestrians and bicyclists. Reduced speed limits, speed reducers (speed humps), and neckdowns are designed to improve safety by reducing vehicles' travel speeds. In the case of exposure, even though on average more exposure is associated with more crashes, the crash rate at high exposure may be significantly less than that at low exposure—the so-called "safety in numbers" phenomenon (Jacobsen 2003). Thus, some countermeasures have been proposed to attract the use of alternative modes (e.g., the major purpose of installing a bus lane is not safety, instead, is to increase transit speed and thus attract more transit riders, and installation of bike lanes to attract more bike use) and at the same time to separate pedestrians and bicyclists from vehicles.

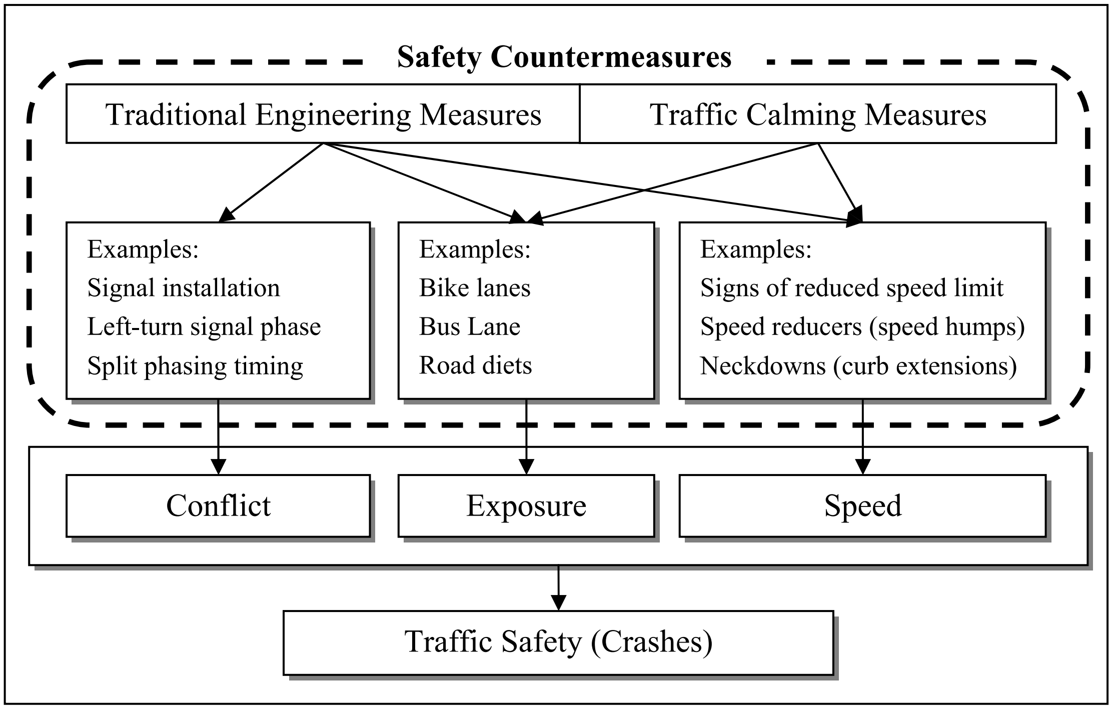

Figure 2.4 Safety Countermeasures of Different Strategies

Some of the safety countermeasures are traditional engineering measures, such as those that change traffic signals, roadway geometry configurations, and signs and markings. Others are traffic calming measures, which are defined as "changes in street alignment, installation of barriers, and other physical measures to reduce traffic speeds and/or cut-through volumes, in the interest of street safety, livability, and other public purposes" (Ewing 1999, Chapter 1, page 3). Traffic calming measures are primarily designed to change "exposure" and "speed". Examples of traffic calming measures installed in New York City include conventional speed reducers (such as speed humps) to reduce vehicle travel speeds, road diets (lane reduction and addition of bike lanes) to slow down traffic and encourage bicycling, and neckdowns (sidewalk extensions at intersections) to slow down the vehicles approaching the intersections (Transportation Alternative 2005).

Some of the thirteen countermeasures were implemented to explicitly address the "who" and "where" dimension in the safety framework. For example, a set of safety countermeasures are specifically designed for pedestrians; they include the Barnes Dance, split phase timing, and high visibility crosswalks. Bike lanes and bus lanes are specially designed for bike users and transit riders. To accommodate the slower walking speed of elderly pedestrians, the walking phase was increased on some wide streets (such as Queens Boulevard and Ocean Parkway) in neighborhoods with a higher percentage of senior citizens. Split phase timing was selected for midtown east in Manhattan, where there is a substantial amount of one-way traffic and narrow streets.

During the past twenty years, NYCDOT has installed different types of safety countermeasures at more than ten thousand treatment locations (either roadway segments or intersections) in the five boroughs to improve the safety of motorists, cyclists, transit passengers and pedestrians of all ages. Figure 2.5 shows the number of locations with safety countermeasures installed by year. The last 10 years has seen substantially more implementations than the previous 10 years and year 2001 has the most number of countermeasures installed. Figure 2.6 shows the distribution of locations for the installed countermeasures in the five boroughs—Queens tops the list with 56%, followed by Brooklyn (17.5%), Manhattan (10.8%), Bronx (10.2%), and Staten Island (5.5%). Figure 2.7 shows the spatial distribution of the safety countermeasures installed in New York City. The *Street Design Manual* (New York City Department of Transportation 2009) developed by NYCDOT provides some detailed guidelines on installing different types of safety countermeasures.

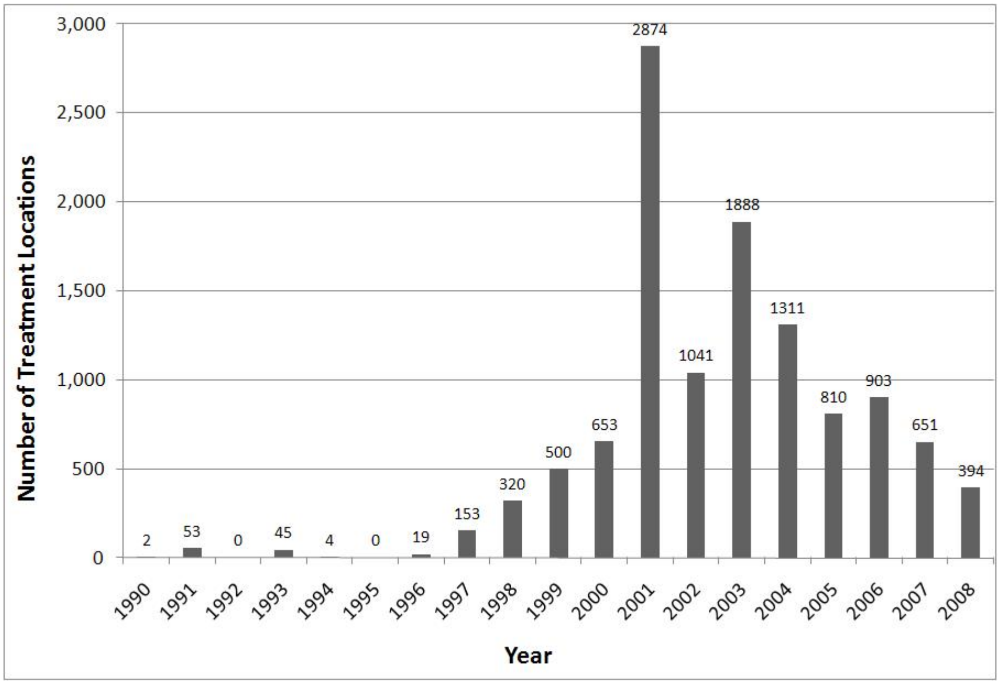

Figure 2.5 Distribution of Safety Treatment Locations by Year

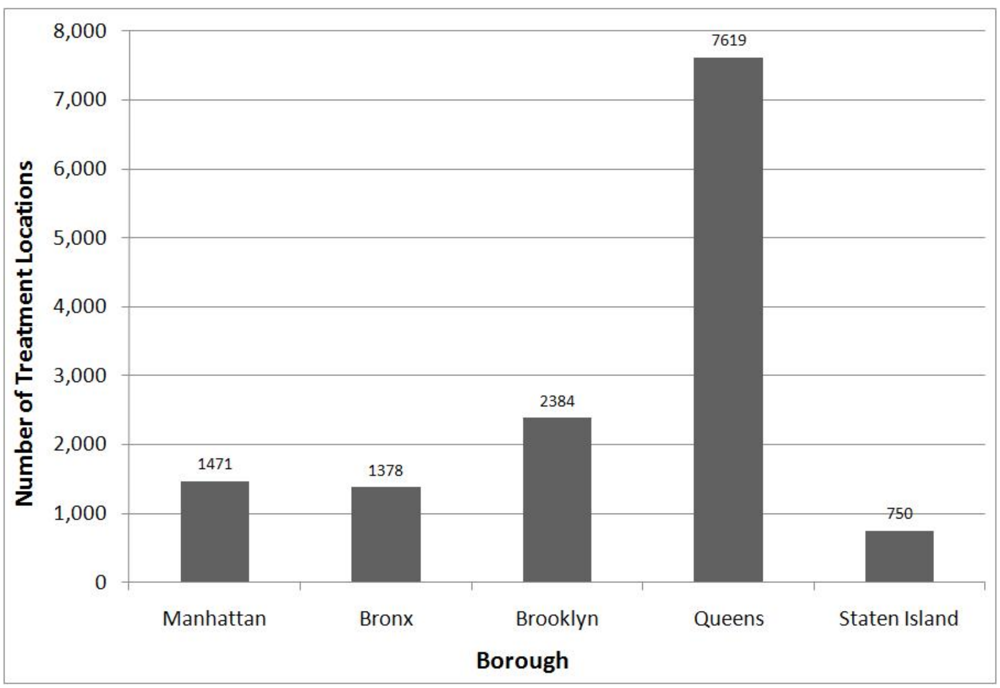

Figure 2.6 Distribution of Safety Treatment Locations in the Five Boroughs

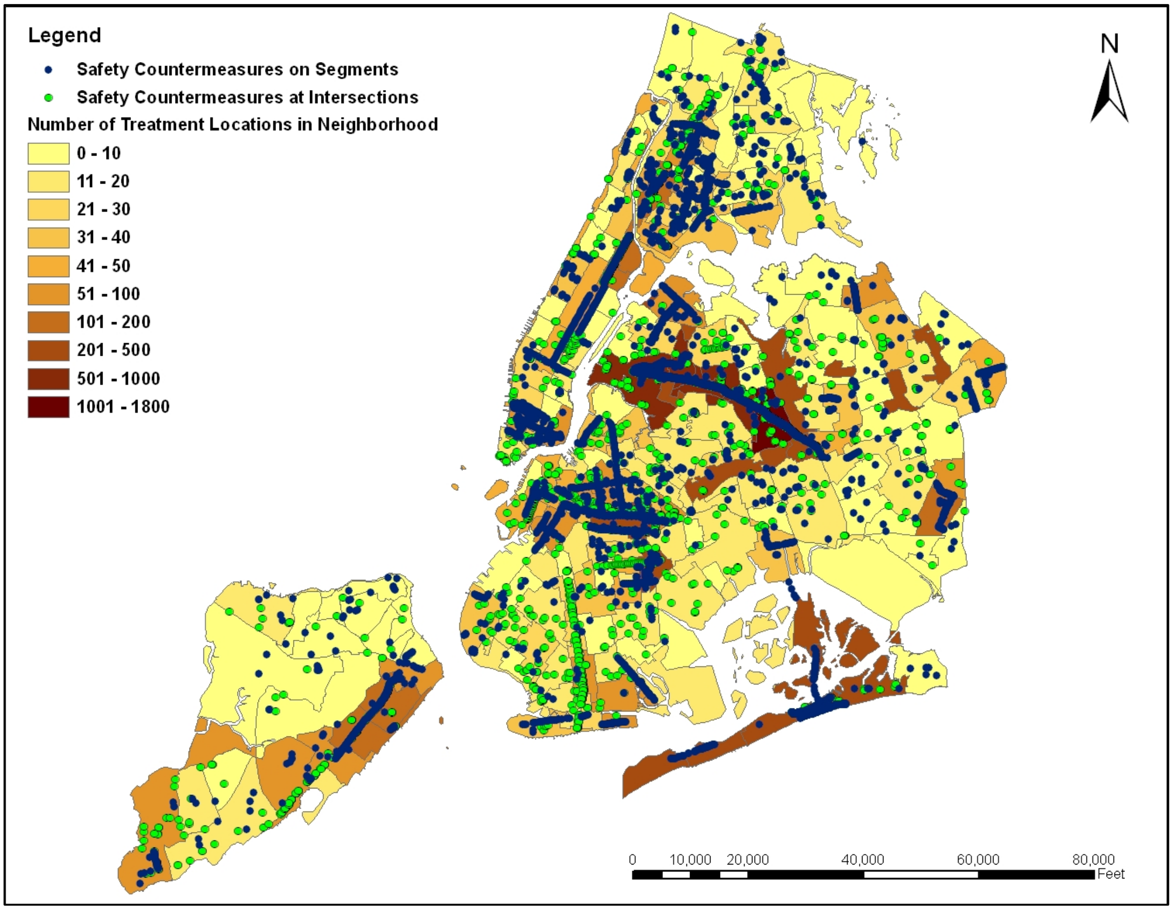

Figure 2.7 Maps of Safety Countermeasures in New York City

The safety countermeasures were categorized as either segment-based (that is, installed along roadway segments, for example, bike lanes, bus lanes, speed humps, and road diets) or intersection-based (such as signal changes, crosswalks, and left-turn bays). Table 2.3 shows some detailed descriptions of the thirteen selected[2] safety countermeasures in New York City: seven are intersection-based and six are segment-based.

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[2] There are actually many more than thirteen safety countermeasures installed in New York City. The thirteen countermeasures described here were selected because they had adequate sample sizes to perform the statistical analysis of their effectiveness in reducing crashes. More details on the criteria of selecting the measures for evaluation can be found in the NYCDOT's project final report (Chen *et al.* 2011).

Table 2.3 Description of Safety Countermeasures

Safety Countermeasures	Number of Locations[a]	Description
Intersection-based		
Barnes Dance	36	A special phase added to the regular two-phase permissive signal timing that stops vehicle traffic in all directions and allows pedestrians to cross in any fashion, including diagonally; also called pedestrian scramble
High Visibility Crosswalk	72	A crosswalk with series of longitudinal white stripes that are constructed from thermoplastic materials; the aim is to increase awareness of pedestrians at intersections by using highly visible marking patterns
Increase Cycle Length	244	An increase length of signal phases on the main and/or cross streets for pedestrian crossing and vehicle movements
Left-Turn Bay	46	A storage area of some length for left-turning vehicles at an intersection, reducing the need for through traffic to decelerate or change lanes near the intersection in order to by-pass left-turning vehicles
Left-Turn Phase	68	The addition of left-turn phases, that changes the signal phasing from permissive to protected/permissive or protected-only
Signal Installation	447	A new signal installed at a non-signalized intersection based on *Manual on Uniform Traffic Control Devices* warrants
Split Phase Timing	30	The division of a signal phase of one direction shared by through traffic, turning vehicles, and crossing pedestrians into two protected phases: a protected pedestrian crossing phase and a protected vehicle turning phase
Segment-based		
Bike Lane	660	A portion of a roadway that has been designated by striping, signs, and pavement markings for the preferential or exclusive use of bicyclists. Bike lanes are installed by narrowing the travel lanes.
Bus Lane	210	A portion of a roadway which has been designated by striping, signing and pavement markings for the preferential or exclusive use of buses
Pedestrian Barrier	144	Pedestrian barriers (pedestrian fencing) installed along the median of the roadway to prevent pedestrians crossing at a mid-block location
Road Diet	502	A reduction in the number of travel lanes (mostly from 4 to 2 lanes, sometimes from 4 to 3 lanes, or from 6 to 4 lane), accompanied by the installation of bike lanes.
Speed Reducer	583	A raised roadway section with 5-foot ramps on either end and a 10-foot flat plateau in the middle – also called speed humps or speed tables
Speed Limit Reduction	270	Reduction of the posted speed limit, for example, from 35 mph to 30 mph on some streets or from 30 mph to 25 mph on some other streets

Note: [a] For intersection-based countermeasures the locations are intersections, and for segment-based countermeasures the locations are segments. The number of locations for each countermeasure is the number of locations with one single treatment, excluding the locations with multiple different treatments.

Geographically , some measures (e.g., the installation of new signals and the speed humps) are installed citywide, throughout the five boroughs of New York City, while others are either installed along major corridors (e.g., posted speed limit reduction), or applied only to a small area with some special traffic and roadway characteristics (e.g., split phase signal timing in midtown east where most of the streets are one-way and there are many turning vehicles and pedestrian crossings)—see Figures 2.8 and 2.9.

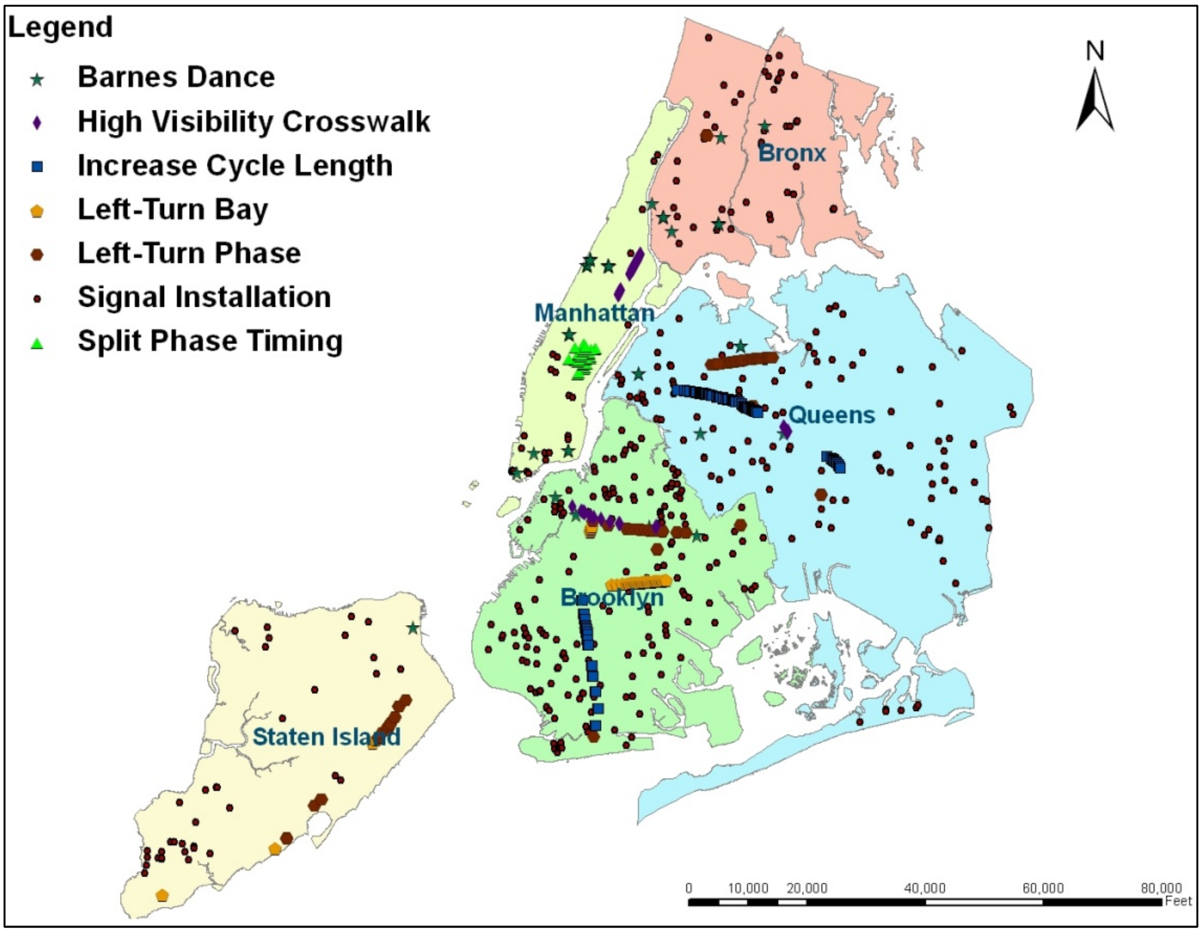

Figure 2.8 Map of Seven Intersection-based Safety Countermeasures in New York City

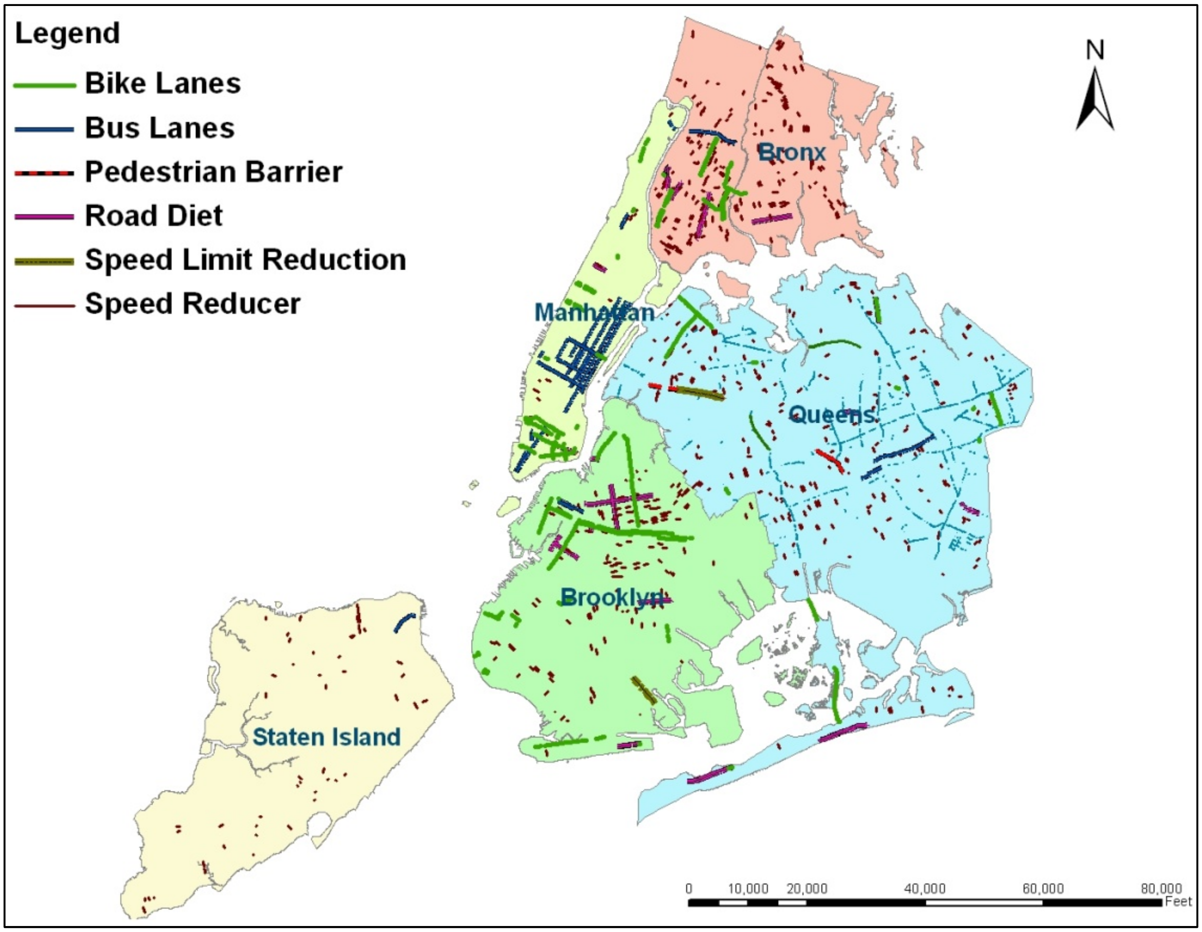

Figure 2.9 Map of Six Segment-based Safety Countermeasures in New York City

2.3 Evaluating New York City's Safety Countermeasures

I studied five types of crashes: all crashes, multiple-vehicle crashes (vehicle-vehicle collisions), pedestrian crashes (pedestrian-vehicle collisions), bicycle crashes (bicycle-vehicle collisions), and crashes with injuries.

Based on the location where the crash occurred, each crash can be either intersection-based (those that occur at an intersection), or segment-based (those that happen on the segment, away from the intersection)[3]. More than 60 percent of the crashes occur at intersections and it is possible that segment-type countermeasures may affect not only crashes on the segment but also those at the end of the segment, or intersection-based crashes. Thus, for countermeasures installed on segments, I evaluated the safety effects for both segment-based crashes and intersection-based crashes.

2.3.1 Quasi-experimental Research Design

I applied a quasi-experimental design (Shadish *et al.* 2002) to evaluate the effectiveness of these thirteen countermeasures. A quasi-experimental design is similar to the traditional

[3] In the crash database, the location type of a crash (within an intersection or on a roadway segment) is based on the police reports—police reported the location type (intersection or segment) through their judgments. Usually those that occurred within 100 feet of an intersection are categorized as intersection-based crashes, while those that occurred in mid-block and far from intersections are considered segment-based crashes.

experimental design but lacks the element of random assignment[4]. Lack of random assignment is almost universally true for transportation improvement measures, as countermeasures are often installed based on a citywide transportation improvement plan and at hot-spot locations (with a high number of crashes). Given the inability to randomly assign safety countermeasures to locations, the quasi-experimental design is the strongest design in identifying the causal relationship from a safety countermeasure to crash reductions.

In a pretest-posttest with a comparison group design, one of the stronger of the quasi-experimental design, a set of untreated locations is selected as the comparison group and crashes during pre and post-treatment periods are collected for both the treated and untreated groups. The changes in crashes from the pre-treatment period to the post-treatment period for the two groups are then compared. If the treatment group experienced a greater reduction in crashes from pre-treatment to post-treatment than the comparison group did, it points to the effectiveness of the countermeasure.

I applied two sets of criteria to select comparison groups for intersection-based and segment-based countermeasures. In both cases, I consider both the "who" and "where" dimension in selecting the criteria. As mentioned earlier, the "where" dimension considers both site characteristics and the surrounding built environment (see Table 2.2). Site characteristics for intersection-based ones include: control type (Poch and Mannering 1996), the number of legs at the intersection (Milton and Mannering 1998, Harkey *et al.* 2008a), direction (one-way vs. two-

[4] With random assignment, locations have the same chance of being assigned to a given treatment and thus it is ensured that both the experimental and control groups are equivalent. In a quasi-experimental design, assignment to a given treatment is based on something other than random assignment.

way) of the major road (Harkey *et al.* 2008a), number of travel lanes for the major road of the intersection, and the distribution of the countermeasures in borough or community district, etc. Site characteristics for segment-type countermeasures include: one-way vs. two-way (Harkey *et al.* 2008a), number of travel lanes (Milton and Mannering 1998, Noland and Oh 2004), presence of parking, being on a bus route or a truck route, and distribution of the countermeasures in the five boroughs or community district. To avoid spillover effects[5] (Council *et al.* 2005, Ewing and Brown 2009), locations that are adjacent to treatment locations are avoided. The surrounding built environment is matched by selecting the comparison group in the same borough, or in some cases, in the same community district within the same borough, if data allow (for example, the selection of comparison group for speed reducers). Table 2.4 summarizes the criteria variables used in the study.

[5] The spillover effects are the safety effects on untreated locations simply due to their proximity to the treated locations. One example is the red light camera (Council *et al.* 2005), in which case, those untreated, but nearby intersections may also experience an effect because drivers also become more compliant to traffic signals in nearby locations. Another example is a traffic calmed street (Ewing and Brown 2009), which may see the diversion of traffic from the treated street to a nearby parallel street.

Table 2.4   Description of Segment-based Safety Countermeasures

Safety Countermeasure	Location Type	Criteria Variables
Barnes Dance	Intersection	Geographical distribution in borough, control type, number of legs, non-adjacent locations
High Visibility Crosswalk	Intersection	Geographical distribution in borough, control type, number of legs, non-adjacent locations
Increase Cycle Length	Intersection	Geographical distribution in borough, control type (signalized), number of legs, one-way or two-way of the major road, non-adjacent locations
Left Turn Bay	Intersection	Geographical distribution in borough, control type, number of legs, non-adjacent locations
Left Turn Phase	Intersection	Geographical distribution in borough, control type (signalized), number of legs one-way or two-way of the major road, number of lanes of the major road, non-adjacent locations
Signal Installation	Intersection	Geographically distribution in borough, control type (non-signalized), number of legs, non-adjacent locations
Split Phase Timing	Intersection	Within the borough of Manhattan, control type (signalized), 4 legs, one-way for both major and minor roads, non-adjacent locations
Bike Lane	Segment	Geographical distribution in borough, one-way or two-way, separated by median or not, and the number of travel lanes, non-adjacent locations
Bus Lane	Segment	Geographical distribution in borough, one-way or two-way, separated by median or not, and the number of travel lanes, non-adjacent locations
Pedestrian Barrier	Segment	Geographical distribution in borough, one-way or two-way, separated by median or not, and the number of travel lanes, non-adjacent locations
Road Diet	Segment	Geographical distribution in borough, one-way or two-way, separated by median or not, and the number of travel lanes, non-adjacent locations
Speed Limit Reduction	Segment	Geographical distribution in borough, one-way or two-way, separated by median or not, and the number of travel lanes, non-adjacent locations
Speed Reducer	Segment	Geographical distribution in community district, one-way vs. two-way, number of lanes, presence of parking, not separated by median, not a truck route, not a bus route, non-adjacent locations

I applied frequency matching[6] between the treatment group and the comparison group (Chen *et al.* 2011). For the segment-based measures where both segment and intersection based crashes were evaluated, a second comparison group—an intersection-based comparison group was also generated[7] for the purpose of evaluating crashes at intersections.

Some measures are sequentially aligned with each other on the same corridor (e.g., pedestrian barrier); or they are concentrated in a small geographical area (e.g., split phase timing). For such countermeasures, I also manually identified locations that are either parallel or close to treatment locations, but not adjacent to them.

2.3.2 Calculation of Crash Modification Factors (CMFs)

After the comparison group was selected for each countermeasure, I applied the Comparison Group Analysis method proposed by Hauer (1997). A key step in the analysis is the calculation of a Crash Modification Factors (CMFs) for each safety countermeasure based on the reduction of crashes from a forecast of the expected number of crashes at the treatment site if the treatment had not been installed. It is assumed that if there were no treatments, crashes in the treatment group will follow a similar trend as those in the comparison group.

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[6] The frequency matching is a procedure to select a set of untreated locations having similar joint distribution of the control variables as the treated locations. The details of this procedure can be found in the project report (Chen *et al.* 2011).

[7] The procedure is to collect all the intersections in the treatment group and the segment-based comparison group. Then the frequency matching method is applied in order to select a subset of intersections from the comparison group so that the distribution of the intersection-based control variables (geographical distribution in borough, control type and number of legs of an intersection) in the intersection-based comparison group match those of the intersections from the treatment group (Chen *et al.* 2011).

Police-reported crashes are collected for each treatment group and comparison group. I use X_{t1} vs. X_{t0} and X_{c1} vs. X_{c0} to represent crashes in the pre-treatment period and in the post-treatment period for the treatment group and the comparison group, respectively. A 5-year pre-treatment period and a 2-year post-treatment period is selected, considering that a crash is a relatively rare event, thus, including a longer 5-year before period allows us to capture a more stable trend prior to the treatment. On the other hand, the selection of a shorter after period than the before period allows us to include more treatment sites. Crash data are only available until 2008, thus implementing a 5-year after period would mean that only treatments installed prior to 2003 could be evaluated and yet, most of the treatments were installed after 2003.

The expected crashes at the treated locations assuming that there had not been a treatment, is termed the counterfactual, which can be defined as the expected value as follows:

$$E(X_{t1}) = X_{t0} \times E\left[X_{c1} / X_{c0}\right] \tag{2.1}$$

Where: $E[\cdot]$ means the expected value of the ratio and it is calculated by the approach in Hauer (1997).

The CMF is defined as the expected ratio between the actual crashes at treated locations in the post-treatment period with treatment and the expected crashes at treated locations in the post-treatment period had there been no treatment:

$$CMF = E\left[X_{t1}/E(X_{t1})\right] \tag{2.2}$$

Where:

X_{t1} = Actual crashes at treated locations in the post-treatment period with treatment;

$E(X_{t1})$ = Expected crashes at treated locations in the post-treatment period had there been no treatment;

$E[\cdot]$ = Expected value of the ratio, calculated by the approach in Hauer (1997).

It is through the assessment of the calculated CMFs that the effectiveness of a countermeasure is evaluated. A CMF of 1.0 indicates no change (0%); a CMF of less than one suggests a reduction in crashes, whereas a CMF of more than one suggests an increase in crashes. The expected percentage changes in crashes can also be calculated from CMF, or:

$$\text{Expected Percentage Change in crashes} = (\text{CMF} - 1) \times 100\% \tag{2.3}$$

If the confidence interval of the CMF falls entirely in the (0, 1) domain, then the countermeasure can be considered effective. The detailed calculation of the expected CMF and its confidence interval is found in Hauer's book (Hauer 1997) and the final report of the study (Chen *et al.* 2011) .

2.3.3 Results

Table 2.5 summarizes the calculated CMFs (estimates and standard errors) of the thirteen countermeasures evaluated in reducing various types of crashes and injuries. The expected percentage changes (as shown in Table 2.6) in crash frequencies are calculated from the CMFs, that is, (CMF - 1) × 100%.

Among the countermeasures that are designed to reduce crashes by reducing conflicts, four of the five signal-related measures are found to reduce crashes: Barnes Dance is found to reduce pedestrian crashes at intersections by 32%. Split phase timing is found to reduce total crashes by 27%, vehicle crashes by 25%, and pedestrian crashes by 39%. Increasing total cycle length is expected to reduce total crashes by 22%, vehicle crashes by 17%, pedestrian crashes by 57% and crashes with injuries by 12%. Signal installations are expected to reduce total crashes by 43%, vehicle crashes by 46%, pedestrian crashes by 34%, bicycle crashes by 49%, and injurious and fatal crashes by 40%.

Table 2.5 Summary Results in terms of CMFs—Estimates and Standard Errors

Purpose	Safety Countermeasures	Note	Crash Location	All Crashes	Multi-Veh Crashes	Pedestrian Crashes	Bicycle Crashes	Injurious Crashes
Reducing Conflict	Barnes Dance	ped-veh	int	0.90 (0.11)	0.88 (0.11)	**0.68 (0.16)**	NA	0.95 (0.13)
	Split Phase Timing	ped-veh	int	**0.73 (0.10)**	**0.75 (0.09)**	**0.61 (0.19)**	0.80 (0.26)	0.73 (0.17)
	Increase Cycle Length	ped-veh	int	**0.78 (0.06)**	**0.83 (0.07)**	**0.43 (0.10)**	NA	**0.88 (0.07)**
	Pedestrian Barrier	ped-veh	seg	0.71 (0.22)	0.74 (0.21)	0.61 (0.33)	NA	0.51 (0.22)
			int	0.89 (0.10)	0.88 (0.11)	0.78 (0.19)	NA	0.89 (0.10)
	Signal Installations	all road users	int	**0.57 (0.05)**	**0.54 (0.05)**	**0.66 (0.13)**	**0.51 (0.22)**	**0.6 (0.05)**
	Left Turn Phase	veh-veh	int	0.87 (0.09)	0.91 (0.09)	**0.57 (0.17)**	0.79 (0.31)	0.88 (0.07)
	Left Turn Bay	veh-veh	int	1.05 (0.14)	1.08 (0.15)	1.09 (0.29)	NA	0.97 (0.13)
Reducing Speed	Posted Speed Limit Reduction	corridors	seg	0.78 (0.16)	0.88 (0.16)	NA	NA	0.83 (0.21)
			int	0.87 (0.09)	0.92 (0.10)	0.64 (0.22)	NA	0.90 (0.10)
	Speed Reducer	city-wide	seg	**0.69 (0.14)**	**0.72 (0.13)**	**0.45 (0.08)**	NA	**0.63 (0.15)**
			int	0.90 (0.05)	**0.89 (0.05)**	0.97 (0.19)	0.97 (0.21)	0.93 (0.07)
Changing Exposure	Road Diet (reducing number of travel lanes and installing bike lanes)	vehicle (-), bicyclists (+)	seg	**0.34 (0.09)**	**0.34 (0.09)**	**0.40 (0.19)**	NA	**0.27 (0.10)**
			int	0.91 (0.07)	0.86 (0.10)	0.96 (0.18)	1.06 (0.31)	0.86 (0.08)
	Bike Lane (narrowing lanes and installing bike lanes)	bicyclists (+)	seg	0.96 (0.11)	0.96 (0.12)	0.83 (0.21)	2.01 (0.79)	1.02 (0.14)
			int	1.04 (0.05)	0.99 (0.08)	1.09 (0.10)	1.31 (0.19)	1.07 (0.05)
	Bus Lane	transit riders (+)	seg	1.23 (0.15)	1.16 (0.18)	1.43 (0.30)	0.99 (0.32)	1.34 (0.23)
			int	1.04 (0.06)	0.98 (0.07)	1.12 (0.10)	1.10 (0.21)	1.09 (0.07)
Other	High Visibility Crosswalk	Ped. safety	int	1.04 (0.17)	1.29 (0.23)	0.61 (0.24)	NA	1.00 (0.14)

Note: The values in parentheses are standard errors; Number in bold means the reduction is significant at 5% level;
NA means the results are unavailable due to small sample sizes; Crash Location: int – intersection, seg – segment.

Table 2.6 Summary Results in terms of Percentage Reduction

Purpose	Safety Countermeasures	Note	Crash Location	All Crashes	Multi-Veh Crashes	Pedestrian Crashes	Bicycle Crashes	Injurious Crashes
Reducing Conflict	Barnes Dance	ped-veh	int	-10%	-12%	**-32%**	NA	-5%
	Split Phase Timing	ped-veh	int	**-27%**	**-25%**	**-39%**	-20%	-27%
	Increase Cycle Length	ped-veh	int	**-22%**	**-17%**	**-57%**	NA	**-12%**
	Pedestrian Barrier	ped-veh	seg	-29%	-26%	-39%	NA	-49%
			int	-11%	-12%	-22%	NA	-11%
	Signal Installations	all road users	int	**-43%**	**-46%**	**-34%**	**-49%**	**-40%**
	Left Turn Phase	veh-veh	int	-13%	-9%	**-43%**	-21%	-12%
	Left Turn Bay	veh-veh	int	5%	8%	9%	NA	-3%
Reducing Speed	Posted Speed Limit Reduction	corridors	seg	-22%	-12%	NA	NA	-17%
			int	-13%	-8%	-36%	NA	-10%
	Speed Reducer	city-wide	seg	**-31%**	**-28%**	**-55%**	NA	**-37%**
			int	-10%	**-11%**	-3%	-3%	-7%
Changing Exposure	Road Diet (reducing number of travel lanes and installing bike lanes)	vehicle (-), bicyclists (+)	seg	**-66%**	**-66%**	**-60%**	NA	**-73%**
			int	-9%	-14%	-4%	6%	-14%
	Bike Lane (narrowing lanes and installing bike lanes)	bicyclists (+)	seg	-4%	-4%	-17%	101%	2%
			int	4%	-1%	9%	31%	7%
	Bus Lane	transit riders (+)	seg	23%	16%	43%	-1%	34%
			int	4%	-2%	12%	10%	9%
Other	High Visibility Crosswalk	Ped. safety	int	4%	29%	-39%	NA	0%

Note: Number in bold means the reduction is significant at 5% level;
NA means the results are unavailable due to small sample sizes;
Crash Location: int – intersection, seg – segment.

The effect of signal installations is substantial—it significantly reduces crashes of all types: all crashes, vehicle crashes, pedestrian crashes, bicycle crashes, and injurious crashes. The other three—Barnes Dance, split phase timing, and increasing cycle length—are all found to be effective in reducing pedestrian crashes, as well as other types of crashes.

Left-turn phase and left-turn bay are designed to improve the safety of left-turning movements by reducing the vehicle-vehicle conflicts at intersections, however, they are found to have little impact on vehicle crashes.

Two safety countermeasures are designed to reduce vehicle travel speeds—speed reducers (speed humps) and signs with reduced speed limit. Speed reducers are found to reduce all crashes by 31%, vehicle crashes by 28%, pedestrian crashes by 55%, and injurious and fatal crashes by 37%. Posting signs with reduced speed limit, however, is found to have little impact on safety.

Those that are designed to change exposure are found to have mixed results. Road diet (reducing the number of travel lanes and installing bike lanes) is found to reduce total crashes by 66%, vehicle crashes by 66%, pedestrian crashes by 60%, and injurious and fatal crashes by 73%; bike lanes (narrowing width of travel lanes and installing bike lanes) are found to have no impact on crashes; and installation of bus lanes is found to have no impact on crashes, either.

Measures that are designed to alert drivers' cognitive attention, for example, high visibility crosswalk and posted speed limit reduction signs appear to have a lesser effect than others. This is not to say that these countermeasures are not useful—both countermeasures tend to reduce crashes, although the impact is not significant.

2.4 Discussion

I argue that it is crucially important that the selection and the implementation of the various safety countermeasures are grounded in a theoretically sound framework (Figure 2.3). The many measures[8] implemented in NYC are designed to affect crashes through three pivotal forces: exposure, speed, and conflicts (Ewing and Dumbaugh 2009). Furthermore, the selection considers multi-modal road users (the "who" component) and the surrounding built environment (the "where" component). As an example, increasing cycle length and thus pedestrian crossing time is particularly helpful on Queens Boulevard, which has 12 lanes in some sections and is located in areas where there is a substantial number of elderly whose crossing speed is low. Another example is split phase signal timing, which is appropriate for intersections in midtown east of Manhattan, where both streets are one-way and there are many pedestrian crossings for shopping and entertaining in this area with a resulting high number of conflicts between pedestrians and left-turning cars.

Traditional engineering measures, in particular, signal-related ones, remain an effective safety countermeasure, when installed at appropriate locations. These measures primarily work to reduce conflicts among multiple vehicles or between different road users. One interesting

[8] As I have explained earlier, many more than the thirteen safety countermeasures have been installed in New York City, which can be found in NYCDOT's reports (New York City Department of Transportation 2008a, 2009).

finding is that signal installation appears to have little impact on pedestrian crashes, even though it significantly reduced all other crash types. Barnes Dance, on the other hand, is only effective in reducing pedestrian crashes. These findings may have something to do with the large number of pedestrians present in New York City—the regular timing for pedestrians (through signal installation) may not be sufficient to release the many pedestrians accumulated in a short time, while Barnes Dance is particularly designed for this purpose. It is also important to note that the effectiveness of signal installation, found through this study, does not necessarily suggest that removal of signals increases crashes, or is ineffective. Studies have shown that the removal of signals at some locations can be effective in reducing crashes (Persaud *et al.* 1997). According to *Manual on Uniform Traffic Control Devices* (MUTCD 2009), signal installation is likely to be effective when the intersection volume exceeds a certain threshold and signal removal can be effective when the volume is low (Persaud *et al.* 1997).

Some traffic calming measures are useful alternatives as they are designed to reduce speed and calm traffic, and thus improve safety, for example, road diets are found to be an effective measure in reducing crashes on road segments. Those that are designed to alert drivers' cognitive attention (e.g., high visibility crosswalk and posted speed limits), however, are found to have little effect on crashes.

Only one countermeasure (signal installation) is found to reduce crashes of all types. Most are found to have an effect on a certain type of crashes, but no impact on others. Some, for example, high visibility crosswalk, are found to have a tendency to increase vehicle collisions while reducing pedestrian crashes, though neither is significant. This suggests that there are likely trade-offs in crash reductions—the safety improvement of one type of road users may compromise the safety of other users. This further strengthens the importance of considering the "who" and the "where" components (Figure 2.3) in the selection of safety countermeasures.

The bus lanes and bike lanes are found to be insignificant in reducing crashes. These treatments, however, have other benefits. For example, bus lanes can increase transit ridership by improving the efficiency of bus service, and bike lanes can encourage the use of bicycles as transportation modes (Dill 2003). As mentioned earlier, the "safety in numbers" (Jacobsen 2003) can potentially reduce crash rates, suggesting that "awareness" can have a significant impact on safety even if the two countermeasures (bus lane and bike lane) that I studied did not have a meaningful impact.

In some cases, as the study indicates, segment-based and intersection-based countermeasures can be used effectively together to work toward the goal of crash reduction. Take the example of bike lane installation: it was found that crashes at the associated intersections slightly increase after the bike lane installation, even though the effect is not significant. This is likely attributed to the combination of an increase of bicyclists after the installation of bike lanes and the disconnectedness of the bike lane at the intersections—bicyclists going straight or turning left will conflict with the opposing traffic. In such cases, measures at the intersection such as bike boxes, or protected signal treatment for bicyclists (when there are a sufficient number of bicyclists) may be helpful.

The study, nevertheless, has limitations, primarily relating to the lack of exposure data, which leads to potentially an over- or an under-statement of the safety effects. In the case of bike lanes, it is almost certain that the bicyclist volume significantly increases after the installation of bicycle lanes (Nelson 1997, Dill 2003, Pucher and Buehler 2005, Barnes *et al.* 2006b, Parkin *et al.* 2008). Yet, not controlling the differential in bicyclist volumes between the before and the after period of the bike lane installation (due to unavailability of such data) likely leads to an understatement of the safety effects—if the differential in bicyclist volume could be properly controlled, it is possible that a significant reduction in crashes in the treatment group would have been observed. In the example of speed humps, motorists may purposely avoid road segments with the speed hump, thus resulting in a reduction in vehicle volume on the treated segments. The inability to control for the difference in vehicle volume before and after due to lack of data may result in an overstatement of the safety effects. This discussion also points to the importance of collecting exposure data both at treated sites as well as at the comparison sites.

Because the study relies on police-reported crash data, there is a likelihood of under-reporting—people sometimes choose not to report to the police particularly when a crash results in only property damages of low costs. It is possible that the under-reporting affects the study results. However, the magnitude of the error is expected to be limited, since this study compares crash differences from before treatment to after treatment for both treatment group and comparison group, assuming that the amount of under-reporting before and after the treatment is similar.

2.5 Summary

New York City has made great progress in improving street safety over the past twenty years—many of the safety countermeasures installed in New York City have been found effective in reducing crashes of various types (Table 2.5), contributing to the citywide long-term decline in fatalities (Figure 2.1) and crashes (Figure 2.2)—and efforts must still be made in order to meet the goal of reducing fatalities by half by 2030 (New York City Department of Transportation 2011). The safety strategies implemented considered all three dimensions (see Figure 3). This study demonstrates that this strategy is successful and significantly contributes to the large crash reductions that New York City has achieved.

At state and local DOTs, a substantial amount of work relates to deciding which treatment or policy should be applied to achieve a certain goal, for example, reduce crashes, relieve congestion, or to improve traffic flow etc. Consequently, early, but rigorous evaluations of these treatments or policies are crucial as they affect decisions on whether a large scale implementation is desired or not. A rigorous evaluation means removing various confounding factors (Shadish *et al.* 2002) and thus requires comparisons of both before and after and between the treatment group and the comparison group. Ideally, the quasi-experiment design adopted in this study should be applied in these evaluation studies whenever possible. With this study, I demonstrate that such a method can be readily applied to, at least, safety evaluation studies.

The selection of comparison group can only control a limited number of factors (see Table 2.4) that might affect crashes, and the other confounding factors such as the built environment factors (such as neighborhood population density, land use, and transportation network characteristics), which have been found to be important factors affecting crashes (Ewing and Dumbaugh 2009), have not been controlled and studied in this study using the method of Comparison Group Analysis (Hauer 1997). A more rigorous methodology, such as regression models, can be explored in future to study the effects of various confounding factors (including both the site-level roadway characteristics and neighborhood-level built environment characteristics) and the effectiveness of safety countermeasures in New York City by accounting for these effects.

In the following three chapters, a rigorous quasi-experimental design and regression models incorporating built environment factors will be developed and applied to the evaluations of safety countermeasures that are designed for the safety of motor vehicles, bicyclists, and pedestrians in New York City.

CHAPTER 3

Evaluation of the Effectiveness of Left-Turn Signal Phases

—for the Safety of Motor Vehicles

Left-turn signal phasing (protected-only or protected/permissive) is a commonly used treatment for the safety of motor vehicles making left-turn at intersections. The objective of this chapter is to evaluate the safety impacts of changing left-turn signal phasing from permissive to protected/permissive or protected-only in crashes at intersections, including the total crashes, multiple-vehicle crashes, and left-turn crashes. A rigorous quasi-experimental design accompanied with regression modeling is used for the evaluation.

3.1 Introduction

Left-turning vehicles at intersections encounter conflicts of various sources: the opposing through and right-turning traffic, through and left-turning traffic from the same approach, and crossing vehicular and pedestrian traffic from other approaches. Consequently, left-turn crashes are one of the most frequently occurring collision types at intersections: based on the twenty-year (1989-2008) history of crashes at intersection in New York City, left-turn crashes rank third, following rear-end and right-angle crashes, and represent 9.5% of all intersection crashes reported (New York City Department of Transportation, 2009). Furthermore, the severity of the injury and the likelihood of fatality of left-turn crashes tend to be grave and high because of the relatively high travel speeds of vehicles involved and the angle of impact (Wang and Abdel-Aty 2008).

Left-turn signal phasing is a frequently applied treatment to intersections with substantial left-turning traffic (Agent and Deen 1979, Stamatiadis *et al.* 1997, Al-Kaisy and Stewart 2001). Left-turning movements at signalized intersections are usually controlled by traffic signals in three ways: permissive-only, protected-only, and protected/permissive. According to the *Manual on Uniform Traffic Control Devices* (MUTCD, 2009 Edition), the permissive-only type provides no exclusive phasing for left-turn traffic—left-turning vehicles make turns on a green signal indication after yielding to pedestrians and/or opposing traffic, if any. A left-turn phase can be either protected-only or protected/permissive: the protected-only type provides an exclusive phasing for left-turn traffic and allows vehicles to make left turns only when a left-turn green arrow signal indication is displayed; the protected/permissive type combines the permissive-only and protected-only left-turn phases in the same cycle, and vehicles are allowed to make left-turns either on a green arrow indication (protected-only phase) or on the circular green (permissive-only phase), during which they must yield to the opposing traffic.

There may be trade-offs between safety and the smooth progression of traffic when deciding whether a left-turning phase shall be installed. On one hand, left-turn signal phases facilitate left-turning traffic and may improve the safety of left-turning movements at the intersections. On the other hand, the addition of a protected left-turn signal phase will usually result in reduced green time available for through traffic and longer total cycle lengths, which will reduce the capacity of an intersection by increasing stops and delays (Agent and Deen 1979, Agent 1987). Sometimes in order to reduce delays and increase capacity at a signalized intersection, permissive left-turn phasing is used as an alternative to protected phasing (Agent 1987).

In practice, the decision on the choice of left-turn phasing at signalized intersections largely depends on local context (Lalani *et al.* 1986, Zhang *et al.* 2008). As a low-cost safety countermeasure, left-turn signal phasing (protected/permissive or protected-only mode) has been popular with many traffic engineers (Federal Highway Administration 2009b). In South Florida, for example, the protected left turn phasing is favored over the permissive type and is almost universally applied (Ewing 2011). On the other hand, some other agencies may be in favor of permissive phasing considering that the protected left turn phases require more green time and they result in long delays for through movements and poor progression. Phoenix, for example, once had permitted left turn movements nearly everywhere (Ewing 2011).

Similarly, the findings from the literature on this question—whether permissive, protected-only, or both shall be applied to an intersection—are mixed. While some studies found that left-turn phasing—protected-only or permissive/protected—reduced left-turn crashes and total intersection crashes (Agent and Deen 1979, Agent 1987, Gibby *et al.* 1992, Shebeeb 1995, Stamatiadis *et al.* 1997), other studies showed that left-turn phasing was ineffective in reducing left-turn crashes or total intersection crashes (Perfater 1983), or in some cases, even increased total intersection crashes (Upchurch 1991, Box and Basha 2003, Srinivasan *et al.* 2008). Hauer's review of 20 studies on the safety impacts of left-turn phasing concluded that there is insufficient and contradictory evidence on whether or not left-turn phasing will have significant impacts on crashes (Hauer 2004).

The purpose of this research is to evaluate the safety effectiveness of left-turning signal phasing installed at 68 intersections in New York City (NYC) where the permissive left-turn phasing was replaced by the protected/permissive or protected-only left-turn phasing. This study advances the existing practice of evaluation by adopting a rigorous before and after quasi-experimental design comprising a treatment group and a comparison group. The study employed negative binomial models to control factors that cannot be controlled by the selection of the comparison group. A Generalized Estimating Equations (GEE) method (Liang and Zeger 1986, Zeger and Liang 1986) was used to account for correlations between repeated measures—crashes in the before and after periods.

3.2 Studies on the Safety Impacts of Left-turn Phasing

Probably the only consensus from the many studies on left-turn phasing is that left-turn phasing—protected only or permissive/protected—tends to reduce left-turn crashes. Agent and Deen (1979) found that the installation of a separate left-turn phasing resulted in an 85% reduction in left-turn crashes. A later study by Agent (1987) indicated that the number of left-turn crashes usually decreased when permissive-only phasing was replaced by protected/permissive phasing. Gibby et al. (1992) also found that the provision of a left-turn phase resulted in fewer left-turn crashes. Shebeeb (1995) compared the mean crash rates (per million vehicles) for different signal modes for left-turn movements, including permissive, protected/permissive and protected-only signal phasing, and found that left-turn crash rate for permissive phasing was higher (though insignificantly so) than that for the protected/permissive phasing. Stamatiadis et al. (1997) also found that the left-turn crash rates (left-turn crashes per year /100,000 left-turn and opposing volume) were higher at locations with permissive signal than those with protected/permissive or protected-only signal phasing.

This is not to say that there is no controversy on the safety impact of left-turn phasing in reducing left-turn crashes. Upchurch (1991), for example, compared left-turn crash rates (number of left-turn crashes divided by million left-turning vehicles) for the three phasing plans—permissive (no left-turn signal phasing), protected/permissive, and protected-only—and found that protected/permissive signal had a higher crash rate than permissive phasing.

Findings on other types of crashes and total intersection crashes are much more ambiguous. Box and Basha (2003) found that annual total crash rate (per 1,000 ADT conflicting movements) was higher for protected/permissive signal phase than for permissive or protected-only left-turn phasing. In addition, there may be safety trade-offs—a study by Srinivasan et al. (2008) showed that after replacing permissive phasing with permissive/protected or protected-only phasing, the reduction in left-turn crashes was accompanied by an increase in all crashes, though the increase was insignificant. The review of the twenty studies by Hauer (2004) also concluded that evidence on the safety impact of left-turn phasing is contradictory and insufficient at best.

Methodologically, the current studies are deficient in identifying the causal relationship—whether the addition of a special phase for left-turns reduces crashes or not. Many of the early studies used simple cross-sectional comparisons of crash rates for different types of left-turn phasing (Gibby *et al.* 1992, Shebeeb 1995, Stamatiadis *et al.* 1997, Box and Basha 2003), and in some, only simple before-after comparisons were conducted (Agent and Deen 1979, Perfater 1983, Agent 1987). A more rigorous quasi-experimental design that involves a treatment group and a comparison group and compares crashes before and after the installation of the left-turn phase is preferred (Krizek *et al.* 2009). Srinivasan et al. (2008) studied the effect of replacing permissive phasing with protected/permissive or protected-only phasing by using the Empirical Bayes (EB) method, in which a reference group was selected and a before-after comparison was conducted. However, the conclusion of this study was that the results cannot be taken as definitive due to the small sample sizes—the study had only 1 intersection for replacing permissive phasing with protected/permissive phasing, 2 intersections for replacing permissive with protected-only phasing, and 3 intersections for replacing protected/permissive with protected-only phasing.

Few existing studies account for differences in settings; a few studies (Agent 1987, Stamatiadis *et al.* 1997) account for site characteristics (such as number of lanes, signal display and signing, speed, and traffic composition) at the intersections, however, no built environment characteristics were accounted for. Recent studies suggest that the built environment is correlated with crashes and injuries(Ewing and Dumbaugh 2009). Therefore, to correctly identify the safety effect of left-turn phasing in reducing crashes, a preferred study design should entail comparing before and after crashes for both the treatment group (with left-turn phasing) and the comparison group (without left-turn phasing), while accounting for differences in the built environment.

3.3 Methods

Police-reported intersection crashes including total crashes, multiple-vehicle crashes (vehicle-vehicle collisions), and left turn crashes (involved left-turning vehicles) were studied. Each intersection was associated with two observations: crashes within a 5-year period prior to the treatment and crashes within a 2-year period after the treatment. A crash is a relatively rare event, thus, including a longer 5-year before period allows us to capture a more stable trend prior to the treatment. On the other hand, the selection of a shorter after period than the before period allows us to include more treatment sites: crash data is only available until 2008, thus implementing a 5-year after-treatment period would mean that only treatments installed prior to 2003 can be evaluated and yet, more than one third of the intersections in the treatment group were treated with protected-only or permissive/protected left-turn phasing after 2003. The difference in the before- and after-period is controlled by an offset variable in the model.

This study involves a two-stage design. In the first stage, a comparison group of signalized intersection without any treatments is identified during the same study period but sharing intersection-level characteristics comparable to those in the treatment group comprising 68 intersections in NYC where their permissive phasing was changed to protected/permissive or protected-only between 2000 and 2007. In the second stage, negative binomial regression models using the GEE method is applied to the dataset comprising observations in the before and after periods for both treatment group and comparison group. The effectiveness of the installation of permissive and protected-only phasing in reducing crashes is evaluated through the coefficients estimated from the model.

3.3.1 Stage One—Comparison Group Selection

In the first stage, a comparison group was generated comprising similar intersections but without the treatment. The selection of the comparison group was based on several intersection-level factors that have been found to have significant effects on crashes: control type (signalized or not) (Poch and Mannering 1996), the number of intersection legs (Milton and Mannering 1998, Harkey *et al.* 2008b), one-way or two-way on the major road, and number of lanes on the major road of the intersection (Harkey *et al.* 2008b). Since the intersections in the treatment group were all signalized and the major roads were all two-way, non-treated intersections with similar characteristics (signalized and two-way major roads) were selected in the comparison group. The distributions of the other two characteristics—number of legs and number of lanes of the major roads—were also controlled in the selection of the comparison group. The geographical distribution (e.g., five boroughs of NYC, as shown in Figure 3.1) of the locations in the comparison group was further controlled to resemble the distribution of those in the treatment group.

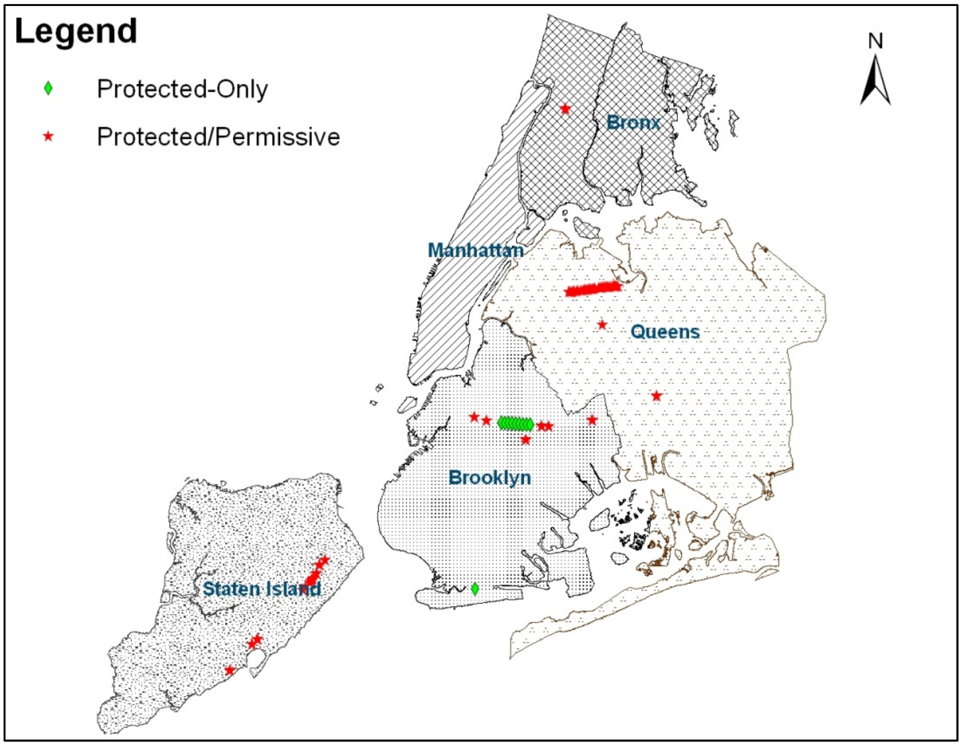

Figure 3.1 Geographical Distribution of Treatment Intersections in New York City

The change of left-turn phasing from permissive to protected/permissive and/or protected-only was completed over a period of 8 years (from 2000 to 2007), and thus the before period and the after period are different for intersections treated in different years. As an example, the 5-year before period and the 2-year after period for signals installed in 2005 are 2000-2004 and 2006-2007, respectively, while those corresponding to signals installed in 2006 are 2001-2005 and 2007-2008, respectively. For this reason, a treatment group was first divided into multiple subsets defined by the year of installation. Then, for each subset, a set of untreated locations were selected by applying the frequency matching technique (Chen *et al.* 2011) to resemble the joint distribution of those selected matching variables (signalized, two-way on major roads, number of legs, and number of lanes on major roads) as well as the geographical distribution (in five boroughs of NYC) of the treatment group. After each subset was identified with a corresponding set of untreated intersections, those untreated intersections were combined into a single comparison group.

Since many of the treated intersections are on parts of long corridors whereas those in the comparison group selected are more likely to be scattered throughout the city. A set of intersections along streets that are parallel to those in the treatment group were also selected manually and added to the comparison group. These procedures resulted in a comparison group of 991 intersections, corresponding to 68 intersections in the treatment group. The distributions of the matching variables in the treatment group and the comparison group are shown in Table 3.1.

Table 3.1 Distributions of Matching Variables

Control Variables	Values	Treatment Group	Comparison Group
Borough	Manhattan	0 (0%)	0 (0%)
	Bronx	1 (1%)	47 (5%)
	Brooklyn	15 (22%)	430 (43%)
	Queens	38 (56%)	433 (44%)
	Staten Island	14 (21%)	81 (8%)
Number of legs	3-leg	3 (4%)	15 (2%)
	4-leg	63 (93%)	971 (98%)
	5 or more	2 (3%)	5 (1%)
Number of lanes (on major road)	1-lane	25 (37%)	264 (27%)
	2-lane	16 (24%)	405 (41%)
	3-lane	11 (16%)	145 (15%)
	4-lane	12 (18%)	161 (16%)
	5 or more	4 (6%)	16 (2%)
Sum		68 (100%)	991 (100%)

3.3.2 Stage Two—Negative Binomial Models using GEE Method

In the second stage regression models were applied to further control those factors, for example, built environment characteristics, that cannot be controlled when selecting the comparison group but are potentially associated with crashes (Ewing and Dumbaugh 2009). Negative binomial regression models were used due to over-dispersion of the crash data.

To account for correlation within observations collected on the same location at two time points (before and after period), the generalized estimating equation (GEE) methodology with an exchangeable correlation structure was applied.

The model is specified below:

$$\begin{aligned} y_{it} &= \exp\left(\alpha + 1 \times \log(year_t) + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + a_1(TG1\_T1) + a_2(TG2\_T1) + b(CG\_T1) + \varphi(If\_TG)\right) \\ &= year_t \times \exp\left(\alpha + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + a_1(TG1\_T1) + a_2(TG2\_T1) + b(CG\_T1) + \varphi(If\_TG)\right) \end{aligned} \tag{3.1}$$

Where,

- y_{it} is the expected crash count at site i during time t (before or after period);
- $year_t$ s the number of years during time t (5 years for pre-treatment period and 2 years for post-treatment period);
- $\mathbf{X}^{(s)}\boldsymbol{\beta}$ are site-level covariates with coefficient $\boldsymbol{\beta}$;

- $\mathbf{X}^{(n)}\boldsymbol{\gamma}$ are neighborhood-level covariates with coefficient $\boldsymbol{\gamma}$;
- *TG1_T1* is equal to 1 if the data point comes from a location in the treatment group (where the signal phases were changed from permissive to protected/permissive) post-treatment and 0 otherwise, and the coefficient for this variable is a_1;
- *TG2_T1* is equal to 1 if the data point comes from a location in the treatment group (where the signal phases were changed from permissive to protected-only) post-treatment and 0 otherwise, and the coefficient for this variable is a_2;
- *CG_T1* is equal to 1 if the data point comes from an un-treated location in the comparison group post-treatment and 0 otherwise, and the coefficient for this variable is b;
- *If_TG* is equal to 1 if the data point comes from a treated location (where signal phases were changed from permissive to protected/permissive or protected-only) and 0 otherwise, and the coefficient for this variable is φ.

The difference between the before (5-year) and the after period (2-year) was accounted for in the model by the offset variable ($year_t$), whose coefficient is restricted to 1, assuming that the crash frequency is proportional to the number of years it is counted.

The model includes two sets of independent variables that may potentially affect crash frequencies: neighborhood-level and site-level covariates. Table 3.2 shows the list of explanatory variables and their sources. At the neighborhood level (calculated as census tract level), it is hypothesized that higher exposure and more conflicts are associated with more crashes (Ewing and Dumbaugh 2009). The daytime population density, retail density, percentage of different age groups (under 21, 21-65, or above 65), motorized or non-motorized mode shares are used to account for the exposure of vehicular traffic and pedestrians. Daytime population density was calculated as the number of residents plus employment minus the number of people who live and work in the same census tract (to remove double counting) divided by the total census tract area; and retail density was calculated as the floor area of retail land use divided by total census tract area. These two variables measure the density of people who live, work, and shop in the neighborhood. Site-level covariates include the number of legs at an intersection and the number of lanes on the major road of an intersection.

Table 3.2 List and Category of Potential Explanatory Variables

Category	Variables	Data Source*
Roadway Geometry	Number of legs at the intersection Number of travel lanes on the major road	NYCDOT
Socio-demographic	Daytime population density (1,000 per sq mi) Median household income ($1,000) Percentage of Asian population (%) Percentage of Black population (%) Percentage of population age between 21 and 65 (%) Percentage of population age under 21 (%) Percentage of population age above 65 (%)	US Census 2000
Mode Share	Percentage of commuting by auto (%) Percentage of commuting by public transportation (%) Percentage of commuting by bicycling (%) Percentage of commuting by walking (%)	US Census 2000
Land Use	Residential land use density (floor area, sqft/sqft) Commercial land use density (floor area, sqft/sqft) Retail land use density (floor area, sqft/sqft)	NYCDCP
Transportation	Percentage of roadway miles that is one-way (%) Percentage of roadway miles that is truck route (%) Percentage of roadway miles with parking lane (%) Subway ridership in the census tract (1,000) Subway station density (number per sq mi) Bus stop density (number per sq mi)	NYCDOT

Note *: NYCDOT – New York City Department of Transportation; NYCDCP – New York City Department of City Planning

It is possible that the before crashes in the treatment group are significantly more than those in the comparison group, leading to a potential regression-to-mean effect. Therefore, in addition to the explanatory variables included in Table 3.2, a dummy variable "*If_TG*", representing the treatment group, was included in the model. A positive coefficient of this dummy variable means that the before-period crashes of the treatment group are significantly more than those of the comparison group and a negative coefficient suggests otherwise.

The coefficients of variables "*TG1_T1*", "*TG2_T1*" and "*CG_T1*", that is, "a_1, a_2, and b" in equation (1), are of our primary interest. If the coefficient for variable "*TG1_T1*" is estimated to be negative, it means that crashes in the after period are expected to be less than those in the before period in the treatment group (*TG1*) where the permissive signal phase was changed to protected/permissive left-turn phasing; a positive coefficient suggests otherwise. Similarly, for variables "*TG2_T1*" and "*CG_T1*", negative coefficients indicate crash reductions and positive coefficients imply crash increases in the treatment group (*TG2*), when signal phases were changed from permissive to protected-only, and in the comparison group (*CG*) over the same period.

The contrast between the two coefficients (a_1-b) represents the difference in the change in crash frequencies from the pre-treatment to the post-treatment period for the treatment group (*TG1*, where the permissive signal phase was changed to protected/permissive left-turn phasing) versus the comparison group (*CG*). In order to test if the difference of the two coefficients is statistically significant at 5% level, the model can be transformed by replacing "*TG1_T1*" and "*CG_T1*" with Z_1 and P_1 as in equation (3.2):

$$y_{it} = year_t \times \exp\left(\alpha + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + c_1(Z_1) + d_1(P_1) + a_2(TG2\_T1) + \varphi(If\_TG)\right) \tag{3.2}$$

Where,

$$Z_1 = (TG1\_T1 - CG\_T1)/2, \qquad P_1 = (TG1\_T1 + CG\_T1)/2$$

Similarly, the contrast between the two coefficients (a_2-b) represents the difference in the change in crash frequencies from the pre-treatment to the post-treatment period for the treatment group (*TG2*, where permissive signal phase was changed to protected-only left-turn phasing) versus the comparison group (*CG*). In order to test if the difference of the two coefficients is statistically significant at 5% level, the model can be transformed by replacing "*TG2_T1*" and "*CG_T1*" with Z_2 and P_2 as in equation (3.3):

$$y_{it} = year_t \times \exp\left(\alpha + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + c_2(Z_2) + d_2(P_2) + a_1(TG1\_T1) + \varphi(If\_TG)\right) \tag{3.3}$$

Where,

$$Z_2 = (TG2\_T1 - CG\_T1)/2, \qquad P_2 = (TG2\_T1 + CG\_T1)/2$$

The coefficient of Z_1 is the difference of the two coefficients associated with "*TG1_T1*" and "*CG_T1*": $c_1 = a_1 - b$. If c_1 is significant and negative, it points to the effectiveness of treatment—changing from permissive to permissive/protected-only phasing reduces crashes. If it is insignificant, it suggests that this treatment has no effect on crashes. Similarly, the coefficient of Z_2 is the difference of the two coefficients associated with "*TG2_T1*" and "*CG_T1*": $c_2 = a_2 - b$. If c_2 is significant and negative, it suggests the effectiveness of treatment—protected-only left-turn signal phasing reduces crashes.

3.4 Results

The before and after crashes of all types, including total crashes, multiple-vehicle crashes and left-turn crashes were compared for the treatment group (59 intersections with protected/permissive left turn phasing and 9 intersections with protected-only left turn phasing) and the comparison group. Given the potential trade-offs in safety impacts (Srinivasan *et al.* 2008), the rear-end collisions and over-taking collisions were also included to understand the impacts of left-turn signal phasing on other types of vehicle collisions. The results are shown in Table 3.3.

Table 3.3 Comparison of Crashes in the Treatment Group and Comparison Group

Crash Type	Group*	Number of Intersections	Before		After		Average Crashes (per intersection per year)		
			Years	Sum	Years	Sum	Before	After	%Change
Total Crashes	CG	991	5	13174	2	3322	2.66	1.72	-35%
	TG	68	5	2447	2	564	7.20	4.15	-42%
	TG1	59	5	1901	2	465	6.44	4.29	-33%
	TG2	9	5	546	2	99	12.13	5.50	-55%
Multiple-Vehicle Crashes	CG	991	5	10686	2	2618	2.16	1.36	-37%
	TG	68	5	2038	2	474	5.99	3.74	-38%
	TG1	59	5	1553	2	388	5.26	3.58	-32%
	TG2	9	5	485	2	86	10.78	4.78	-56%
Left-Turn Crashes	CG	991	5	1258	2	301	0.25	0.16	-36%
	TG	68	5	261	2	64	0.77	0.54	-30%
	TG1	59	5	207	2	59	0.70	0.58	-17%
	TG2	9	5	54	2	5	1.20	0.28	-77%
Rear-End Collisions	CG	991	5	2698	2	663	0.54	0.34	-37%
	TG	68	5	619	2	138	1.82	1.08	-41%
	TG1	59	5	451	2	105	1.53	0.97	-37%
	TG2	9	5	168	2	33	3.73	1.83	-51%
Over-Taking Collisions	CG	991	5	1110	2	127	0.22	0.07	-70%
	TG	68	5	206	2	29	0.61	0.22	-64%
	TG1	59	5	157	2	22	0.53	0.19	-63%
	TG2	9	5	49	2	7	1.09	0.39	-64%

Note: * Group
CG – Comparison group
TG – Treatment group (combination of subgroup TG1 and TG2)
TG1 – Subgroup of treatment group comprising intersections where signal phases were changed from permissive to protected/permissive
TG2 – Subgroup of treatment group comprising intersections where signal phases were changed from permissive to protected-only

Over time, crash reduction was experienced by both treatment group and comparison group, reflecting a city-wide downward trend in crashes. This also adds to the earlier point that a simple before-and-after comparison is insufficient in the evaluation of the effectiveness of left-turn phasing in reducing crashes. The magnitudes of crash reductions vary between groups. For total crashes, the reduction (in the average crash per intersection per year) in the comparison group was less (35%) than that in the treatment group (42%). For vehicle collisions, the two groups experienced similar reductions (38% for the treatment group versus 37% for the comparison group). The reduction in left-turn crashes was, 30% for the treatment group versus 36% for the comparison group. The reduction in rear-end collisions in the comparison group was less (37%) than that in the treatment group (41%), while the reduction for over-taking collisions in the comparison group was higher (70%) than that in the treatment group (64%).

A much greater reduction can be observed for the protected-only phasing than the permissive/protected phasing—77% reduction in left-turn crashes for the former as opposed to 17% reduction for the latter. A similar trend exists for other crash types, though at a less degree. Intersections with protected-only phasing experienced 55% and 56% reductions in total crashes and multiple-vehicle crashes, respectively, as compared to 33% and 32% reductions for intersections with permissive/protected phasing. Similarly, protected-only phasing experienced a 51% reduction in rear-end collisions corresponding to a 37% reduction with protected/permissive phasing. For over-taking collisions, on the other hand, the two types (protected-only and protected/permissive left-turn phasing) experienced similar reductions—63% versus 64%, and both are less than the reduction in the comparison group (70%).

The results of the three models (total crashes, multiple-vehicle crashes, and left-turn crashes) are shown in Table 3.4. On the role of the built environment, our results conform to those in the literature (Ewing and Dumbaugh 2009). Variables measuring the exposure of travelers, for example, daytime population density, retail density, percentages of commuters by auto, bus stop density, were all found to be positively correlated with crashes. Variables such as the percentages of 4-leg intersections, roadways with parking, and truck routes in the census tract were included to measure conflicts at the intersection (Ewing and Dumbaugh 2009). The results suggest that areas with a higher percentage of roadways with parking and more 4-leg intersections are associated with more pedestrian crashes. Census tract-level social effects, for example, population of different ethnic groups, were also examined and it was found that census tracts with a higher percentage of black or Asian population have more crashes.

The coefficients of the dummy variable "*If_TG*" for the three crash types—total crashes, multiple-vehicle crashes, and left-turn crashes are all positive and significant at 5% level (p-value < 0.0001), confirming the potential existence of the regression to the mean effect.

Table 3.4 Estimates (Std. Errors) of the Model Coefficients and Effectiveness

Covariates	Total Crashes			Multiple-Vehicle Crashes			Left-Turn Crashes		
	Estimate	S.E.	p-value	Estimate	S.E.	p-value	Estimate	S.E.	p-value
Intercept	-3.6005	0.6015	<.0001	-3.4885	0.5944	<.0001	-7.738	0.9163	<.0001
Site-level (Intersection)									
number of legs	0.6063	0.1314	<.0001	0.5692	0.1320	<.0001	0.8552	0.2118	<.0001
number of lanes on major road	0.1993	0.0265	<.0001	0.1890	0.0284	<.0001	0.3020	0.0408	<.0001
Neighborhood-level (Census tract)									
log(daytime population density)	0.1011	0.0502	0.0443	0.0632	0.0487	0.1942			
Percent of Black population	0.0085	0.0012	<.0001	0.0099	0.0012	<.0001	0.0129	0.0018	<.0001
Percent of Asian population	0.0099	0.0020	<.0001	0.0126	0.0021	<.0001	0.0189	0.0039	<.0001
Percent of commuter by auto	0.0039	0.0021	0.0694	0.0082	0.0022	0.0002	0.0143	0.0029	<.0001
Retail density	0.0081	0.0056	0.1437						
Percent of roadway with truck route				0.0032	0.0029	0.2658			
Percent of roadway with parking	0.0077	0.0029	0.0084				0.0078	0.0048	0.1014
Percent of 4-leg intersections				0.0040	0.0017	0.0187			
Bus stop density	0.0020	0.0007	0.006	0.0021	0.0007	0.0051	0.0036	0.0013	0.0042
Dummy Variables [a]									
If from TG1 in the after period (a_1)	-0.4213	0.0722	<.0001	-0.3756	0.0790	<.0001	-0.1780	0.1508	0.2377
If from TG2 in the after period (a_2)	-0.6989	0.1806	0.0001	-0.7225	0.1927	0.0002	-1.3697	0.2680	<.0001
If from CG in the after period (b)	-0.4490	0.0262	<.0001	-0.4746	0.0290	<.0001	-0.4757	0.0690	<.0001
If from TG (φ)	0.8087	0.0942	<.0001	0.8413	0.1056	<.0001	0.9233	0.1399	<.0001
Effectiveness									
[b] Estimate of the difference TG1 vs. CG: a_1-b	0.0277	0.0769	0.7182	0.0990	0.0842	0.2396	0.2977	0.1659	0.0727
[c] Estimate of the difference TG2 vs. CG: a_2-b	-0.2498	0.1821	0.1701	-0.2479	0.1944	0.2023	**-0.8940**	**0.2758**	**0.0012**

Note:

[a] The coefficients of these dummy variables are estimated using equation (1).
TG1 – Subgroup of treatment group comprising intersections where signal phases were changed from permissive to protected/permissive;
TG2 – Subgroup of treatment group comprising intersections where signal phases were changed from permissive to protected-only;
TG – Treatment group (combination of TG1 and TG2); CG – Comparison group

[b] The estimate of the effectiveness of changing from permissive to protected/permissive left-turn signal phasing, by using equation (2).

[c] The estimate of the effectiveness of changing from permissive to protected-only left-turn signal phasing, by using equation (3).

As shown in Table 3.4, the difference between "a_1" and "b", that is, "$a_1 - b$", is positive for total crashes, multiple-vehicle crashes and left-turn crashes, suggesting an increase in the crashes in the treatment group after the change of left-turning signal phase from permissive to protected/permissive. However, they are insignificant at 5% level for all three crash types.

The difference between "a_2" and "b", that is, "$a_2 - b$", is negative for total crashes, multiple-vehicle crashes and left-turn crashes—crashes decreased more in the treatment group than in the comparison group, suggesting a decrease in crashes in the treatment group after the change of left-turning signal phase from permissive to protected-only. The differences "$a_2 - b$" in left-turn crashes is significant at 5% level, however, the differences for total crashes and vehicle collisions are insignificant.

3.5 Conclusions

It has been found that changing from permissive to protected-only phasing significantly reduces left-turn crashes, a finding consistent with many existing studies (Agent and Deen 1979, Upchurch 1991, Gibby *et al.* 1992, Stamatiadis *et al.* 1997, Box and Basha 2003). The likely reason: this signal phasing separates left-turning movements from the opposing traffic completely, and thus reduces conflicts between the left-turning and opposing vehicles. Left-turn crashes were not fully eliminated by the protected signal phasing—even though left-turn signal phasing significantly reduces conflicts for between left-turning vehicles and opposing through traffic, there are other collision patterns, such as collisions between vehicles making left-turns, collisions between left-turning vehicles and free right-turning vehicles, or collisions between left-turning and crossing traffic when one of which was against signal. A study of left-turn crashes by Wang and Abdel-Aty (2008) found that left-turn phasing may not be effective in reducing these other collision patterns.

On the other hand, the impact of left-turn phasing on total crashes and multiple crashes proves insignificant. Furthermore, when the protected-only phasing is combined with the permissive, there is an unexpected increase (though insignificant) in all three types of crashes. While Srinivasan et al. (2008) argued that the introduction of a protected left-turn phase will tend to increase mostly rear-end crashes, the study found an increase in over-taking crashes after the installation of left-turn signal phasing (as shown in Table 3.3). This may be explained by the situation that vehicles making left-turns would probably overtake other through traffic in their rush to turn within the protected left turn phase and avoid the long wait when missing it. The reduced green time and the resulting increased queues may also contribute to the increase in over-taking crashes.

In conclusion, the study results indicate that the protected/permissive left-turn phasing provides no significant safety benefits relative to permissive-only signal phasing. Protected left-turn phasing can be effective in reducing left-turn crashes; however, it may be compromised by an increase in other types of crashes and the traffic delay at intersections. These results suggest that left-turn phasing should not be treated as a universal solution that is always better than the simple permissive control for left-turning vehicles.

Left-turn phasing must be carefully selected and implemented by considering the trade-offs between safety and delay, as well as many other factors—the literature shows that various factors, such as crash experience, traffic flow at the intersections, and intersection geometry, need to be considered (Agent and Deen 1979, Stamatiadis *et al.* 1997, Al-Kaisy and Stewart 2001, Zhang *et al.* 2008). In addition to left-turn signal phasing, several other means can be used to accommodate left-turn movements at signalized intersections. Potential solutions may include geometric improvements, such as addition of left turn lanes or left turn bays, or even prohibiting left-turns. However, these treatments have their own pros and cons and thus the implied impacts on safety and traffic need to be studied.

Lastly, this study demonstrated that characteristics of the built environment should be included in safety studies. Built environment attributes have been largely disregarded in existing studies assessing the effect of left-turn phasing. Our two-stage approach offers a number of advantages over simple before-after or comparison group analysis by further controlling those built environment factors, quantifying their impacts on crashes and accounting for repeated measures for the same location using GEE method.

CHAPTER 4

Evaluation of the Effectiveness of Bike Lanes

—for the Safety of Bicyclists

On street bike lanes have been installed in many cities in the United States to encourage bicycling and promote public health. What's the impact of bike lanes in safety? In this chapter the effectiveness of bike lanes in reducing crashes, including total crashes, bicycle crashes, pedestrian crashes, vehicle collisions, and injury and fatal crashes, is studied.

4.1 Introduction

Bicycling is a healthy, environmentally friendly alternative compared to personal automobile usage (Cavill *et al.* 2006, Bassett *et al.* 2008, Wen and Rissel 2008). Yet bicycling in the U.S. is primarily considered a recreational pursuit rather than a means of utilitarian travel. Among the nearly 140 million commute trips made every day, slightly less than 0.5 percent are made by bicycle (Census Bureau 2009). Of trips for all purposes in the United States, only 1 percent are made by bicycle (Federal Highway Administration 2009a). The contrasting statistic is that less than 5% of adults obtain the recommended level of 150 minutes of moderate-intensity physical activity per week (Troiano *et al.* 2008, Surgeon General 2010). Approximately 25% of all trips are less than one mile, and 75% of these short trips are made by automobile (Burbidge and Goulias 2009). If some of these short trips were made by active modes such as walking or cycling, more people would have reached the recommended level of physical activity.

Integrating physical activity into daily routines such as bicycling to work (Reynolds *et al.* 2009) will also lead to a sustained increase in habitual physical activity (Benjamin 2010).

The health and environmental benefits of cycling are clear and significant. Yet, it is also undebatable that bicyclists are a vulnerable group of people who share the same roadway with motorized vehicles. At intersections, they must maneuver their way through conflicting vehicular movements if a turn needs to be made. Indeed, among the various barriers, safety remains a major concern that discourages people from bicycling (Forester 2001, Pucher and Dijkstra 2003). When a crash happens, the likelihood and the severity of injury to bicyclists are much greater than to motor vehicle users. Therefore, there is a need to gain a full understanding of the safety impacts of cycling. This is particularly evident in the current time when many American cities are installing extensive bike lane networks to encourage the use of cycling for commutes (Dill 2003).

4.2   Studies on the Safety Impacts of Bike Lanes

Studies of the safety impacts of bike lanes in the U.S. go back to as early as 1970s. Some of the early studies compared bicycle crash rates on different types of roadway, such as roads with or without marked bike lanes and off-road trails, based on self-reported data from surveys of bicyclists or police reports. These studies reported lower bicycle crash rates for roads with bike lanes than those without (Kaplan 1975, Lott and Lott 1976, Moritz 1997, Rodgers 1997, Moritz 1998). However, causality cannot be inferred from these neighborhood-level studies because of confounding factors. Results from studies at the segment or intersection level are mixed (Smith 1988, Coates 1999, Jensen 2008).

A major limitation of the existing studies is that they lack a rigorous quasi-experimental design that involves a treatment group and a comparison group and compares crashes before and after the installation of bike lanes for both groups (Hauer 1997). On the built environment impact on physical activity, a report by the Transportation Research Board and Institute of Medicine of the National Academies describes the existing literature on the built environment and physical activity this way:

> …most of the studies conducted to date have been cross sectional. Longitudinal study designs using time-series data are also needed to investigate causal relationships between the built environment and physical activity (TRB Committee on Physical Activity 2005).

The report goes on to say:

> When changes are made to the built environment—whether retrofitting existing environments or constructing new developments or communities—researchers should view such natural experiments as "demonstration" projects and analyze their impacts on physical activity (TRB Committee on Physical Activity 2005).

The same limitation applies to those studies evaluating the impact of the installation of bike lanes on safety. In a before-after study of bike lanes on two 1.3-mile arterial roads in

Madison, Wisconsin, Smith found an increase in bicyclist crashes on the two roads with bike lanes; however, the increase was insignificant when compared to the increase observed in city-wide bicyclist crashes (Smith 1988). In another before and after study of bike lanes of 26 kilometers in Oxford, increases in crashes post-installation were found (Coates 1999). Only one study was found to have used both a treatment group and a comparison group in a before-and-after study in the evaluation of the safety impacts of bike lanes (Jensen 2008). In this study, the analysis of bike lanes of 5.6 kilometers installed in Copenhagen, Denmark between 1988 and 2002 revealed increases in most types of crashes and injuries on roadway segments and at intersections with bike lanes, though none was significant at the 5% level.

4.3 Methods

The present study adopts a quasi-experimental design that includes a treatment group and a comparison group and conducts the before-and-after analysis of 43 miles of bike lanes installed in the five boroughs of New York City (NYC) between 1996 and 2006. The five boroughs in NYC vary greatly—for example, the population densities for Manhattan, Brooklyn, Bronx, Queens and Staten Island are about 70 thousand, 36 thousand, 33 thousand, 21 thousand, and 8 thousand people per square mile, respectively (U.S. Census Bureau 2000).

The dependent variable is police-reported crashes that occur on a roadway segment or at an intersection. A roadway segment is defined as a continuous section of the roadway uninterrupted by a cross-road or an intersection. Five types of crashes—total crashes, multiple-vehicle crashes (crashes involving multiple vehicles, without any bicyclists or pedestrians), bicyclist crashes (crashes involving bicyclists, such as vehicle-bicycle collisions), pedestrian crashes (vehicle-pedestrian collisions), and injurious and fatal crashes (crashes that caused at least one injury or fatality)—have been investigated in this study.

For each segment or intersection (in the treatment group or in the comparison group), two observations of crash were identified: crashes within 5-year period prior to the installation and crashes within 2-year period after the installation. A crash is a relatively rare event, thus, including a longer 5-year before period allows us to capture a more stable trend prior to the treatment. On the other hand, the selection of a shorter after period than the before period allows us to include more treatment sites: Crash data is only available until 2008, thus implementing a 5-year after period would mean that only treatments installed prior to 2003 can be evaluated and yet, nearly 50% of the bike lane treatments were installed after 2003 (as shown in Table 4.1).

Table 4.1 Yearly Distributions of Bike Lane Installations in New York City

Project Year	**Bike Lanes**	
	Number of Segments	**Percent**
1996	2	0.3
1997	36	6.2
1998	2	0.3
2000	3	0.5
2001	20	3.5
2002	22	3.8
2003	209	36.1
2004	45	7.8
2005	29	5.0
2006	211	36.4
Sum	**579**	**100**

This study involves a two-stage design. In the first stage, a comparison group was identified, comprising locations without a bike lane during the same study period but sharing segment- or intersection-level characteristics comparable to those in the treatment group. The difference in the before- and after-periods is controlled by an offset variable in the model. In the second stage, the Poisson and negative binomial regression models were applied, using the generalized estimating equations (GEE) method (Liang and Zeger 1986, Zeger and Liang 1986) to the dataset comprising observations before and after the installation of bike lanes for both treatment group and comparison group, to account for correlations within repeated observations and to further control factors that cannot be controlled by the use of the comparison group. The safety impact of bike lanes in the treatment group is evaluated through the coefficients estimated from the model.

4.3.1 Stage One—Comparison Group Selection

Crashes on roadway segments and at intersections were studied separately, due to their distinct nature—intersections are high-risk locations for bicycle-vehicle collisions because of the conflicts between bicyclists and motor vehicle users (Wang and Nihan 2004). For this reason, two comparison groups: a segment-level comparison group and an intersection-level comparison group were selected.

The segment-level comparison group was first selected. The selection was based on three segment-level factors that have been found to have a significant impact on crashes: one-way vs. two-way (Oregon State Highway Department 1959), divided roadway vs. undivided (if two-way)

(Harkey *et al.* 2008b, Ewing and Dumbaugh 2009), and the number of travel lanes (Milton and Mannering 1998, Noland and Oh 2004). The geographical distribution of the locations in the comparison group is further controlled to resemble the distribution of those in the treatment group.

Since bike lanes were installed over a period of more than 10 years (from 1996 to 2006), the treatment group comprises bike lane segments installed in different years. In other words, the before period and the after period for different bike lane segments are different, even though they are of the same length. As an example, the 5-year before period and the 2-year after period for bike lanes installed in 2000 are 1995-1999 and 2001-2002, respectively, while those for bike lanes installed in 2005 are 2000-2004 and 2006-2007, respectively. For this reason, the treatment group is divided into multiple subsets defined by the year of installation. Then, for each subset, a set of untreated locations were selected by applying frequency matching techniques (Chen *et al.* 2011) to resemble the joint distribution of those segment-level variables as well as the geographical distribution of the treatment group. After each subset of the treatment group is identified with a corresponding set of locations untreated with bike lanes, those untreated locations are combined into the segment-level comparison group.

Many of the bike lane segments in the treatment group are part of long corridors whereas those in the comparison group selected are more likely to be scattered around in the city. Therefore, those roadway segments that are parallel to those in the treatment group were manually selected and added to the comparison group. These procedures resulted in a segment-level comparison group of 1,926 segments, corresponding to 579 bike lane segments. Figure 4.1

shows the distribution of the bike lane segments in New York City and those segments in the comparison group.

From the segment-level comparison group, a second comparison group—an intersection-level comparison group—was identified. The control type (signalized or not) (Poch and Mannering 1996) and the number of legs at the intersection (Milton and Mannering 1998, Harkey *et al.* 2008b) were used to select the intersection-level comparison group; both variables have been found to be significant in affecting crashes at intersections. The same set of procedures as described above was applied to generate this comparison group, which comprises 1,653 intersections, corresponding to 578 intersections in the treatment group. The comparison of the attributes for the locations (segments and intersections) in the treatment group and the comparison group is shown in Table 4.2.

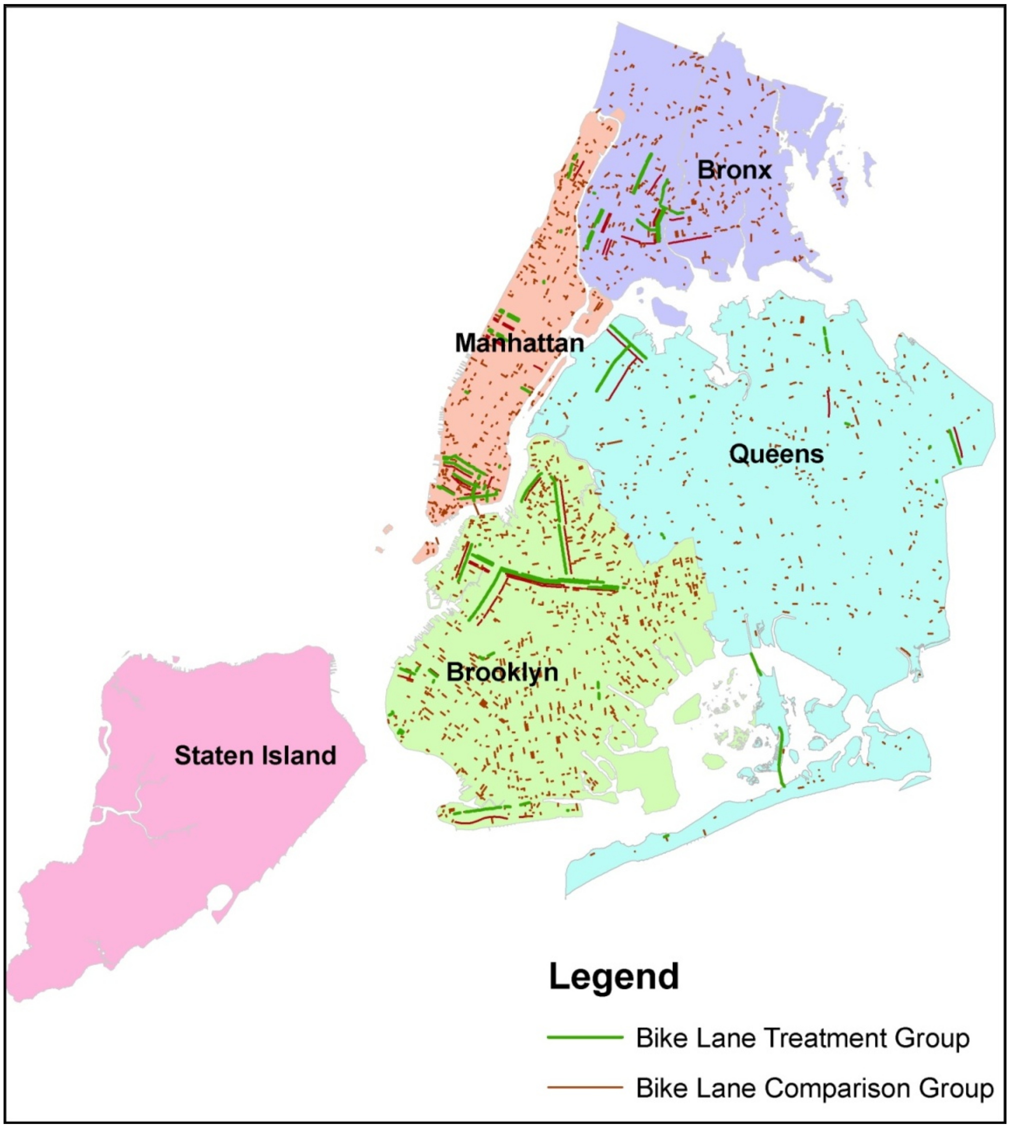

Figure 4.1 Map of Bike Lanes in NYC: Treatment Group and Comparison Group

Table 4.2 Characteristics of Locations in Treatment Group and Comparison Group

Control Variables	Values	Treatment Group	Comparison Group
Segments characteristics			
Borough	Manhattan	80 (13.8%)	269 (14.0%)
	Bronx	91 (15.7%)	285 (14.8%)
	Brooklyn	273 (47.2%)	940 (48.8%)
	Queens	135 (23.3%)	432 (22.4%)
	Staten Island	0 (0.0%)	0 (0.0%)
One-way or Two-way	One-way	288 (49.7%)	979 (50.8%)
	Two-way	291 (50.3%)	947 (49.2%)
Divided or not	Undivided	502 (86.7%)	1702 (88.4%)
	Divided	77 (13.3%)	224 (11.6%)
Number of Travel lanes	1-lane	317 (54.8%)	1067 (55.4%)
	2-lane	212 (36.6%)	689 (35.8%)
	3-lane	14 (2.4%)	47 (2.4%)
	4-lane	30 (5.2%)	101 (5.2%)
	5 or more	6 (1.0%)	22 (1.1%)
Sum		579 (100%)	1926 (100%)
Intersection characteristics			
Borough	Manhattan	97 (16.8%)	236 (14.3%)
	Bronx	95 (16.4%)	221 (13.4%)
	Brooklyn	278 (48.1%)	852 (51.5%)
	Queens	108 (18.7%)	344 (20.8%)
	Staten Island	0 (0.0%)	0 (0.0%)
Control type	Signalized	349 (60.4%)	965 (58.4%)
	All-way stop	15 (2.6%)	50 (3.0%)
	Stop on minor	107 (18.5%)	332 (20.1%)
	No control	107 (18.5%)	306 (18.5%)
Number of legs	3-way	148 (25.6%)	399 (24.1%)
	4-way	415 (71.8%)	1218 (73.7%)
	5 or more	15 (2.6%)	36 (2.2%)
Sum		578 (100%)	1653 (100%)

4.3.2 Stage Two—Regression Models using GEE Method

The identified segment- and intersection-level comparison groups were combined with the corresponding treatment group to generate two datasets, one for segment-level crashes and the other for intersection-level crashes.

To control for correlation within observations collected on the same location at two time points—crashes during the five-year period prior to the installation and crashes during the 2-year period after the installation, the generalized estimating equation (GEE) methodology was applied. In GEE method various correlation specifications (e.g., independent, exchangeable, auto-regressive, unstructured, etc.) can be used to build weight matrices in a weighted regression. As there are only two repeated measures for each locations, the exchangeable correlation structure was used in the GEE modeling.

Due to the fact that crashes are count data in nature, they are estimated either with a Poisson model or with a negative binomial model, depending on the dispersion of the crash data. If the crash data is over-dispersed[9], negative binomial model is used; otherwise, Poisson model is applied. The model is as specified as below:

$$
\begin{aligned}
y_{it} &= \exp\left(\alpha + 1 \times \log(year_t) + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + a(TG\_T1) + b(CG\_T1) + \varphi_1(If\_TG) + \varphi_2(If\_CG\_P\_T0)\right) \\
&= year_t \times \exp\left(\alpha + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + a(TG\_T1) + b(CG\_T1) + \varphi_1(If\_TG) + \varphi_2(If\_CG\_P\_T0)\right)
\end{aligned}
\tag{4.1}
$$

[9] The Wald test was used to determine whether there was over-dispersion in the crash data. If the crash data is over-dispersed, the Negative Binomial model is used; otherwise, the Poisson model is applied.

Where:

- y_{it} = expected crash count at site *i* during time *t* (before or after period);
- $year_t$ = number of years during time *t* (5 years for pre-treatment period and 2 years for post-treatment period);
- $\mathbf{X}^{(s)}\boldsymbol{\beta}$ = site-level covariates with coefficient $\boldsymbol{\beta}$;
- $\mathbf{X}^{(n)}\boldsymbol{\gamma}$ = neighborhood-level covariates with coefficient $\boldsymbol{\gamma}$;
- *TG_T1* = 1 if the data point comes from the treatment group post-treatment and 0 otherwise, and the coefficient for this variable is *a*;
- *CG_T1* = 1 if the data point comes from the comparison group post-treatment and 0 otherwise, and the coefficient for this variable is *b*;
- *If_TG* = 1 if the data point comes from the treatment group and 0 otherwise;
- *If_CG_P_T0* = 1 if the data point comes from the comparison group and the location is parallel to those in the treatment group and is in the pre-treatment period and 0 otherwise.

Table 4.3 presents a more detailed description of the variables entered in the model. The number of years ($year_t$) during which the crash count was collected is included in the model as an offset variable to account for the difference between the before period (5-year) and the after period (2-year). The coefficient of the offset variable was restricted to one, assuming that the crash counts are proportional to the length of the before- and after-periods.

Table 4.3 Summary of Variables in the Model

Variables	**Description**
Site-level covariates	
Segment	
Log_Length	natural log of the length (in feet) of the segment
Presence of bus stop	1 if there is bus stop on the road; 0 otherwise
Presence of parking	1 if there is parking on the road; 0 otherwise
Truck route	1 if the road segment is on truck route; 0 otherwise
Intersection	
Control type	1 if the intersection is signal-control; 0 otherwise
Number of Legs	number of legs at the intersection (3, 4, 5, 6)
Number of lanes on major road	number of lanes for the major road of the intersection (1, 2, 3, 4, 5)
One-way or two-way on major road	1 if major road of the intersection is one-way; 0 otherwise
Presence of subway station	1 if there is subway station at the intersection; 0 otherwise
Neighborhood-level covariates	
Log_daytime population density	natural log of the day time population density in the tract
Percent below poverty level	percent of population below poverty level in the census tract
Retail density	retail land use floor area per square mile area in the census tract (100 sq. mi. / sq. mi.)
Bus stop density	number of bus stop per square mile area in the census tract (1/sq. mi.)
Subway ridership	the maximum subway ridership in the census tract (in 1000)
Bicycle trip density	number of workers commuting by bicycle per mile of roadway in the census tract (1000/mile)
Indicator variables	
TG_T1	1 if the data point comes from the treatment group in the after period; 0 otherwise
CG_T1	1 if the data point comes from the comparison group in the after period; 0 otherwise
If_TG	1 if the data point comes from the treatment group; 0 otherwise
If_CG_P_T0	1 if the data point comes from the comparison group and is parallel to the treated locations and in the before period; 0 otherwise

A set of neighborhood-level and site-level (segment- or intersection-level) variables were entered in the model to control exposure and conflicts. It is hypothesized that higher exposure and more conflicts are associated with more crashes (Ewing and Dumbaugh 2009). At the neighborhood level, daytime population density, retail density, and bicycle trip density to were used account for the exposure of vehicular and bicyclist traffic. Daytime population density was calculated as the number of residents plus employment minus the number of people who live and work in the same census tract (to remove double counting) divided by the total area of a census tract; and retail density was calculated as the floor area of retail land use divided by total area of a census tract. These two variables measure the density of people who live, work, and shop in the neighborhood. Bicycle trip density was calculated by the number of bicycle commuters divided by the total length of roads in the census tract. Site-level covariates include the presence of bus stops or parking on road segments, being on the truck route or not, control type (signalized or not), and the number of legs at the intersection. These variables are to account for the conflicts that bicyclists have with motorized vehicles.

The dummy variables "*TG_T1*" and "*CG_T1*" are used to account for the changes in crashes from the before period to the after period for treatment group and comparison group, respectively. If the coefficient of the variable "*TG_T1*" is estimated to be negative, it means crashes in the after period are expected to be fewer than the crashes in the before period in the treatment group; if the coefficient is estimated to be positive, it means crashes in the after period are expected to be more than those in the before period. Similarly, for the variable "*CG_T1*", a negative coefficient means crash reduction and a positive coefficient means crash increase in the comparison group.

It is possible that crash counts tend to be higher for the treatment group and lower for the comparison group. This difference will lead to potential regression-to-mean effects—locations with more crashes are more likely to experience a crash reduction in the after period than those with fewer crashes. The same reasoning may apply to those locations in the comparison group that are parallel to the treatment group vs. the rest of the locations in the comparison group—due to the proximity to the treatment group, it is possible that those locations in the comparison group that are parallel to the treatment group will have more crashes in the before period than the rest of the locations in the comparison group. Two dummy variables "*If_TG*" and "*If_CG_P_T0*" were included in the model to control the potential regression-to-mean effect. For example, if the coefficient of variable "*If_TG*" is estimated to be positive, it means the crashes in the treatment group are in general more than those in the comparison group. Similarly, if the coefficient of the variable "*If_CG_P_T0*" is estimated to be positive, it means crashes at locations in the comparison group that are parallel to the treatment group during the before period are in general more than the rest of the locations in the comparison group. Through these dummy variables, the potential regression-to-mean effect is alleviated.

The coefficients for variables "*TG_T1*" and "*CG_T1*" (denoting post-installation crashes for the treatment and the comparison group, respectively), that is, *a* and *b* in the model specification, are of our primary interest. The contrast between the two coefficients represents the difference in changes in crash frequencies from pre-treatment to post-treatment periods for the treatment group versus the comparison group. In order to test if the difference of the two coefficients is statistically significant at 5% level, the model can be transformed by replacing the two variables "*TG_T1*" and "*CG_T1*" with Z_1 and Z_2:

$$y_{it} = year_t \times \exp\left(\alpha + \mathrm{X}^{(s)}\boldsymbol{\beta} + \mathrm{X}^{(n)}\boldsymbol{\gamma} + c(Z_1) + d(Z_2) + \varphi_1(If\_TG) + \varphi_2(If\_CG\_P\_T0)\right) \tag{4.2}$$

Where,

$$Z_1 = (TG\_T1 - CG\_T1)/2\,, \qquad Z_2 = (TG\_T1 + CG\_T1)/2$$

The coefficient of Z_1 is the difference[10] of the two coefficients associated with "*TG_T1*" and "*CG_T1*", or $c = a - b$. If c is significant and negative, it points to the effectiveness of bike lane in reducing crashes. If it is insignificant, it suggests that bike lane has no effect on crashes.

4.4 Results

Table 4.4 shows crashes in the 5-year before period and 2-year after period for the treatment group and the comparison group. For segment-level crashes, total crashes, multiple-vehicle crashes, pedestrian crashes, and injurious and fatal crashes all decreased for both groups. There was a slight increase (1.1%) for bicyclist crashes in the treatment group while those in the comparison group decreased. For intersection-level crashes, total crashes, multiple-vehicle

[10] By rearranging the terms, we can obtain the following:

$$\begin{cases} Z_1 = (\mathrm{TG\_T1} - \mathrm{CG\_T1})/2 \\ Z_2 = (\mathrm{TG\_T1} + \mathrm{CG\_T1})/2 \end{cases} \Rightarrow \begin{cases} \mathrm{TG\_T1} = Z_1 + Z_2 \\ \mathrm{CG\_T1} = Z_2 - Z_1 \end{cases}$$

Thus, $a(\mathrm{TG\_T1}) + b(\mathrm{CG\_T1}) = a(Z_1 + Z_2) + b(Z_2 - Z_1) = (a-b)Z_1 + (a+b)Z_2 = cZ_1 + dZ_2$

Therefore, $c = a - b$ and $d = a + b$

crashes, and injurious crashes also decreased for both groups. However, pedestrian crashes and bicyclist crashes increased in the treatment group, while both experienced a decrease in the comparison group. The increases are likely due to increased exposure as bicyclists take advantage of the new bike lanes. The difference in bicyclist/pedestrian volumes between before and after the installation of bike lanes was not controlled due to unavailability of such data.

Table 4.5 and 4.6 present the coefficient estimate and standard errors for various variables in the models, for crashes on segments and crashes at intersections, respectively. For total crashes, multiple-vehicle crashes, pedestrian crashes, and injurious and fatal crashes, Negative Binomial models were estimated since over-dispersion was detected for these crash types. For bicycle crashes, Poisson models were estimated since no over-dispersion was detected.

Table 4.5 shows the effects of bike lanes on segment-level crashes. The difference between *a* and *b* is negative for total crashes, multiple-vehicle crashes, pedestrian crashes, and injurious and fatal crashes—crashes decreased more in the treatment group than in the comparison group for segment-level crashes. For bicyclist crashes, the difference between *a* and *b* is positive, suggesting an increase in bicyclist crashes in the treatment group after the installation of bike lanes. However, the increase is insignificant at 5% level. Table 4.6 shows the effects of bike lanes on intersection-level crashes. The difference between *a* and *b* is positive for all five crash types, suggesting increases in those crashes in the treatment group after the installation of bike lanes. Likewise, all increases are insignificant at 5% level.

Table 4.4 Comparison of Crashes for Treatment Group and Comparison Group

Crash Type	Group[a]	Before Period (5 years) Sum	Before Period (5 years) Average[b]	After Period (2 years) Sum	After Period (2 years) Average[b]	Change[c] (%)
Crashes on Segments						
Total Crashes	T	827	0.2857	209	0.1805	-36.8
	C	2164	0.2247	537	0.1394	-38.0
Vehicle Crashes	T	559	0.1931	137	0.1183	-38.7
	C	1511	0.1569	367	0.0953	-39.3
Pedestrian Crashes	T	175	0.0604	43	0.0371	-38.6
	C	446	0.0463	118	0.0306	-33.9
Bicycle Crashes	T	47	0.0162	19	0.0164	1.2
	C	112	0.0116	25	0.0065	-44.0
Injury and Fatal Crashes	T	612	0.2114	153	0.1321	-37.5
	C	1504	0.1562	363	0.0942	-39.7
Crashes at Intersections						
Total Crashes	T	4577	1.5837	1494	1.2924	-18.4
	C	13450	1.6273	4124	1.2474	-23.3
Vehicle Crashes	T	3358	1.1619	969	0.8382	-27.9
	C	10199	1.2340	2925	0.8848	-28.3
Pedestrian Crashes	T	767	0.2654	333	0.2881	8.6
	C	2213	0.2678	843	0.2550	-4.8
Bicycle Crashes	T	317	0.1097	155	0.1341	22.2
	C	680	0.0823	244	0.0738	-10.3
Injury and fatal Crashes	T	3748	1.2969	1196	1.0346	-20.2
	C	10861	1.3174	3215	0.9725	-26.2

Note:
[a] Group: T-treatment group, C-comparison group
[b] Average: average number of crashes per location per year
[c] Change in the average number of crashes

Table 4.5 Estimates (Std. Errors) of Effects for the Five Types of Crashes on Segments

Variables		Total Crashes	Vehicle Crashes	Pedestrian Crashes	Bicycle Crashes	Injurious and Fatal Crashes
Constant		**-7.334 (0.704)**	**-7.236 (0.696)**	**-12.504 (0.634)**	**-10.873 (0.911)**	**-7.726 (0.611)**
TG_T1 (a)		**-0.464 (0.083)**	**-0.484 (0.107)**	**-0.500 (0.205)**	0.011 (0.263)	**-0.475 (0.096)**
CG_T1 (b)		**-0.407 (0.064)**	**-0.426 (0.081)**	**-0.343 (0.119)**	**-0.401 (0.235)**	**-0.420 (0.071)**
If_TG		0.14 (0.097)	0.092 (0.099)	0.098 (0.158)	0.247 (0.202)	0.197 (0.106)
If_CG_P_T0		**0.180 (0.080)**	**0.177 (0.090)**	**0.324 (0.131)**	**0.552 (0.191)**	**0.205 (0.089)**
Site-level covariates						
Log_length		**0.735 (0.097)**	**0.696 (0.094)**	**1.030 (0.103)**	**0.718 (0.128)**	**0.718 (0.085)**
Presence of bus stop		**0.572 (0.098)**	**0.486 (0.109)**	**0.745 (0.115)**	**0.629 (0.177)**	**0.645 (0.105)**
Presence of parking				0.128 (0.218)	**0.635 (0.273)**	
Truck route		**0.771 (0.115)**	**0.840 (0.122)**	**0.474 (0.160)**	**0.522 (0.208)**	**0.798 (0.117)**
Neighborhood-level covariates						
Log_daytime population density		**0.284 (0.089)**	**0.236 (0.092)**	**0.738 (0.096)**	**0.331 (0.112)**	**0.316 (0.097)**
Retail density		**0.012 (0.004)**	**0.011 (0.005)**			0.007 (0.005)
Bus stop density		**0.002 (0.001)**	**0.002 (0.001)**	0.001 (0.001)	0.0003 (0.002)	**0.002 (0.001)**
Subway ridership				0.010 (0.006)	**0.007 (0.003)**	
Bicycle trip density				0.008 (0.008)	0.019 (0.012)	
Dispersion parameter		**1.385 (0.079)**	**1.601 (0.104)**	**1.543 (0.197)**	n/a	**1.398 (0.095)**
TG_T1 (*a*)		**-0.464 (0.083)**	**-0.484 (0.107)**	**-0.500 (0.205)**	0.011 (0.263)	**-0.475 (0.096)**
CG_T1 (*b*)		**-0.407 (0.064)**	**-0.426 (0.081)**	**-0.343 (0.119)**	**-0.401 (0.235)**	**-0.420 (0.071)**
a - b	Est. (SE)	-0.057 (0.106)	-0.058 (0.134)	-0.157 (0.236)	0.412 (0.352)	-0.056 (0.120)
	95% C.I.	(-0.265, 0.150)	(-0.321, 0.205)	(-0.619, 0.369)	(-0.279, 1.102)	(-0.290, 0.178)
% Change in Crashes	Est. (SE)	-5.6 (10.1)	-5.6 (12.8)	-14.5 (21.0)	50.9 (58.3)	-5.4 (11.4)
	95% C.I.	(-25.4, 14.2)	(-30.7, 19.5)	(-55.7, 26.8)	(-63.4, 165.2)	(-27.8, 17.0)

Note: Number in bold means significant at 5% level

Table 4.6 Estimates (Std. Errors) of Effects for the Five Types of Crashes at Intersections

Variables		Total Crashes	Vehicle Crashes	Pedestrian Crashes	Bicycle Crashes	Injurious and Fatal Crashes
Constant		**-3.730 (0.248)**	**-3.886 (0.255)**	**-6.009 (0.306)**	**-6.406 (0.306)**	**-4.155 (0.234)**
TG_T1 (a)		**-0.209 (0.040)**	**-0.339 (0.047)**	0.090 (0.072)	0.201 (0.107)	**-0.218 (0.044)**
CG_T1 (b)		**-0.264 (0.030)**	**-0.346 (0.034)**	0.027 (0.050)	-0.047 (0.083)	**-0.286 (0.032)**
If_TG		-0.007 (0.054)	-0.051 (0.059)	0.006 (0.078)	**0.291 (0.095)**	-0.025 (0.057)
If_CG_P_T0		**0.116 (0.047)**	0.065 (0.053)	**0.283 (0.072)**	**0.215 (0.105)**	**0.124 (0.048)**
Site-level covariates						
Control type		**0.673 (0.054)**	**0.603 (0.058)**	**1.121 (0.078)**	**0.648 (0.092)**	**0.722 (0.057)**
Number of Legs		**0.633 (0.056)**	**0.694 (0.059)**	**0.346 (0.066)**	**0.520 (0.066)**	**0.666 (0.054)**
Number of lanes on major road		**0.121 (0.022)**	**0.140 (0.024)**	**0.083 (0.026)**	0.033 (0.033)	**0.117 (0.022)**
One-way or two-way on major road		**-0.330 (0.051)**	**-0.360 (0.055)**	**-0.435 (0.064)**	-0.083 (0.080)	**-0.363 (0.050)**
Presence of subway station		**0.440 (0.148)**		**0.928 (0.184)**	**0.539 (0.203)**	
Neighborhood-level covariates						
Log_daytime population density		**0.232 (0.030)**	**0.134 (0.034)**	**0.474 (0.044)**	**0.210 (0.054)**	**0.201 (0.033)**
Percentage below poverty level			**0.435 (0.149)**	**0.537 (0.170)**	**0.465 (0.211)**	**0.656 (0.140)**
Retail density					**0.001(0.0001)**	
Bus stop density		**0.002(0.0004)**	**0.001(0.0005)**	**0.002(0.0006)**	**0.002(0.0006)**	**0.002 (0.0004)**
Bicycle trip density				**0.009 (0.003)**	**0.020 (0.004)**	
Dispersion parameter		**0.986 (0.030)**	**1.080 (0.035)**	**0.975 (0.057)**	n/a	**1.010 (0.033)**
TG_T1 (*a*)		**-0.209 (0.040)**	**-0.339 (0.047)**	0.090 (0.072)	0.201 (0.107)	**-0.218 (0.044)**
CG_T1 (*b*)		**-0.264 (0.030)**	**-0.346 (0.034)**	0.027 (0.050)	-0.047 (0.083)	**-0.286 (0.032)**
a - b	Est. (SE)	0.055 (0.050)	0.007 (0.058)	0.063 (0.088)	0.248 (0.135)	0.068 (0.055)
	95% C.I.	(-0.042, 0.153)	(-0.105, 0.120)	(-0.108, 0.235)	(-0.016, 0.514)	(-0.039, 0.175)
% Change in Crashes	Est. (SE)	5.7 (5.3)	0.7 (5.9)	6.5 (9.4)	28.1 (17.5)	7.0 (5.9)
	95% C.I.	(-4.7, 16.1)	(-10.7, 12.2)	(-12.0, 20.0)	(-6.3, 62.4)	(-4.5, 18.5)

Note: Number in bold means significant at 5% level

Few existing studies evaluating the impact of bike lanes on safety have included built environment attributes. The estimated models show that most of the neighborhood-level variables are significant at 5% level. To provide a better understanding of the role of these built environment characteristics on crashes, elasticities—the percentage change in changes in response to 1% increase in an attribute—were calculated[11]. An elasticity of 1 indicates that in response to a 1% increase in an attribute, the percentage change in crashes is exactly 1%.

As shown in Table 4.7 and Table 4.8, the effect of daytime population density is the largest among all built environment characteristics for crashes (in particular, for pedestrian crashes) on segments and at intersections—every 1% increase in daytime population density is associated with a 0.738% increase for segment-level crashes and a 0.474% increase for intersection-level crashes. These elasticities should be interpreted with caution given that we were not able to control the difference in bicyclist/pedestrian volume between before and after the installation of bike lanes—it is possible that density may increase bicyclist and pedestrian volume much faster than it increases crashes. Retail density and bicyclist trip density appear to exert the smallest role—both are under 0.1% and for intersection-level crashes, the effect of

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[11] In Poisson or Negative Binomial models, the expected crash count (y) is in exponential function:

$$y = \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \gamma_1 \log(\theta_1) + \gamma_2 \log(\theta_2) + ...) = (\theta_1^{\gamma_1})(\theta_2^{\gamma_2}) \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + ...)$$

For those covariates that are linear ($x_1, x_2 ...$), elasticity is calculated as:

$$e_{x1} = \frac{\partial y}{\partial x_1}\frac{x_1}{y} = \beta_1 \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \gamma_1 \log(z_1) + \gamma_2 \log(z_2) + ...)\frac{x_1}{y} = \beta_1 x_1$$

For those covariates that are in log form ($\theta_1, \theta_2 ...$), elasticity is calculated as:

$$e_{\theta 1} = \frac{\partial y}{\partial \theta_1}\frac{z_1}{y} = \gamma_1 (\theta_1^{\gamma_1 - 1})(\theta_2^{\gamma_2}) \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + ...)\frac{\theta_1}{y} = \gamma_1$$

retail density is negligible. The effect of the density of bus stops is larger for intersection-level crashes—most hovering around 0.2, than for segment-level crashes, which are mostly much smaller than 0.2. The density of subway stops does not appear to have a large effect—it is not significant for intersection-level crashes; for segment-level crashes, the calculated elasticities are mostly around 0.02. One socio-demographic characteristic of a neighborhood, represented by the percentage below the poverty level in a neighborhood, is found significant for intersection-level crashes—the percentage increase in crashes appears to increase as the percentage of the population below poverty level increases.

Table 4.7 Elasticities of Neighborhood-level Covariates for Crashes on Segments

Neighborhood Level Covariates	Values		Crashes on Segments: Total Crashes	Vehicle Crashes	Pedestrian Crashes	Bicycle Crashes	Injurious and Fatal Crashes
Daytime population density* (1000 per sq. mi.)	Average	52.517	0.284	0.236	0.738	0.331	0.316
	25th Percentile	22.498					
	50th Percentile	38.437					
	75th Percentile	57.924					
Retail density (100 sq. mi. retail land use per sq. mi. area)	Average	5.762	0.069	0.063			0.040
	25th Percentile	1.185	0.014	0.013			0.008
	50th Percentile	3.213	0.039	0.035			0.022
	75th Percentile	6.202	0.074	0.068			0.043
Bus stop density (Number of bus stops per sq. mi.)	Average	83.892	0.159	0.143	0.101	0.025	0.168
	25th Percentile	47.143	0.090	0.080	0.057	0.014	0.094
	50th Percentile	80.386	0.153	0.137	0.096	0.024	0.161
	75th Percentile	115.028	0.219	0.196	0.138	0.035	0.230
Subway ridership (in 1000)	Average	2.698			0.027	0.019	
Road bicycle trip density (1000 per mile)	Average	3.261			0.026	0.062	

Note: * The elasticity of daytime population density is independent of the value of this variable based on the model specification.

Table 4.8 Elasticities of Neighborhood-level Covariates for Crashes at Intersections

Neighborhood Level Covariates	Values		Crashes at Intersections: Total Crashes	Vehicle Crashes	Pedestrian Crashes	Bicycle Crashes	Injurious and Fatal Crashes
Daytime population density* (1000 per sq. mi.)	Average	61.478	0.232	0.134	0.474	0.210	0.201
	25th Percentile	28.843					
	50th Percentile	44.831					
	75th Percentile	68.167					
Percentage below poverty level (%)	Average	0.267		0.116	0.144	0.124	0.175
	25th Percentile	0.122		0.053	0.066	0.057	0.080
	50th Percentile	0.244		0.106	0.131	0.114	0.160
	75th Percentile	0.382		0.166	0.205	0.177	0.250
Retail density (100 sq. mi. retail land use per sq. mi. area)	Average	7.684				0.008	
	25th Percentile	1.921				0.002	
	50th Percentile	4.281				0.004	
	75th Percentile	8.368				0.008	
Bus stop density (Number of bus stops per sq. mi.)	Average	97.062	0.165	0.116	0.223	0.233	0.175
	25th Percentile	60.533	0.103	0.073	0.139	0.145	0.109
	50th Percentile	91.771	0.156	0.110	0.211	0.220	0.165
	75th Percentile	127.898	0.217	0.153	0.294	0.307	0.230
Road bicycle trip density (1000 per mile)	Average	4.395			0.040	0.088	

Note: * The elasticity of daytime population density is independent of the value of this variable based on the model specification.

4.5 Discussions and Conclusions

The results of this study indicate that the installation of bike lanes does not lead to an increase in crashes, this despite a likely increase in the number of bicyclists after the installation of bike lanes. The differential in bicyclist volumes between the before and the after period of the installation of bike lanes were not controlled due to unavailability of such data. Existing literature shows a positive association between the presence of bike lane infrastructure and bicycle volumes (Nelson 1997, Dill 2003, Pucher and Buehler 2005, Barnes *et al.* 2006a, Parkin *et al.* 2008). The limited NYC data shows that bicyclist volumes increased about 50% at one location (Ninth Avenue) from 2007 (before bike lane installation) to 2008 (after bike lane installation), while the city-wide counts increased 14% during the same period. At another location (Grand Street), the increase in bicycle volumes from 2008 (before period) to 2009 (after period) was 36% compared to 25% city-wide increase for the same period. In other words, if the differential in bicyclist volume could be properly controlled, it is possible that a significant reduction in crashes in the treatment group would be observed. This also points to the need to collect before and after bicycle volume data not only for locations in the treatment group but also for the comparison group.

The reasons that no significant increases in crashes were observed after the installation of bike lanes, even though bicyclist volumes are likely to have significantly increased, are several. Reduced vehicle speeds due to the awareness of bicyclists or lane narrowing and reduced conflicts due to the separation between vehicles and bicyclists are likely primary ones. Crashes at intersections appear to increase, though not significantly; this is likely due to that for almost all locations in the treatment group, bike lanes discontinue at the intersections and there are no lane markings at the intersections that can guide the maneuver of a bicyclist. Two policies are recommended for this purpose. One is bike box, which is “an advance waiting area for bicyclists at intersections, in front of the ‘stop’ line for cars” (New York City Department of Transportation 2010b). Bicyclists are encouraged to position themselves in front of the cars at a red light and make the turn when the light turns green. This increases the visibility of bicyclists stopping at the red light and permits bicyclists to clear the intersection before vehicular traffic, thus reducing conflicts (Moeur 1999). Another treatment is the provision of colored lane markings at intersections to reduce conflicts. Examples include raised bicycle crossings installed in Gothenburg, Sweden (Garder *et al.* 1998), blue bike-lane treatments at locations of bicyclist-vehicle conflicts (Hunter *et al.* 2000), and marked bicycle overpasses at intersections in Denmark (Jensen *et al.* 1997).

The results indicate that characteristics of the built environment should be included in safety studies. Built environment attributes have been largely excluded in existing studies assessing the effect of bike lanes (Smith 1988, Coates 1999, Jensen 2008). The significance of these variables in our models indicates that the mere use of a comparison group is often not sufficient to ensure the similarity of the two groups. Our two-stage approach offers a number of advantages over Jensen’s study (Jensen 2008), the seemingly only bike lane evaluation study that analyzed before and after crashes for both a treatment group and a comparison group. First, when a potential confounding factor is continuous, it needs to be converted into a categorical variable for frequency matching when selecting a comparison group. Such conversion is often arbitrary. Second, even though all potential confounding factors can be applied in the selection of the comparison group, it usually results in a sample that is too small to render useful for evaluation. Third, the use of those confounding factors in the selection of the comparison group also means that the effects of those factors can no longer be quantified. The second-stage regression models applied in our study further controls those factors that cannot be controlled when selecting the comparison group, quantifies their impacts on crashes, and accounts for repeated measures for the same location.

CHAPTER 5

Comparison of the Relative Effectiveness of Five Countermeasures —for the Safety of Pedestrians

Pedestrians are vulnerable road users and thus, improving the safety of pedestrians is critical for livable communities. In this chapter, the relative safety effectiveness of five pedestrian countermeasures—increasing cycle length for pedestrian crossing, Barnes Dance, split phase timing, signal installation, and high visibility crosswalk—is studied for both pedestrians and motorists.

5.1 Introduction

There is a growing need for safe and walkable communities—where people can walk more often, walk to more places, and walk more safely. Walking, whether for utilitarian or recreational purposes, has many benefits, including improved physical health (Frank *et al.* 2003), reduced traffic congestion, enhanced quality of life and economic vitality (Florida 2002). However, pedestrians are vulnerable road users and safety concerns can discourage the decision to walk. According to National Highway Traffic Safety Administration (NHTSA), there were 59,000 pedestrian injuries and 4,092 deaths resulted from traffic crashes in 2009 in the United States (National Highway Traffic Safety Administration 2011). Twelve percent of the traffic fatalities involved pedestrians (National Highway Traffic Safety Administration 2011). In cities with population exceeding 1 million, the percentage is much higher. In New York City (NYC), for example, 52 percent of traffic fatalities from 2005 to 2009 involved pedestrians (New York

City Department of Transportation 2010b). Selecting effective countermeasures to improve pedestrian safety is a critical component in creating pedestrian-friendly communities.

Intersections entail one of the most complex traffic situations, with different crossing and entering movements by vehicle drivers, pedestrians, and bicyclists. Consequently, the risk of crashes and injuries is high at intersections—in 2009, more than 50 percent of the fatal and injurious crashes occur at intersections (National Highway Traffic Safety Administration 2010b, Federal Highway Administration 2011). In New York City about 60 percent of the total crashes and 65 percent of the pedestrian crashes occurred at intersections between 1989 and 2008.

Multiple countermeasures may be candidates for improving pedestrian safety at intersections (Zegeer *et al.* 2002, Harkey and Zegeer 2004, Fitzpatrick *et al.* 2011). The relative effectiveness of one countermeasure as compared to others is one of the most important criteria in deciding what strategy should be deployed (National Highway Traffic Safety Administration 2010a). Many studies have evaluated the effectiveness of individual countermeasures (Fitzpatrick *et al.* 2011). Though the relative effectiveness of different countermeasures can be compared across different studies, differences in the study context can make the comparison across studies difficult. For example, all three dimensions of the built environment—density, diversity, and design—have been found to be associated with crashes and injuries (Dumbaugh and Rae 2009, Dumbaugh and Li 2011) . Differences in research design, analysis methods, and outcome measurements between studies can further add to the difficulty in comparisons. Most of the existing evaluations used surrogate measures—behavioral or operational measures, such as pedestrian-vehicle conflicts, motorist yielding, pedestrian looking behavior, or pedestrian compliance with traffic signals, instead of actual crash reductions (Fitzpatrick *et al.* 2011).

The purpose of this study is to conduct a quantitative evaluation of the relative effectiveness of five countermeasures in improving pedestrian safety at urban intersections. The five treatments are: increasing cycle length for pedestrian crossing, Barnes Dance (also called pedestrian scramble), split phase timing, signal installation, and high visibility crosswalk. Except signal installation, the other four treatments are specifically designed to improve pedestrian safety. Signal installation was included in the study since it can be used to improve the safety of all road users.

Countermeasures designed to improve pedestrian safety can compromise the safety of motorists (Ewing 1999, Dumbaugh and Li 2011). For example, increasing cycle length for pedestrian crossing is associated with a longer wait for motorists, which may increase speeding and crash risk. Is it possible for countermeasures to achieve safety for both pedestrians and motorists? Split phase, an invention by the New York City Department of Transportation, may achieve safety for both pedestrians and motorists by separating pedestrians and motorists into two protected phases. The secondary purpose of this study is to understand how countermeasures designed for pedestrian safety affect vehicle-vehicle crashes.

5.2 The Five Pedestrian Countermeasures in New York City

Conflict is one of the three principal factors responsible for crashes (Ewing and Dumbaugh 2009)[12]. Even with a signal, conflicts occur. Within a phase, pedestrians and left- and right-turning vehicles, left-turning vehicles and opposing through traffic, or left-turning vehicles and opposing right-turning vehicles have conflicting movements. Between phases, conflicts could arise due to inadequate time allocated to road users (e.g., pedestrians).

Four of the five countermeasures selected in this study attempt to resolve conflicts within a phase or between phases. Two of them—increasing the total cycle length and Barnes Dance attempt to reduce conflicts between phases by lengthening the time to cross the street or releasing pedestrians in all directions at once. The other two —signal installation and split phase—are designed to reduce conflicts by separating conflicts in time and space. Signal installation further differs from split phase in that in the former, conflicts may still remain, while in the latter case all conflicts are eliminated, assuming compliance of the different groups of road users. The fifth one selected—high visibility crosswalk—is designed to improve safety via raising drivers' awareness of pedestrians when approaching the intersection.

5.2.1 Increasing cycle length for pedestrian crossing

Increasing the total cycle length to lengthen pedestrian crossing time can be particularly useful for older persons whose walking speed is relatively slow. The downside is that vehicles

[12] The other two factors are exposure and speed.

on the main street must wait longer at a red signal due to the longer green phase for the cross street and consequently a longer queue may accumulate during the peak period. In addition, pedestrians waiting to cross the cross street may also become impatient and decide to cross against the signal.

The cycle lengths of many of the intersections on Queens Boulevard (Figure 5.1) and Ocean Parkway (Figure 5.2) were increased as a traffic safety countermeasure. Queens Boulevard is a 12-lane thoroughfare, with 3 lanes in each direction on the central major road and 3 lanes in each direction on service roads. Similarly, Ocean Parkway has a central 7-lane roadway, two service roads, two medians with trees, and pedestrian paths. On both streets, the pedestrian crossing time was lengthened by increasing the existing total signal cycle length, for example, from 120-second to 150-second during peak periods on Queens Boulevard between 63rd and 83rd Avenue, of which the green phase for the main street was increased from 80 to 90 seconds and that for the cross street was increased from 40 to 60 seconds (New York City Department of Transportation 2008a). This allows an additional 20-second walk time for pedestrians crossing the very wide main street (Queens Boulevard). The cycle length of all off-peak timing patterns for intersections on Ocean Parkway (between Church and Sea Breeze Avenues) was increased from 90 to 120 seconds, allowing an increase in pedestrian crossing time from 6 to 17 seconds on Ocean Parkway (New York City Department of Transportation 2008a).

Figure 5.1 Intersections on Queens Boulevard (East-West direction), New York City
(Source: Google Map Satellite View)

Figure 5.2 Intersections on Ocean Parkway (North-South direction), New York City
(Source: Google Map Satellite View)

No previous studies that examined the impact of increasing total cycle length on crashes have been found. The only relevant study was conducted by Ng et al. (1987) who examined the relationship between cycle time and crashes using a cross-sectional dataset of intersections with different cycle lengths and found no apparent relationship between the two.

5.2.2 Barnes Dance

Barnes Dance[13], also called pedestrian scramble, is a special phase added to the regular two-phase permissive signal timing, which stops vehicle traffic in all directions and allows pedestrians to cross in any fashion, including diagonally. Figure 5.3 shows the three phases in one traffic cycle: in Phase 1 (20 seconds) the East-West traffic is stopped and the North-South traffic and pedestrians have the right-of-way; in Phase 2 (37 seconds) the North-South traffic is stopped and the East-West traffic and pedestrians have the right-of-way; and in Phase 3 (33 seconds) all traffic is stopped and pedestrians of all directions have complete right-of-way. Figure 5.4 shows pictures of intersections in the special phase (Phase 3).

[13] Barnes Dance was named after NYC traffic commissioner Henry Barnes in the 1960s by a City Hall Reporter named John Buchanan. The concept was not invented by the commissioner, however, he promoted its widespread use (Federal Highway Administration 2008b).

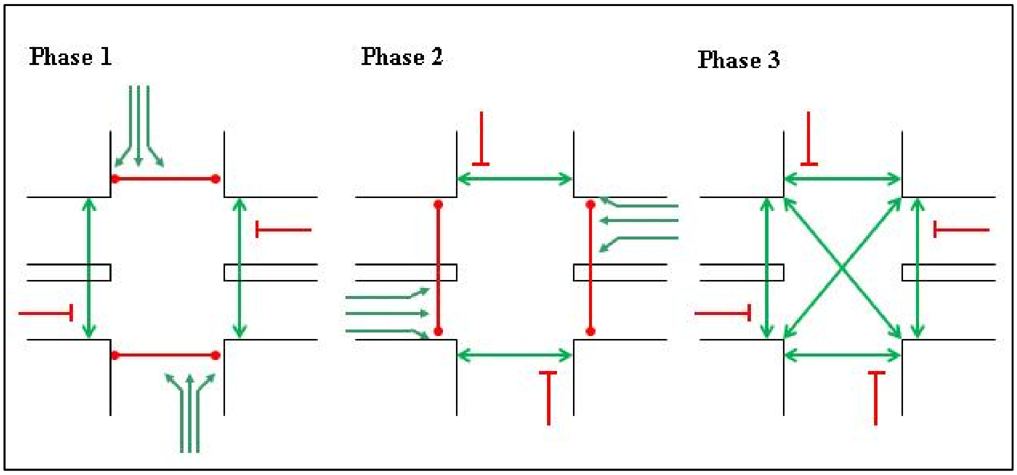


Figure 5.3 Barnes Dance Signal Timing

Figure 5.4 Examples of Barnes Dance

During this 3rd special phase, any potential conflict between pedestrians and motorists is removed. The downside is that diagonally-crossing pedestrians must wait 57 seconds and the time for diagonal crossing is only 33 seconds, much shorter than the 53-second and 70-second pedestrian crossing time for North-South and East-West directions, respectively, if there were not a 3rd phase. The lack of sufficient crossing time may prompt pedestrians to cross diagonally against signal. In addition, Barnes Dance creates "lost time"[14]—the time available for through and turning vehicles of all directions at the intersections reduced, resulting in a loss of roadway capacity.

Bechtel et al. (2003) studied Barnes Dance at one intersection in Chinatown in Oakland, California and found a 50% reduction in pedestrian-vehicle conflicts. Kattan et al. (2009) studied Barnes Dance at two intersections in downtown Calgary, Canada. They measured the number of pedestrian-vehicle conflicts and pedestrian violations (crossing against signal) and found that Barnes Dance decreased the number of pedestrian-vehicle conflicts occurring at the intersection but increased the number of violations after the implementation of Barnes Dance.

5.2.3 Split phase timing

In split phase timing, the regular two phases of a traffic cycle are split into three phases as shown in Figure 5.5. Under this operation, pedestrians receive a "walking person" display while the parallel movement of traffic that would normally turn left or right through the crosswalk is held with a left or right red arrow signal and the through movement proceeds on a green signal (as shown in Figure 5.6). After the pedestrian crossing is completed, a red "steady hand" is

[14] "Lost time" is a term in traffic engineering for the time during which no vehicles are able to pass through an intersection.

displayed and the turns are then made on a green arrow signal while the through movement continues to move. Split phase requires dedicated turn lanes since through and turning movements are governed by different signal indications.

Split phase timing allows pedestrian crossings and bicycle movements to be completely free from conflicts with turning vehicles. Assuming pedestrian compliance, left-turn vehicle progression is smoother than the before situation without split phase timing. The downside is that the time available for pedestrian crossings and the time allowed for vehicle turning movements are less than what would be if they were allowed to move concurrently with the through traffic. Consequently, pedestrians with low walking speed may not have sufficient time to complete the crossing; for intersections with a high volume of turning vehicles, this could result in a long queue waiting for their right-of-way. No other studies investigating the safety impacts of this countermeasure were found.

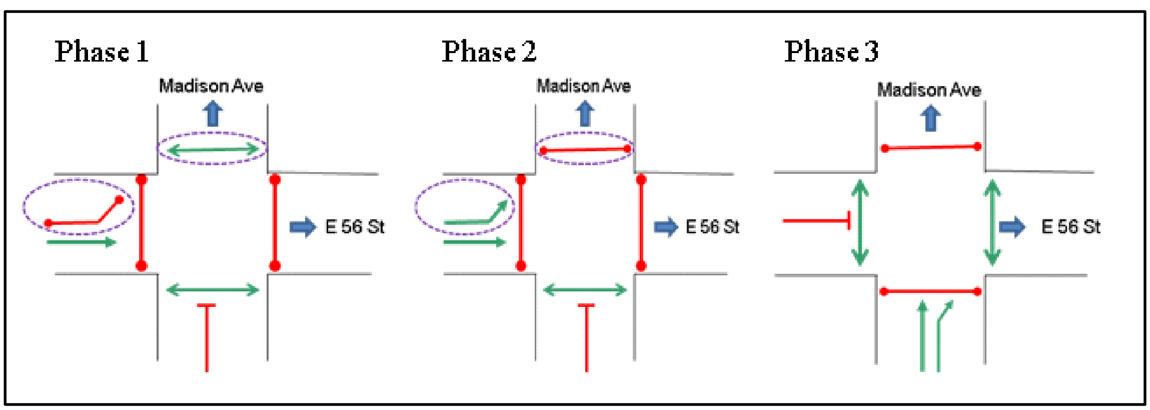


Figure 5.5   Split Phase Signal Timing

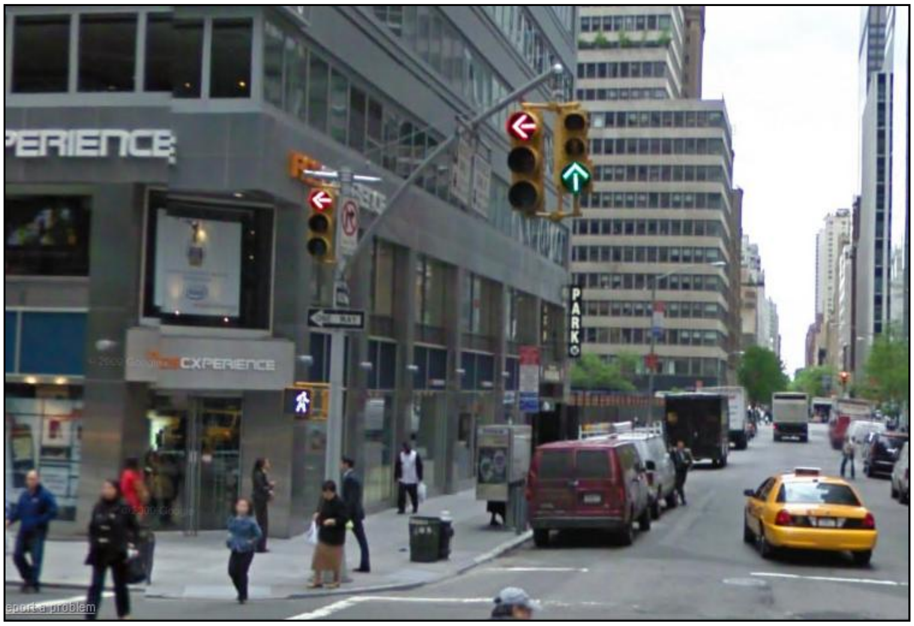


Figure 5.6 Split Phase Timing at East 56th Street and Madison Avenue, New York City
(Source: Google Map Street View)

5.2.4 Signal installation

New signals were installed at hundreds of non-signalized intersections in NYC based on *Manual on Uniform Traffic Control Devices* (MUTCD 2009 Edition) warrants. Signal installation works on the principle of conflict reduction by separating pedestrians from vehicular traffic and separating different traffic movements through signal phasing. However, compared with stop-controlled intersections, it is possible that motorists may be less likely to reduce their speeds when approaching an intersection during the green phase, and thus could be less ready for a potential hazard (e.g., vehicles or pedestrians crossing against the signal).

McGee et al. (2003) examined the safety impact of installing traffic signals at locations that were previously controlled by stop signs. Data from 122 intersections in urban areas in

California, Florida, Maryland, Virginia, Wisconsin, and Toronto, were used. The results indicated that fatal and injurious crashes at both 3-leg and 4-leg intersections decreased following the installation of traffic signals, though the effect was insignificant due to a small crash count and large standard errors. Crashes involving pedestrians, however, were not studied separately.

5.2.5 High visibility crosswalk

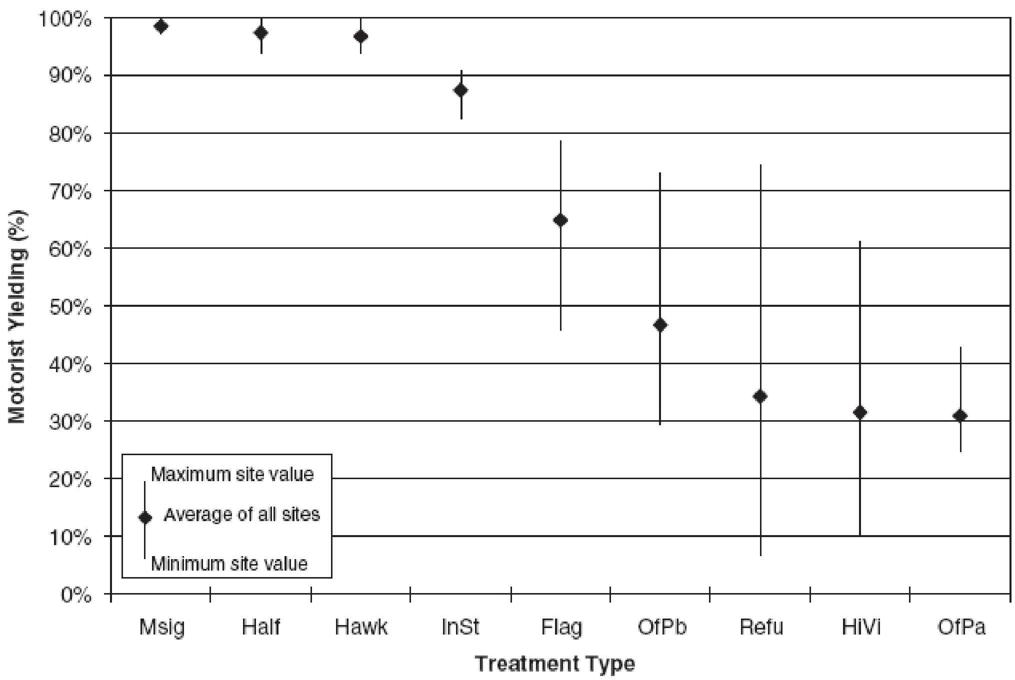
High visibility crosswalks aim to increase awareness of pedestrians at intersections by using highly visible marking patterns. The MUTCD recommends the use of high visibility crosswalk markings at high conflict locations:

> "For added visibility, the area of the crosswalk may be marked with white diagonal lines at a 45-degree angle to the line of the crosswalk or with white longitudinal lines parallel to traffic flow… This type of marking may be used at locations where substantial numbers of pedestrians cross without any other traffic control device, at locations where physical conditions are such that added visibility of the crosswalk is desired, or at places where a pedestrian crosswalk might not be expected" ((MUTCD 2009) p. 385).

High visibility crosswalks installed in NYC have a series of longitudinal white stripes that are constructed from thermoplastic materials (Figure 5.7). The possible problems with crosswalks generally is that motorists may be less alert to pedestrians crossing at other locations and pedestrians at crosswalks may less alert to potentially conflicting vehicle traffic.

Figure 5.7 High Visibility Crosswalk in New York City
(Source: New York City Department of Transportation 2010b, p. 19)

Findings on the high visibility crosswalk are mixed. Nitzburg and Knoblauch (2001) studied high visibility ladder style crosswalk markings at two non-signalized intersections in Clearwater, Florida. An experimental and control evaluation procedure was used. The study found that the high-visibility crosswalk resulted in significant increases in drivers' daytime yielding behavior—drivers were 30 percent to 40 percent more likely to yield after the treatment and the percentage of pedestrians using the crosswalk increased. The study concluded that high visibility crosswalk had a positive effect on pedestrian and driver behavior at the two locations studied. Conversely, a comparative evaluation of different crossing treatments found much lower driver compliance rates with high visibility signs and markings than with other measures—see Figure 5.8 from Fitzpatrick et al. (2006). Zegeer et al. (2001) found that marked crosswalks at uncontrolled intersections on two-lane roads were insignificant in reducing pedestrian crashes, and on wider roads with traffic volume more than 12,000 vehicles per day, they were associated with higher pedestrian crash rates.



Abbreviations: Msig=midblock signal; Half=half signal; Hawk=HAWK signal beacon; InSt=in-street crossing signs; Flag=pedestrian crossing flags; OfPb=overhead flashing beacons (pushbutton activation); Refu=median refuge island; HiVi=high-visibility signs and markings; OfPa=overhead flashing beacons (passive activation)

Figure 5.8 Average and Range of Percentage Motorists Yielding to Pedestrians by Crossing Treatment

(Source: Fitzpatrick *et al.* 2006, p. 49)

The five pedestrian countermeasures are summarized in Table 5.1 for their design principles and their pros and cons.

Table 5.1 Summary of the Design Principles and Pros and Cons of the Five Pedestrian Countermeasures

Measure	Design Principle	Pros	Cons
Increasing cycle length for pedestrian crossing	Increase the length of signal phases on the main street and cross street for pedestrian crossing and vehicle movements.	• Pedestrians have longer time of right-of-way to complete the street-crossing during one traffic cycle, so that the chances of being stuck in the middle of roadway and conflicting with moving vehicles are reduced.	• Vehicles on main street (the wide street) have to wait longer upon red signals and a longer queue may accumulate during the busy hours; • Pedestrians may also be impatient for the longer waiting time before crossing the street and thus increase crash risk.
Barnes Dance	Add a signal phase in which pedestrian have the complete right-of-way at intersections, while the length of the original regular East-West and North-South traffic signal phases are shortened.	• Separate the pedestrian crossing and moving vehicles completely in a special phase, thus reducing pedestrian-vehicle conflicts.	• Diagonal crossing might not have enough time and thus crossing against signal will occur; • Motor vehicle capacity on roadway is reduced due to the "lost time".
Split phase timing	Split the signal phase of one direction shared by through traffic, turning vehicles and crossing pedestrians into two protected phases: protected pedestrian crossing phase and protected vehicle turning phase.	• Reduce conflicts between crossing pedestrians and turning vehicles; • Allow the turning movement to process better assuming pedestrian compliance.	• The time available for the protected pedestrian crossing is shorter than normal and pedestrians may not have enough time to complete the crossing; • The time allowed for turning movement is less than normal and thus turning vehicles may accumulate at intersections with high volume of turning movements.

Table 5.1 Summary of the Design Principles and Pros and Cons of the Five Pedestrian Countermeasures – cont'd

Measure	Design Principle	Pros	Cons
Signal installation	Install new signals, that is, allocate the time (signal phase) during which pedestrians and motor vehicles of each direction have their own right-of-way for movements at the intersections, MUTCD warrants required.	• Separate the vehicle traffic and pedestrians of different directions into different signal phases and reduce the conflicts.	• Motor vehicles might approach the intersections without reducing their speed when they are on their right-of-way (green signal phase) and thus be less ready for a potential hazard (e.g., vehicles or pedestrians against signal) compared with stop controls.
High visibility crosswalk	Define the space where pedestrians have the right-of-way at intersections for crossing the roadways, while the time when pedestrians have the right-of-way is not defined by this measures, instead, the time is defined by other traffic controls such as signals or stop signs; the ladder pattern and thermoplastics materials make the crosswalk more visible to both pedestrians and motorists.	• Encourage pedestrians using the crosswalk; • Increase motorists' awareness of pedestrian crossing at intersections; • May increase yielding behavior of drivers.	• Motorists may be less alert on pedestrians not walking on crosswalks; • Sometimes pedestrians walking on crosswalk may assume their right-of-way without looking into the traffic signal and the potential conflicting vehicle traffic; • The occurrence of a sudden stop by the first driver approaching the crosswalk, leaving insufficient time for subsequent drivers to stop, and thus may increase rear-end crashes.

5.3 Methods

Police-reported pedestrian crashes (vehicle-pedestrian collisions) and multiple-vehicle crashes (vehicle-vehicle collisions) were studied. Each intersection was associated with two observations: crashes within 5-year period prior to the installation and crashes within 2-year period after the installation. A crash is a relatively rare event, thus, including a longer 5-year before period allows us to capture a more stable trend prior to the treatment. On the other hand, the selection of a shorter after period than the before period allows us to include more treatment sites: Crash data are only available until 2008, thus implementing a 5-year after period would mean that only treatments installed prior to 2003 could be evaluated and yet, most of the treatments were installed after 2003. The difference in the before- and after-period is controlled by an offset variable in our models.

5.3.1 Stage One—Selection of Comparison Groups

Figure 5.9 shows the distribution of the five countermeasures in NYC. New signals were equipped at intersections throughout the city; Barnes Dance was mostly installed in residential areas where pedestrian volumes are high; split phase timing was concentrated in midtown east Manhattan; lengthening of signal phases for pedestrian crossings was implemented on wide streets (Queens Boulevard and Ocean Parkway); and high visibility crosswalks were installed on long corridors such as Fulton Street and Park Avenue.

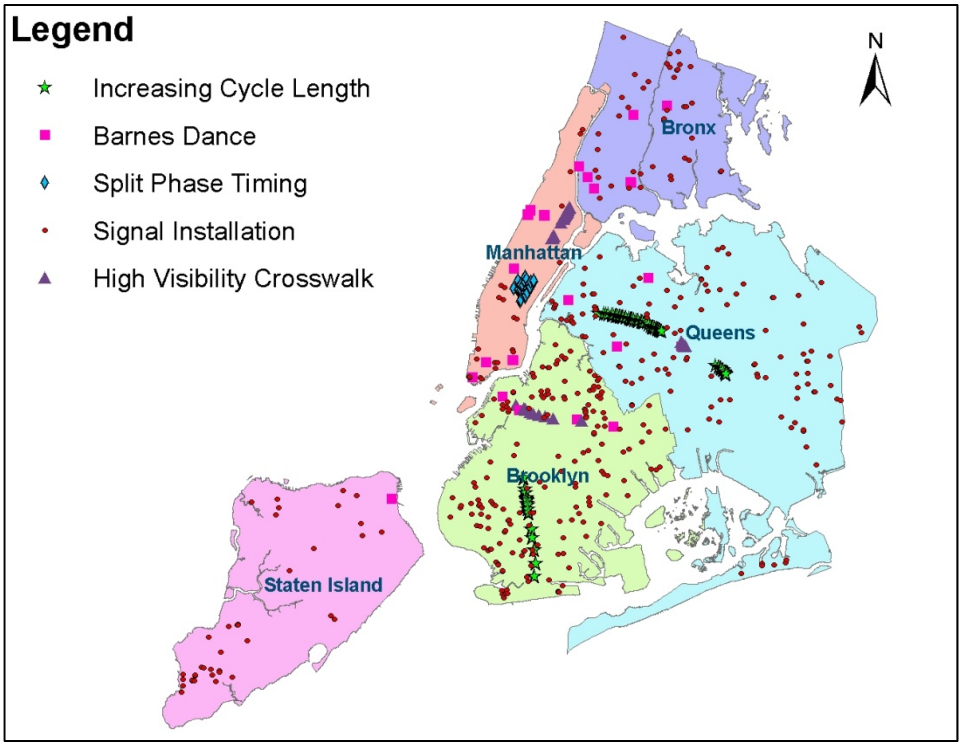


Figure 5.9 Map of the Five Pedestrian Countermeasures in New York City

In the first stage, for each treatment group (a group of intersections installed with one of the five countermeasures), a comparison group was generated comprising similar intersections but without the countermeasure. The selection of the comparison group was based on several intersection-level factors that have been found important in affecting crashes: control type (signalized or not) (Poch and Mannering 1996), the number of intersection legs (Milton and Mannering 1998, Harkey *et al.* 2008b), and one-way vs. two-way on the major road at the intersection (Harkey *et al.* 2008b). The geographical distribution of the locations in the comparison group was further controlled to resemble the distribution of those in the treatment group. Table5.2 shows the variables used for the selection of the comparison groups.

Table 5.2 Variables for Comparison Group Selection

Countermeasure	Criteria Variables
Increasing cycle length for pedestrian crossing	Geographical distribution in borough, control type (signalized), number of legs, one-way or two-way of the major road
Barnes Dance	Geographical distribution in borough, control type, number of legs
Split phase timing	Within the borough of Manhattan, control type (signalized), four-leg, one-way for both major and minor roads
Signal installation	Geographical distribution in borough, control type, number of legs
High visibility crosswalk	Geographical distribution in borough, control type, number of legs

For the same countermeasure, the before period and the after period are different for intersections treated in different years. As an example, the 5-year before period and the 2-year after period for signals installed in 2005 are 2000-2004 and 2006-2007, respectively, while those corresponding to signals installed in 2006 are 2001-2005 and 2007-2008, respectively. For this reason, a treatment group was first divided into multiple subsets defined by the year of installation. Then, for each subset, a set of untreated locations were selected by applying frequency matching techniques to resemble the joint distribution of those selected matching variables (those in Table 5.2) as well as the geographical distribution of the treatment group. The subsets were then combined into a single comparison group. This procedure repeated for each countermeasure to generate a single comparison group for each.

Because two countermeasures—increasing cycle length and high visibility crosswalk—were installed on parts of long corridors, those intersections along streets that are parallel to those in the treatment group were also manually selected and added to the corresponding comparison group. Table 5.3 shows the distributions of the matching variables in the treatment group and the comparison group for the five pedestrian countermeasures.

5.3.2 Stage Two—Negative Binomial Models using GEE Method

In order to account for other potential confounding factors, such as built environment characteristics that were not controlled in the comparison group selection but are potentially associated with crashes (Ewing and Dumbaugh 2009), negative binomial[15] regression models were applied.

To control for correlation among observations on the same location at two time points (before and after period), generalized estimating equation (GEE) methodology exchangeable structure[16] was applied.

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[15] Because the crash count data at those intersections in both the treatment group and comparison group are over-dispersed (variance is greater than the mean), negative binomial regression instead of Poisson is used.

[16] In the general estimating equations (GEE) method, the dependency of repeated measures is taken into account by specifying a correlation structure for the repeated measures. The choices include: independent (assuming no dependency), exchangeable (assuming every observation within an individual is equally correlated with every other observation from that individual), autoregressive (decreasing correlation for farther time periods) and unstructured (estimate all correlations separately). Because in our study each intersection has only two repeated measures—crash in the before period and crash in the after period, the exchangeable correlation structure is selected as it is the simplest one and fits the data well. When there are more measurements collected over time, the choice of exchangeable correlation structure may not be reasonable, since the correlations most likely will diminish as the time lag between observations increases.

Table 5.3 Treatment Group and Comparison Group for the Five Pedestrian Countermeasures

Measure	Increasing cycle length		Barnes Dance		Split phase timing		Signal installation		High visibility crosswalk	
Group*	T	C	T	C	T	C	T	C	T	C
Number of Intersections	244	1173	36	516	30	493	447	442	72	1009
Borough										
Manhattan	0	0	19 (45%)	222 (43%)	30 (100%)	493 (100%)	29 (6%)	25 (6%)	51 (71%)	697 (63%)
Bronx	0	0	10 (24%)	98 (19%)	0	0	41 (9%)	41 (9%)	0	0
Brooklyn	44 (18%)	230 (20%)	4 (10%)	70 (14%)	0	0	187 (42%)	186 (42%)	13 (18%)	240 (22%)
Queens	200 (82%)	943 (80%)	8 (19%)	112 (22%)	0	0	147 (33%)	147 (33%)	8 (11%)	162 (15%)
Staten Island	0	0	1 (2%)	14 (3%)	0	0	43 (10%)	43 (10%)	0	0
Signalization										
non-signalized	0	157 (13%)	0	56 (11%)	0	0	447 (100%)	442 (100%)	22 (31%)	414 (38%)
signalized	244 (100%)	1016 (87%)	42 (100%)	460 (89%)	30 (100%)	493 (100%)	0	0	50 (69%)	685 (62%)
Number of legs										
3-leg	34 (14%)	201 (17%)	10 (24%)	98 (19%)	0	0	111 (24%)	111 (25%)	17 (24%)	314 (29%)
4-leg	198 (81%)	940 (80%)	27 (64%)	376 (73%)	30 (100%)	493 (100%)	330 (74%)	325 (74%)	55 (76%)	785 (71%)
5-leg or more	12 (5%)	32 (3%)	5 (12%)	42 (8%)	0	0	6 (1%)	6 (1%)	0	0
One-way (major road)										
one-way	0	0	2 (5%)	76 (15%)	30 (100%)	493 (100%)	43 (10%)	40 (9%)	0	122 (11%)
two-way	244 (100%)	1173 (100%)	40 (95%)	440 (85%)	0	0	404 (90%)	402 (91%)	72 (100%)	977 (89%)

Note: * T = Treatment Group, C = Comparison Group

The model is specified below:

$$y_{it} = year_t \times \exp\left(\alpha + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + \sum_{j=1}^{5}\left[a_j\left(Imp_j\_T1\right) + b_j\left(Cmp_j\_T1\right) + \varphi_j\left(if\_Imp_j\right)\right] \right)$$

(5.1)

Where,

- y_{it} is the expected crash count at site i during the time t (before or after period),
- $year_t$ s the number of years during time t (5 years for pre-treatment period and 2 years for post-treatment period),
- $\mathbf{X}^{(s)}\boldsymbol{\beta}$ are site-level covariates with coefficient $\boldsymbol{\beta}$;
- $\mathbf{X}^{(n)}\boldsymbol{\gamma}$ are neighborhood-level covariates with coefficient $\boldsymbol{\gamma}$;
- Imp_j_T1 is equal to 1 if the data point comes from the locations with treatment j post-treatment and 0 otherwise, and the coefficient for this variable is a_j;
- Cmp_j_T1 is equal to 1 if the data point comes from the un-treated locations in the comparison group for treatment j post-treatment and 0 otherwise, and the coefficient for this variable is b_j;
- If_Imp_j is equal to 1 if the data point comes from locations with treatment j and 0 otherwise, and the coefficient for this variable is c_j.

The model includes two sets of independent variables that may potentially affect crash frequencies: neighborhood-level and site-level covariates (Table 5.4). It is hypothesized that higher exposure and more conflicts are associated with more crashes (Ewing and Dumbaugh 2009). At the neighborhood level, for example, daytime population density, retail density, percentage of different age groups (under 21, 21-65, or above 65), and motorized or non-motorized mode shares were used to account for the exposure of vehicular traffic and Daytime population density was calculated as the number of residents plus employment minus the number of people who live and work in the same census tract (to remove double counting) divided by the total area of the census tract; and retail density was calculated as the floor area of retail land use divided by total census tract area. These two variables measure the density of people who live, work, and shop in the neighborhood. Site-level covariates include control type (signalized or non-signalized), the number of legs at the intersections, one-way or two-way and number of lanes on the major roads of the intersections. These variables are mostly to account for the conflicts that pedestrians have with motorized vehicles.

It is possible that there exists a significant difference in before-period crashes between the treatment group and the comparison group, leading to a potential regression-to-mean effect. Therefore, in addition to the explanatory variables included in Table 5.4, five dummy variables were included in the model: variables "if_Imp_1"~"if_Imp_5", representing the data point from the five treatment groups, respectively. A positive coefficient of the dummy variable "if_Imp_j" means that for treatment j, the before-period crashes of the treatment group are significantly more than those of the comparison group and a negative coefficient suggests otherwise.

Table 5.4 List and Category of Explanatory Variables

Category	Variables
Roadway Geometry	Control type (1 if signalized; 0 non-signalized) Number of legs at the intersection One-way or two-way on the major road Number of travel lane on the major road
Socio-demographic	Daytime population density (1,000 per sq mi) Median household income ($1,000) Percent below poverty (%) Percent foreign born population (%) Percent Asian population (%) Percent Black population (%) Percent Hispanic population (%) Percent population age between 21 and 65 (%) Percent population age under 21 (%) Percent population age above 65 (%)
Mode Share	Percent travel by auto (%) Percent travel by public transportation (%) Percent travel by bicycling (%) Percent travel by walking (%)
Land Use	Residential land use density (floor area, sqft/sqft) Commercial land use density (floor area, sqft/sqft) Retail land use density (floor area, sqft/sqft)
Transportation	Percent of one-way roadway (%) Percent of roadway that is truck route (%) Percent of roadway with parking lane (%) Percent of 4-leg intersection (%) Percent of signalized intersection (%) Maximum subway ridership in the census tract (1,000) Subway station density (number per sq mi) Bus stop density (number per sq mi)

The coefficients of variables "Imp_j_T1" and "Cmp_j_T1", that is, a_j and b_j in the model specification, are of our primary interest. The contrast between the two coefficients represents the difference in change in crash frequencies from the pre-treatment to the post-treatment period for the treatment group versus the comparison group for treatment j. In order to test if the difference of the two coefficients is statistically significant at 5% level, the model can be transformed by replacing "Imp_j_T1" and "Cmp_j_T1" with Z_j and P_j:

$$y_{it} = year_t \times \exp\left(\alpha + \mathbf{X}^{(s)}\boldsymbol{\beta} + \mathbf{X}^{(n)}\boldsymbol{\gamma} + \sum_{j=1}^{5}\left[c_j(Z_j) + d_j(P_j) + \varphi_j(if\_Imp_j)\right]\right) \tag{5.2}$$

Where,

$$Z_j = (Imp_j\_T1 - Cmp_j\_T1)/2\,, P_j = (Imp_j\_T1 + Cmp_j\_T1)/2\,, \forall\, j = 1, 2, \ldots, 5$$

The coefficient of Z_j is the difference of the two coefficients associated with "Imp_j_T1" and "Cmp_j_T1": $c_j = a_j - b_j$. If c_j is significant and negative, it points to the effectiveness of treatment j in reducing crashes. The differences among the c_j ($j = 1, 2, \ldots, 5$) suggest the relative effectiveness of the five countermeasures: the more negative a coefficient is, the more effective the corresponding countermeasure is.

5.4 Results

Pedestrian and vehicle-vehicle crash counts before and after the treatments are shown in Tables 5.5 and 5.6.

Table 5.5 Pedestrian Crash Counts Before and After Treatments

Measure	Group*	Number of Intersections	Before		After		Average Pedestrian Crashes (per intersection per year)			
			Years	Sum	Years	Sum	Before	After	Change	% Change
Increasing cycle length	T	244	5	155	2	31	0.13	0.06	-0.06	-50%
	C	1173	5	1382	2	528	0.24	0.23	-0.01	-4%
Barnes Dance	T	36	5	97	2	19	0.54	0.26	-0.28	-51%
	C	516	5	878	2	275	0.35	0.32	-0.03	-9%
Split phase timing	T	30	5	212	2	52	1.41	0.87	-0.55	-39%
	C	493	5	2005	2	740	0.81	0.75	-0.06	-8%
Signal Installation	T	447	5	382	2	136	0.17	0.19	0.02	12%
	C	442	5	93	2	51	0.04	0.07	0.03	67%
High visibility crosswalk	T	72	5	63	2	15	0.18	0.10	-0.07	-40%
	C	1099	5	1637	2	539	0.30	0.25	-0.05	-18%

*Group: T = Treatment Group, C = Comparison Group

Table 5.6 Multiple-Vehicle Crash Counts Before and After Treatments

Measure	Group*	Number of Intersections	Before		After		Average Multi-Vehicle Crashes (per intersection per year)			
			Years	Sum	Years	Sum	Before	After	Change	% Change
Increasing cycle length	T	244	5	1609	2	357	1.32	0.73	-0.59	-45%
	C	1173	5	10604	2	2673	1.81	1.14	-0.67	-37%
Barnes Dance	T	36	5	336	2	150	1.93	2.13	0.19	10%
	C	516	5	3380	2	1147	1.46	1.27	-0.18	-12%
Split phase timing	T	30	5	590	2	103	3.93	1.72	-2.22	-56%
	C	493	5	5662	2	1264	2.30	1.28	-1.02	-44%
Signal Installation	T	447	5	2936	2	509	1.31	0.67	-0.65	-49%
	C	442	5	1022	2	309	0.46	0.40	-0.06	-14%
High visibility crosswalk	T	72	5	262	2	85	0.73	0.59	-0.14	-19%
	C	1099	5	6468	2	1573	1.18	0.72	-0.46	-39%

*Group: T = Treatment Group, C = Comparison Group

For "increasing total cycle length", the average pedestrian crashes (per intersection per year) decreased at the treated and untreated intersections, but the reduction for the former is much higher than the latter (-50% vs. -4%). The average multiple-vehicle crashes also decreased for both treated and untreated intersections, though the difference between the two is smaller (-45% vs. -37%).

In the case of "Barnes Dance", the average pedestrian crashes were found to decrease in the treatment group and the comparison group, and the former experienced a much higher reduction than the latter (-51% vs. -9%). The average multiple-vehicle crashes, on the other hand, increased (10%) post-treatment for the treatment group but decreased (-12%) for the comparison group.

For "split phase timing", it was found that the average pedestrian crashes and the multiple-vehicle crashes decreased in the treatment group and the comparison group. The reduction in pedestrian crashes at treated locations is much larger than the compared intersections (-39% vs. -8%), while the reductions in multiple-vehicle crashes at treated intersections and at the compared intersection are similar (-56% vs. -44%).

As for "signal installation", pedestrian crashes increased at both treated and compared intersections, though the increase in the treated intersections was smaller than the compared intersections (12% vs. 67%). Multiple-vehicle crashes, on the contrary, decreased at the treated and compared intersections, and the reduction for the former was larger than the latter (-49% vs. -14%).

In the case of "high visibility crosswalk", the reduction in pedestrian crashes at treated intersections was higher than that at the compared intersections (-40% vs. -18%), while the reverse is true for multiple-vehicle crashes (-19% vs. -39%), indicating that high visibility crosswalk could potentially reduce pedestrian crashes, but increase multiple-vehicle crashes.

The estimation results of model (as equation 5.2) are shown in Table 5.7. On the role of the built environment, our results conform to those in the literature (Ewing and Dumbaugh 2009). Variables measuring the exposure of pedestrians, for example, daytime population density, retail density, subway ridership, and percentages of commuters by alternative modes (for example, public transit), and variables measuring the exposure of vehicles, for example, percentage of commuters by auto, are all found to be positively correlated with pedestrian and multiple-vehicle crashes, respectively. Some variables, for example, subway ridership, are found to explain both crashes. Variables such as the percentages of 4-leg intersections, roadways with parking, and truck routes in the census tract were included to measure conflicts at the intersection (Ewing and Dumbaugh 2009, Dumbaugh and Li 2011). The results suggest that areas with a higher percentage of roadways with parking and more 4-leg intersections are associated with more pedestrian crashes. The percentage of signalized intersections, on the other hand, is associated with fewer multiple-vehicle crashes.

Census tract-level social effects, for example, elderly, young, and poor population, were also examined. Census tracts with a higher percentage of people younger than 21 years old and a higher percentage of black population have more multiple-vehicle crashes, while those with a higher percentage of the population in poverty have more pedestrian crashes.

Table 5.7 Estimates (Std. Errors) of Covariates in the Models

Covariates	Pedestrian Crashes			Multiple-Vehicle Crashes		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
Intercept	-6.603	0.364	<.0001	-4.867	0.304	<.0001
Site-level Covariates (intersection)						
number of legs	0.471	0.057	<.0001	0.713	0.048	<.0001
signalized intersection	1.367	0.087	<.0001	1.257	0.080	<.0001
number of lanes on major road	0.152	0.023	<.0001	0.176	0.025	<.0001
one-way on major road	-0.370	0.058	<.0001	-0.123	0.055	0.025
Neighborhood-level Covariates (census tract)						
log(daytime population density)	0.318	0.037	<.0001	0.024	0.035	0.497
Percent of population age under 21				0.013	0.003	<.0001
Percent of population below poverty level	0.010	0.002	<.0001			
Percent of black population				0.003	0.001	0.002
Percent of commuter by auto				0.002	0.002	0.350
Percent of commuter by public transit	0.009	0.002	<.0001			
Retail density	0.0003	0.0002	0.172			
Percent of roadway with truck route				0.004	0.002	0.011
Percent of roadway with parking	0.007	0.002	0.0003	0.004	0.002	0.035
Percent of signalized intersections				-0.005	0.002	0.002
percent of 4-leg intersections	0.005	0.002	0.022	0.009	0.002	<.0001
maximum subway ridership	0.004	0.001	0.001	0.004	0.001	0.004
bus stop density	0.001	0.000	0.137			
Effectiveness ($c_i = a_i - b_i$)						
Increasing cycle length: $a_1 - b_1$	**-0.647**	0.199	**0.001**	-0.110	0.106	0.299
Barnes Dance: $a_2 - b_2$	**-0.547**	0.250	**0.029**	0.140	0.220	0.523
Split phase timing: $a_3 - b_3$	**-0.474**	0.159	**0.003**	**-0.303**	0.122	**0.013**
Signal installation: $a_4 - b_4$	**-0.468**	0.179	**0.009**	**-0.600**	0.118	**<.0001**
High visibility crosswalk: $a_5 - b_5$	-0.245	0.383	0.522	0.158	0.142	0.267

The estimated coefficients for c_i suggest that the four signal-related countermeasures are effective in reducing pedestrian crashes. Two of them: split phase timing and signal installation, are also effective in reducing vehicle crashes. High visibility crosswalk, on the other hand, is ineffective in reducing either type of crashes. These findings appear to suggest that countermeasures designed to reduce conflicts work better in reducing pedestrian and multiple vehicle crashes than those trying to raise drivers' awareness. That split phase timing and signal installation also reduce multiple vehicle crashes is understandable since these two countermeasures also attempt to reduce conflicts between vehicles. For some, notably, Barnes Dance and high visibility crosswalk, there appears to be a trade-off between reducing pedestrian crashes and multiple vehicle crashes. In both cases, there is a tendency for multiple vehicle crashes to increase, though the effect is insignificant. This increased tendency may be related to the lost time with Barnes Dance, in which vehicles have less time to cross or turn at intersections, and the occurrence of a sudden stop by the first driver approaching an intersection with a high visibility crosswalk, leaving insufficient time for subsequent drivers to stop. The 1998-2008 crash database in NYC indeed shows an increase in rear-end and overtaking crashes at intersections with high visibility crosswalks—these two collision types accounted for 22% of the total collision types in the before period and increased to 31% during the after period.
At the same time, a countermeasure effective in reducing pedestrian crashes is not necessarily equally effective in reducing vehicle crashes. One example is that of increasing total cycle length: this countermeasure is most effective in reducing pedestrian crashes, but its effect on multiple-vehicle crashes is insignificant. Table 5.8 summarizes findings on the relative effectiveness of the five countermeasures, as compared to those in the literature.

Table 5.8 Summary of the Relative Effectiveness of the Five Countermeasures in This Study and Literature

Measure	Effectiveness in this study (New York City)	Current Literature	
		Effectiveness	Study Area
Increasing cycle length for pedestrian crossing	Most effective in reducing pedestrian crashes but insignificant in reducing multiple vehicle crashes	Inconclusive on whether longer cycle times have fewer crashes (Ng, Hauer, & Lovell, 1987)	Metropolitan Toronto, Canada
Barnes Dance	Effective in reducing pedestrian crashes, but insignificant in reducing multiple vehicle crashes	Effective in reducing pedestrian-vehicle conflicts; seemingly to increase pedestrians' violations (Bechtel, MacLeod, & Ragland, 2003; Kattan, Acharjee, & Tay, 2009)	Oakland, California Calgary, Canada
Split phase timing	Effective in reducing pedestrian crashes and multiple vehicle crashes	n/a	n/a
Signal Installation	Effective in reducing pedestrian crashes and multiple vehicle crashes	Effective in reducing fatal and injurious crashes, though the effect is insignificant (McGee, Taori, & Persaud, 2003)	Urban areas in California, Florida, Maryland, Virginia, Wisconsin, and Toronto
High visibility crosswalk	No significant impacts in reducing either pedestrian crashes or multiple-vehicle crashes	Effective in increasing driver daytime yielding behavior and percentage of pedestrians using the crosswalk (Nitzburg & Knoblauch, 2001); lower driver compliance rates with high visibility signs and markings than with other measures (Fitzpatrick et al. 2006)	Clearwater, Florida

5.5 Conclusions and Recommendations

It has been found that signal-related countermeasures are more effective in reducing crashes than high visibility crosswalks. This finding is consistent with others that have largely found that crosswalk markings are ineffective in reducing crashes (Zegeer *et al.* 2001). This finding should not be generalized to all measures that rely on drivers' awareness. In fact, many of such countermeasures—for example, increased intensity of roadway lighting (Pegrum 1972, Polus and Katz 1978), bus stop relocation from near side to far side of an intersection (Berger and Knoblauch 1975), and diagonal parking[17] were found effective in reducing pedestrian crashes (Retting *et al.* 2003).

There are trade-offs between improving pedestrian safety and motorist safety. The results show that those that indirectly resolve conflicts—increasing total cycle length and Barnes Dance—are more effective in reducing pedestrian crashes and yet less effective in reducing vehicle crashes than those that directly separate conflicts—split phase and signal installation. In the case of Barnes Dance, there is a potential increase in vehicle crashes. This finding suggests that selection of a specific countermeasure at a location highly depends on the characteristics of the location and the problem at hand.

Increasing total cycle length is suitable for certain locations, for example, near senior centers, where there is a higher percentage of elderly pedestrians. Barnes Dance is appropriate in

[17] Diagonal parking: vehicles park at an angle, typically about 30 degrees, to the curb in the direction of traffic.

downtown locations where there is a fast accumulation of pedestrians. As this study suggests, Barnes Dance potentially affects vehicle traffic negatively. Therefore, there may be a need to divert traffic away from the location where Barnes Dance is installed. Split phase timing separates pedestrian and turning vehicles completely and thus it is most desirable for locations with some turning movements and narrow streets so that pedestrians can complete the crossing in a relatively short time. For signal installation, our study suggests that this traditional engineering countermeasure remains a very effective approach when the traffic volume meets the MUTCD warrants.

In closing, the study results suggest that at least in contexts similar to the study area—a large, dense urban area—traditional engineering approaches continue to play an important role in improving the safety of pedestrians and motorists and there are trade-offs to be considered between improving pedestrian safety and motorist safety. The transferability of these findings is subject to debate. In general, the results are likely applicable to other similar urban areas (e.g., San Francisco, Chicago) for two main reasons. First, unlike prior studies that typically involve a few intersections, the sample sizes of the five countermeasures in our study are large. Second, the use of our two-stage methodology not only accounts for differences at the intersection level, but also those at the neighborhood level. Indeed, a recent study in San Francisco on Barnes Dance, modified signal timing, advanced stop lines, and many others (Federal Highway Administration 2008a) showed that Barnes Dance "is potentially effective for certain situations (e.g., smaller intersections with heavy volumes of turning vehicles and pedestrians), but can be difficult to use in some situations (e.g., wide intersections with heavy through traffic volumes, including transit service).” The same study also showed that many people felt safer after the signal timing change.

Furthermore, the transferability of the results likely varies with treatments. To a large extent, the question on transferability depends on how the treatment group is selected—random sampling defies threats to transferability (Shadish *et al.* 2002). Among the five countermeasures, the selection of the intersections for some treatments represents more like a random selection than for others. As mentioned earlier (Figure 5.8), intersections treated with signal installation scattered around in the city, resembling the result of a random sample most, followed by those treated with Barnes Dance, which spread out in residential areas in four boroughs except Staten Island. The other three treatments are much more geographically concentrated—those with split phase timing are all in Midtown East Manhattan; those whose cycle lengths were increased are mostly on Ocean Parkway and Queens Boulevard; and those with high visibility crosswalk are mostly on long corridors. From this perspective, the transferability of the effectiveness found for signal installation and Barnes Dance is likely higher than those found for the other three countermeasures.

CHAPTER 6 Conclusions

In this chapter the study results are summarized, and policy recommendations, limitation of the study, and future research areas are also discussed.

6.1 Summary of the Study

In this dissertation research, I investigate New York City's experience in improving safety for all users on the streets, especially vulnerable users such as pedestrians, by developing a safety framework grounded in safety theory that captures unique characteristics of multi-modal transportation system in New York City, and reviewing various safety countermeasures installed throughout New York City in the last 20 years. A preliminary evaluation of thirteen safety countermeasures is first conducted using the Comparison Group Analysis method (Hauer 1997). Then a more rigorous quasi-experimental design, that is, a before-after analysis with a comparison group, followed by regression models using the generalized estimating equations (GEE) methodology (Liang and Zeger 1986, Zeger and Liang 1986) is applied to evaluate safety countermeasures for various road users, including motor vehicles, bicyclists and pedestrians.

The following briefly lists the findings on the effectiveness of safety countermeasures.

- The preliminary evaluation of thirteen safety countermeasures shows that some signal related treatments, such as spilt phase timing, signal installations, Barnes Dance, and increasing total cycle lengths, remain very effective, in particular, in reducing crashes with pedestrians, while measures that are designed to alert drivers' cognitive attention, for example, high visibility crosswalk and posted speed limit reduction signs, appear to have a lesser effects. Two traffic calming measures, road diets (reduction in the number of travel lanes) and speed reducers (speed humps) are found to be effective in reducing crashes for vehicles, pedestrians and bicyclists.

- The detailed study of left-turn signal phasing found that the change of permissive left-turn signal phasing to protected/permissive or protected-only signal phasing does not result in a significant reduction in intersection crashes. Though the protected-only signal phasing does reduce the left-turn crashes, this reduction was offset by a potential increase in over-taking crashes.

- The installation of bike lanes does not result in an increase in crashes (no significant impacts are found for bike lanes on crashes), despite a likely increase in the number of bicyclists after the installation of bike lanes. This suggests that if the difference[18] in bicyclists volumes were properly controlled, a positive safety effect may be found.

- The comparison of the relative effectiveness of five pedestrian countermeasures (increasing cycle length for pedestrian crossing, Barnes Dance, signal phase timing, signal installation, and high visibility crosswalk) finds that signal-related countermeasures are more effective in reducing pedestrian crashes than crosswalk markings. Split phase timing and signal installation are also effective in reducing

[18] The difference is not controlled because of lack of data.

multiple vehicle crashes. These findings based on the regression models are consistent with those from the preliminary study using the Comparison Group Analysis method.

The results conform to those in the literature (Ewing and Dumbaugh 2009, Ewing and Cervero 2010) concerning the role of the built environment. Variables measuring the exposure of vehicle or pedestrians, for example, daytime population density, retail density, subway ridership, and percentages of commuters by alternative modes (for example, percentage of commuters by auto or public transit), are all found to be positively correlated with crashes. Variables measuring the conflicts, such as the percentages of 4-leg intersections, signalized intersections, roadways with parking, and truck routes in the census tract were also found to be associated with crashes. Analysis of the elasticities of the built environment factors provides a further understanding of the role of the built environment characteristics: the effect of daytime population density is the largest among all built environment characteristics for crashes (in particular, for pedestrian crashes) on segments and at intersections, while retail density and bicyclist trip density appear to exert the smallest role. The effect of the density of bus stops is larger for intersection-level crashes than for segment-level crashes, while the density of subway stops does not appear to have a large effect.

The methodology used in this research in the evaluation of a set of safety countermeasures in New York City represents the state of the art approach in safety evaluations and offers a number of advantages over the conventional methods. First, in the quasi-experimental design, comparison groups are first generated and before-after analyses are done for both the treatment group and the comparison group. This study design is much more rigorous than the simple before-after study or cross-sectional analysis in that both the factors other than the treatment itself (for example, roadway geometry and neighborhood characteristics) and the general area-wide crash trend can be accounted for in this study design (Shadish *et al.* 2002). Second, for some confounding factors that are not controlled in the comparison group selection process[19], such as the built environment factors that might have significant impacts on crashes, I apply the regression models to control and quantify their effects on safety. Third, the correlations between repeated measures (the observations collected at the same locations at two different time points, the before period and the after period) are accounting for by the use of the GEE methodology with an exchangeable correlation structure. One additional benefit of the modeling is that the regression models developed in this research can be adapted to different purposes and situations. The model can be developed for the effectiveness of a single type of treatment—bike lanes; or for the situation of two types of treatments in the treatment group, such as the protected-only and protected/permissive left-turn signal phasing, versus a signal comparison group consisting of untreated intersections; or for the comparison of the relative effectiveness of multiple treatments, using the combined dataset comprising five treatment groups and five comparison groups.

[19] This is because the number of control variables in the selection of the comparison group is usually limited in order to get a sample size that is big enough for a statistically sound analysis, or to quantify the effects of some factors.

6.2 Policy Recommendations

Based on the traffic safety strategy framework and the evaluation results of the thirteen safety countermeasures in New York City, several policy recommendations can be made for transportation planners and policy makers in solving safety problems for large urban areas.

First, in designing, selecting and implementing safety countermeasures to reduce crashes and improve safety for an urban area, not only the three factors (exposure, conflict, and speed) that affect crashes, but also the unique characteristics of each urban area, including the transportation system and the built environment, need to be considered. This is shown in the safety framework proposed in Chapter 2. Our study results show that the safety countermeasures are very effective in reducing crashes through reducing conflicts (e.g., signal related measures to reduce the conflicts between vehicles, or conflicts between vehicles and pedestrians), reducing speeds (e.g., speed humps), or reducing vehicle exposure and encouraging non-motorized modes (e.g., bike lanes). These countermeasures are designed to adapt to the characteristics of the multi-modal transportation system in New York City—the complex and extensive multi-modal networks, high percentage of walking and bicycling, dense population and diverse land use, aging and narrow streets, and the many cultures brought with its many immigrants. The results of this study confirm the importance of including built environment characteristics in the evaluation of safety countermeasures. Crashes at locations with different socio-demographics, land use, and transportation network characteristics are different in nature and thus the effects of the same measures at different locations may vary a lot. When implementing and evaluating safety countermeasures, not only the roadway geometry and traffic flows, but also the neighborhood characteristics need to be studied.

Second, it is suggested that when implementing a safety countermeasure, the trade-offs between the safety of different road users need to be considered. In dense urban areas, the traffic is mixed, with higher percentages of pedestrians and bicyclists. The selection and implementation of countermeasures thus should consider the types of conflicts and balance the time for different groups of road users on the roads so that the improvement of the safety of one group does not compromise that of other groups. Barnes Dance, for example, has been found to be effective in promoting pedestrian safety, however, it can potentially increase multiple vehicle crashes. Thus Barnes Dance is most appropriately applied in areas with many pedestrians and a modest amount of traffic. Similarly, high visibility crosswalks have been found to reduce pedestrian crashes but tend to increase the vehicle collisions, thus they shall not be installed to locations with high vehicle traffic volume. When evaluating the effectiveness of a safety countermeasure, it is suggested that its impacts on different groups of users be studied.

Third, with regards to the locations (road segments or intersections) where the safety countermeasures are to be installed, one needs to consider the characteristics of the road infrastructure networks, the built environment, and the design of the measures. Take the example of the measure "increasing cycle length for pedestrian crossing": the design purpose of this measure is to improve the safety of pedestrians with slow walking speed, such as the seniors and thus, it is most appropriate for corridors with wide travel lanes at neighborhood with more senior residents. Some measures having similar target group may fit for locations with quite different characteristics. For example, Barnes Dance and split phase timing are both signal phase design for pedestrian safety, however, Barnes Dance is found to be appropriate in residential areas with many pedestrians and a modest amount of traffic, while split phase signal timing is designed for intersections with only one-way traffic and many pedestrian crossings, such as the midtown east of Manhattan. The study also indicates that segment-based measures and intersection-based measures should not be separated, meaning that when applying segment-based treatments, it may also be worthwhile to apply some treatments at the associated intersections. Take the example of bike lane installation: in order to reduce conflicts between bicyclists going straight or turning left at an intersection and the opposing traffic, it is suggested that measures such as bike boxes be installed at intersections. Paths that guide bicyclists through the intersection can also be very helpful.

Last, the study focuses mainly on the effectiveness of the physical aspects of the safety countermeasures. Sometimes in order for some of the measures to achieve their design purpose, enforcement and education are also very important. For example, the bus lanes have been installed in New York City to improve bus services and encourage more transit ride. However, the study finds that the crash tends to increase after the installations of bus lane. One of the problems being observed with the bus lanes in New York City is that many commercial vehicles park in bus lanes for loading/unloading and sometimes even police cars stop and block bus lanes. When a new treatment (such as a new signal phase or traffic rules) is installed, educations are often needed to avoid confusions.

6.3 Limitations and Future Research

The results in this study are set in the context of a large, dense urban area—New York City, thus one needs to be careful when trying to apply the results to other areas. In general, the results are likely applicable to other similar urban areas (e.g., San Francisco, Chicago) for those safety countermeasures with large sample sizes and being implemented at random selected locations with varying characteristics at both site-level and neighborhood-level.

There have been countless research efforts conducted to develop statistical models to better understand the factors that are significant in determining crash frequency and past research shows that traffic volume is a important variable influencing the number of crashes (Elvik and Vaa 2004). However, in real world, it is quite possible that the traffic count data might be unavailable for some or all of the locations in the treatment and/or comparison group, especially for the before period and the local streets in urban area (states usually keep records of AADT data for the arterial and principal highways). With the improvements to the conditions of walking and bicycling and access to the public transit, more people will be attracted to traveling by non-motorized modes. For example, bicycle volumes have been found to increase after the installation of bike lanes (Nelson 1997, Dill 2003, Pucher and Buehler 2005, Barnes *et al.* 2006a, Parkin *et al.* 2008). The increase in the bicyclists and/or pedestrians may contribute to the crash changes from the before-period to the after period. However, the volume data of bicyclists and pedestrians are very limited and thus their effects are usually unable to be explored.

Based on travel demand forecasting theory, the traffic count in the highway network is the results of travel demand and supply, which depends on the land use, socio-economics, and roadway infrastructure fundamentally. Traffic count data, exposure in other words, are actually one of the mediator factors (Ewing and Dumbaugh 2009). In current research the built environment factors are incorporated into the regression models and significant effects have been found on crashes. However, the question—whether the models with the more fundamental explanatory variables (such as the built environment factors) produce similar or even better prediction of crash than those with only traffic volume data—cannot be answered due to the limitation on the volume data. When more volume data are available, the two types of models can be compared to find out the best solutions.

One assumption in most of the existing studies using a comparison group is that the safety in the comparison group (untreated locations) is unaffected by treatment. This may not always be the case, however. There may be spillover effects, that is, those effects on crash numbers at untreated locations that are close to a location where a measure has been implemented. An example is the Red Light Camera (RLC). The installation of RLC will not only affect crashes at intersection with RLC installed, but also at nearby locations without RLC (Council *et al.* 2005). It is also possible that not only the nearby locations, but also some locations far from the treated locations may be affected by the treatment. For example, a treatment may lead to residents and/or retails relocation and thus the exposure in the treated location and the untreated locations where the residents/retails move to will also be changed. This spillover effect could be explored in future to improve the estimation of the safety impacts of the measures.

The current research is limited to the evaluation of the effectiveness of a single treatment and the effects of multiple treatments, that is, two or more treatments installed at the same locations, has not been explored due to the small sample size of the multiple-treatment locations. In New York City, some locations (street segments or intersections) have multiple treatments installed. It will be very useful to find out if the combination of two or more different treatments will produce safety benefits even greater than the sum of the effect from every single treatment, or the addition of a treatment will have negative impact on the other treatment. This knowledge will help traffic safety professionals select the appropriate treatment(s) and avoid installing treatments that will compromise the safety benefit of others.

APPENDICES

Appendix A: List of Safety Countermeasures in New York City

Code	Description
1	*Signal Changes*
1.1	**Changes in signal timing/phase**
1.1.01	Addition of a left-turn phase, including dual left turn phase
1.1.02	Leading Pedestrian Interval (LPI)
1.1.03	Changes in total cycle length
1.1.03a	Increase total cycle length
1.1.03b	Decrease total cycle length
1.1.04	Reallocation of a green time phase
1.1.05	Additional green time for an approach (or some approaches)
1.1.06	Service roads stopping before the main roads (e.g.,15 sec.)
1.1.07	Addition of a clearance interval
1.1.08	Extension of all-red clearance
1.1.09	Change of left-turn phase from leading to lagging
1.1.10	Pedestrian crossing signals re-timed (increase time for pedestrian crossing)
1.1.11	Signal re-timing for off-peak / weekend hours
1.1.12	Signal timing adjustment for coordination
1.1.13	Signal timing adjustment for new street geometry/alignment
1.2	**Changes in control**
1.2.01	Change from non-signalized to signalized
1.2.02	Installations of pedestrian signal
1.2.03	Change from no-control to stop control
1.3	**Physical changes of signal**
1.3.01	Removal/modification of signal face
1.3.02	Removal of right arrow signal
1.3.03	Reposition/moving of signal
1.3.04	Installations of 12-inch red lenses on signals / larger red signal display
1.3.05	Louvered signals
1.3.06	Modernized signals from red green indicators to red, amber and green displays
1.4	**Red light camera**
1.5	**Signal Installations**
1.6	**Barnes Dance**
1.7	**Spilt Phase Timing**
2	*Geometric Treatment*
2.1	**Roadway & Lanes**
2.1.01	Mixed Roadway
2.1.02	Bike Lanes & Paths
2.1.02a	On-roadway Bike Lane
2.1.02b	Separated Bike Path (off-road)
2.1.03	Bus Lanes & Busways & Bus Stops

2.1.03a	On-roadway Bus Lane
2.1.03b	Separated Busways
2.1.03c	Bus Stops
2.1.03ca	Addition of bus stop
2.1.03cb	Extension of bus stop
2.1.03cc	Relocation of bus stop (from near side to far side)
2.1.03cd	Elimination of bus stop
2.1.04	Shared Street
2.1.05	Turning Lane / Bay
2.1.05a	Left-turn lanes
2.1.05aa	Addition of left turn lanes
2.1.05ab	Removal of left turn lanes
2.1.05ac	Lengthening left turn lanes
2.1.05ad	Center two-way left turn lanes
2.1.05ae	Dual left turn lane change to single left turn lane
2.1.05b	Left-turn bay
2.1.05ba	Addition of left turn bay
2.1.05bb	Removal of left turn bay
2.1.05bc	Lengthening left turn bay
2.1.05c	Right-turn bay
2.1.06	Conversion in One-way or Two-way Operation
2.1.06a	Conversion from two-way to one-way operation
2.1.06b	Conversion from one-way to two-way operation
2.1.07	Change in Number of Lanes
2.1.07a	Lane Reduction
2.1.07b	Lane Increase
2.1.07c	Road Diet
2.1.08	Slip Roadway / Ramps
2.1.08a	Installations of slip roadway
2.1.08b	Close slip roadway
2.1.08c	Redesign slip roadway
2.1.08d	Relocate slip roadway
2.1.09	Stop Bar / Line
2.1.09a	Installations of stop bar / stop line / stop message
2.1.09b	Relocation of stop bar and signal (supposedly only back)
2.1.09c	Removal of stop bar
2.1.10	Lane Line / Signs / Markings
2.1.10a	Lane assignment signs
2.1.10b	Edge line
2.1.10c	Installations of lane line (to define moving lane)
2.1.10d	Wide turn zones (WTZs) markings
2.1.11	Peg-A-Tracs
2.1.12	Rumble Strip
2.2	**Sidewalk & Medians**

2.2.01	Sidewalk
2.2.01a	Full sidewalk
2.2.01b	Ribbon sidewalk
2.2.01c	Widened sidewalk (with markings/delineator)
2.2.02	Curb Extension
2.2.02a	Bus bulb
2.2.02b	Neckdown (at corner)
2.2.02c	Neckdown (mid-block)
2.2.03	Median
2.2.03a	Installations of median
2.2.03aa	Full median
2.2.03ab	Raised center median
2.2.03ac	Painted median
2.2.03ad	Flexible bollard in centerline
2.2.03b	Installations of Median Refuge Island
2.2.03c	Median widening
2.2.03d	Median closure
2.2.03e	Median extension
2.2.03f	Installations of end cap barrier on center medians
2.3	**Traffic Calming**
2.3.01	Speed Reducer
2.3.01a	Raised speed reducer (speed hump)
2.3.01b	Speed Cushion
2.3.01c	Speed Board
2.3.02	Gateway
2.3.03	Traffic Diverter
2.3.03a	Median Barrier
2.3.03b	Forced Turn
2.3.03c	Diagonal Diverter
2.3.03d	Half Closure
2.3.03e	Full Closure
2.3.04	Chicane
2.3.05	Neighborhood Traffic Circle
2.3.06	Roundabout
2.3.07	Raised Crossing
2.3.08	Raised Intersection
2.3.09	Pedestrian-priority zone/street
2.3.10	Pedestrian-only zone
2.3.11	Channelization
2.3.12	Sharp turn / Normalization of intersection
2.3.13	Posted speed limit reduction
2.4	**Planting**
3	***Turn Restriction***
3.1	No Left Turn

3.2	No Right Turn
3.3	No U Turn
4	***Parking Related***
4.1	Decrease Parking
4.1.01	From parking to restricted parking
4.1.02	From parking/restricted parking to no parking/no standing
4.2	Increase Parking
4.2.01	From restricted parking to parking
4.2.02	From no parking/no standing to parking/restricted parking
4.2.03	Conversion of excess roadway to parking
4.3	Daylighting
4.4	Replacement of parking with truck loading/unloading zone
4.5	Angle Parking
5	***Pedestrian Related***
5.1	Crosswalk
5.1.01	Installations of crosswalk
5.1.02	Crosswalk widening
5.1.03	Crosswalk markings with high visibility
5.1.04	Mid-block crosswalk
5.2	Pedestrian Barrier
5.3	Pedestrian Bridge
5.3.01	Pedestrian bridge installations
5.3.02	Staggered fencing design
5.4	Pedestrian Crossing Warning Signs
5.4.01	Advanced pedestrian crossing warning signs
5.4.02	Reposition of pedestrian crossing signs
5.4.03	“Yield to Pedestrian” signs
5.4.04	“Wait for Walk Signal” pavement message
6	***Oversized Signs***
6.1	Oversized street name signs
6.2	Center illuminated signs
6.3	Oversized turn prohibition signs
6.4	Oversized one-way arrow

Appendix B: Frequency Matching Procedure

The procedure used to match between the treatment group and the comparison group is frequency matching. The matching procedure is described below.

Step 1: Treatment data preparation

For a treatment of interest, determine the matching variables, denoted as: $X_1, X_2, \cdots, X_n$; Study the basic descriptive statistics about the distribution of the matching variables. Divide the treatment group into subgroups by the year of installations. For each subgroup, identify the joint distribution of the matching variables. The matching variables can be categorical variables (e.g., control type), dummy variables (e.g., truck route, bus route, separate or not, one-way or not, or ordered categorical data (e.g., number of lanes = 1, 2, 3, 4, 5,…). In other words, it is possible to obtain a complete enumeration of all possible combinations of the matching variables. Denote Z_m=($X_1 = a_m, X_2 = b_m, \cdots, X_n = c_m$). The frequency of Z_m can be calculated as: $f(Z_m)=N_{m(year)}$, where $N_{m(year)}$ is the frequency of combination Z_m for a subgroup of a particular year. For example, if the treatment was installed for a consecutive five years from 1995-1999, the frequencies for each year, that is, $N_{m(1995)}$, $N_{m(1996)}$, …, and $N_{m(1999)}$ need to be found.

Step 2: Frequency matching

Prepare a database containing all untreated locations, or locations that do not have any kind of treatment for a particular year of interest. Within this database, find the frequency of Z_m: $f(Z_m)=M_m$, where M_m is the frequency of combination Z_m in the comparison group. For each combination Z_m, calculate the ratio: $r_{m(year)}=M_m/N_{m(year)}$. Find the minimum ratio:

$MinR_{(year)}=Min(M_1/N_{1(year)}, M_2/N_{2(year)}, \ldots, M_m/N_{m(year)})$. Then, calculate the needed number of locations for each attribute combination Z_m by multiplying $MinR_{(year)}$ with $N_{m(year)}$: $W_{m(year)}=MinR_{(year)} \times N_{m(year)}$, where $W_{m(year)}$ is the required number of locations with characteristic Z_m from the comparison group for a treatment of a particular installations year.

Step 3: Adjustment for all treatment years

Sum the required number of locations with characteristic Z_m for all the treatment years: $W_m = \Sigma_{year} W_{m(year)}$. Compare W_m with M_m. If $W_m > M_m$, that means the total required number of locations with characteristic Z_m exceeds the available number of locations in the database of untreated locations. Adjustment is needed so that the required number of locations in the comparison group will be no more than the available number of locations. Let $MinR_{adj}=Min(M_1/W_1, M_2/W_2, \ldots, M_m/W_m)$, then the adjusted $W_{madj(year)}=MinR_{adj} * MinR_{(year)} * N_{m(year)}$ and the adjusted total required number of locations with characteristic Z_m for all the treatment years is $W_{madj} = \Sigma_{year} W_{madj(year)}$.

Step 4: Random selection

A sample of size $W_{madj(year)}$ is then randomly selected from the database of untreated locations with characteristics Z_m. The number of sample locations for each treatment year is the sum of different characteristics Z_m ($m = 1, 2, \ldots$) for that specific year: $W_{(year)}=\Sigma_m W_{madj(year)}$. After the random selection, the total number of locations in the comparison group is: $W = \Sigma_{year} W_{(year)}$.

Appendix C: Method of Calculating CMF

The method described here involves calculating the expected crashes for the treatment group if no treatment were implemented and the associated standard error, and concluding on the effectiveness of the treatment (Hauer 1997).

Step 1:

Calculate the expected crashes for all locations in the treatment group in the post-treatment period if there were no treatment via the following formula:

$$E[x_{t1}] = x_{t0}\hat{r}_t\,,\ \hat{r}_t = \frac{x_{c1}/x_{c0}}{1 + 1/x_{c0}}$$

Where: x_{c1} is the total number of crashes post-treatment for all locations in the comparison group, and x_{c0} is the total number of crashes pre-treatment for all locations in the comparison group. $\hat{r}_t$ is the expected crash ratio of crashes in the post-treatment period to those in the pre-treatment period. The ratio x_{c1}/x_{c0} is adjusted by dividing by ($1+1/x_{c0}$) in order to get an unbiased estimation of change in the number of crashes in the comparison group. This calculation assumes that the change in the number of crashes in the treatment group follows the same trend as that in the comparison group.

The estimated variance of crashes for all locations in the treatment group in the post-treatment period if there were no treatment is calculated via the following formula (Hauer 1997):

$$\mathrm{var}(x_{t1}) \cong E[x_{t1}]^2 \left(1 + 1/x_{t0} + 1/x_{c0} + 1/x_{c1} + \mathrm{var}(\varpi)\right)$$

Where: $\mathrm{var}(\varpi)$ is the variance of the odds ratios of different years prior to the treatment. An odds ratio is a measure to examine if the change in crashes in the comparison group and those in the treatment group are similar. It is defined as follows: $\varpi = r_c / r_t$, where r_c is the change in crashes in the comparison group and r_t is the change in crashes in the treatment group. We can calculate an odds ratio for each available year prior to the treatment. If the mean of the odds ratio over different pre-treatment years is close to 1, it means that pre-treatment crashes between the treatment group and the comparison group are similar; that is, the trends exhibited in the pre-treatment period are similar between the comparison group and the treatment group.

<u>Step 2</u>:

Then calculate the expected Crash Modification Factor (*CMF*), which is equal to:

$$E[CMF] = \frac{x_{t1} / E[x_{t1}]}{\left(1 + 1/x_{t0} + 1/x_{c0} + 1/x_{c1} + \mathrm{var}(\omega)\right)},$$

Where: the ratio $x_{t1}/E[x_{t1}]$ is adjusted by $\left(1 + 1/x_{t0} + 1/x_{c0} + 1/x_{c1} + \mathrm{var}(\omega)\right)$ so that the estimated CMF is unbiased. The variance and standard error of CMF is calculated via the following equation (Hauer 1997):

$$Var(CMF) \cong E[CMF]^2 \frac{\left(1 + 1/x_{t1} + 1/x_{t0} + 1/x_{c0} + 1/x_{c1} + \mathrm{var}(\varpi)\right)}{\left[1 + \left(1 + 1/x_{t0} + 1/x_{c0} + 1/x_{c1} + \mathrm{var}(\omega)\right)\right]^2}$$

$$SE[CMF] = \sqrt{Var(CMF)}$$

Step 3:

The 90% and 95% confidence intervals for CMF are then calculated:

95% confidence interval: (E[CMF]-1.96*SE[CMF], E[CMF]+1.96*SE[CMF])

90% confidence interval: (E[CMF]-1.64*SE[CMF], E[CMF]+1.64*SE[CMF])

The point estimate of the expected CMF is the midpoint of the interval. As mentioned earlier, a CMF of less than 1 suggests a reduction in crashes while a CMF of more than 1 indicates an increase.

Step 4:

If the confidence interval falls entirely in the [0,1] domain, then the conclusion is that the effect of the treatment is statistically significant. When the 95% confidence interval (between the low point and the high point) crosses threshold 1, it means that the effect is insignificant at the 5% level.

A critical assumption with this method is that the comparison group shares similar traits on all factors that potentially play a role in affecting the effectiveness of the treatment, and equally important, that the comparison group should have a sufficient sample size. It is possible that these two criteria work against each other—placing more matching variables in the selection of the comparison group will result in smaller comparison groups, while enlarging the comparison group often makes the comparison group less similar to the treatment group. In some cases, judgmental decisions must be made to balance the two criteria.

Appendix D: Generalized Estimating Equations Method

The generalized estimating equations (GEE), introduced by Zeger and Liang (1986), is a method of analyzing correlated data that otherwise could be modeled as a generalized linear models (GLMs). This method is used to account for the correlation among the repeated observations from the same subject (roadway segment or intersection in this study) during different time period (e.g., 5-year before period or 2-year after period).

Consider the observations $(y_{ij}, \mathbf{x}_{ij})$, where y_{ij} is the crash count for location *i* (*i* = 1, 2, ..., K) during the time period *j* (*j* = 1, 2, ..., n_i) and $\mathbf{x}_{ij}$ is a $P \times 1$ vector of explanatory variables ($\mathbf{x}_{ij} = (x_{ij1,\ldots,} x_{ijP})'$). Let $\mathbf{y}_i$ be the $n_i \times 1$ vector $(y_{i1,\ldots,} y_{in_i})'$ and $\mathbf{x}_i$ be the $n_i \times P$ matrix $(\mathbf{x}_{i1,\ldots,} \mathbf{x}_{in_i})'$ for the i^{th} location.

The GEE for estimating regression parameter β is an extension of the GLMs to the correlated data and the estimator of β is the solution of the equation system:

$$S(\beta) = \sum_{i=1}^{K} \frac{\partial \boldsymbol{\mu}'_i}{\partial \beta} \mathbf{V}_i^{-1} (\mathbf{y}_i - \boldsymbol{\mu}_i(\beta)) = 0$$

Here $\boldsymbol{\mu}_i = (\mu_{i1,\ldots,} \mu_{in_i})'$ is the corresponding mean of the vector of responses $\mathbf{y}_i$ and $\mathbf{V}_i$ is the $n_i \times n_i$ covariance matrix for $\mathbf{y}_i$ (crash counts for location *i* during different period of time):

$$
\mathbf{V}_i = \begin{bmatrix} \sigma^2_{y/t} & a_{12} & \cdots & a_{1n_i} \\ a_{21} & \sigma^2_{y/t} & & a_{2n_i} \\ \vdots & & \ddots & \vdots \\ a_{n_i 1} & a_{n_i 2} & \cdots & \sigma^2_{y/t} \end{bmatrix},
$$

Because $g(\mu_{ji}) = \mathbf{x}'_{ij}\beta$, where the function g is referred to as the “link” function (McCullagh 1983), the partial derivatives of the mean with respect to the regression parameter for the i^{th} location is given by:

$$
\frac{\partial \boldsymbol{\mu}'_i}{\partial \beta} = \begin{bmatrix} \dfrac{x_{i11}}{g'(\mu_{i1})} & \cdots & \dfrac{x_{in_i 1}}{g'(\mu_{in_i})} \\ \vdots & & \vdots \\ \dfrac{x_{i1P}}{g'(\mu_{i1})} & \cdots & \dfrac{x_{in_i P}}{g'(\mu_{in_i})} \end{bmatrix}
$$

The covariance matrix of $\mathbf{y}_i$ is specified as $\mathbf{V}_i = \mathbf{A}_i^{1/2}\mathbf{R}_i(\alpha)\mathbf{A}_i^{1/2}/\phi$, where $\mathbf{A}_i$ is a $n_i \times n_i$ diagonal matrix with $g(\mu_{ji})$ as the j^{th} diagonal element, $\mathbf{R}_i(\alpha)$ is a working correlation matrix, and ϕ is a scale parameter. In GEE, the correction for within subject correlations (pair-wise correlations between time points) is carried out by assuming *a priori* a correlation structure for the repeated measurements. There are several choices for the working correlation matrix $\mathbf{R}_i$ and usually the simplest structure (uses up the fewest degrees of freedom) that fits data well is selected.

- Independent (naïve analysis)

  Assume the repeated observations are uncorrelated.

$$[\mathbf{R}_i(\alpha)]_{jk} = Corr(y_{ij}, y_{ik}) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

- Exchangeable

  Also known as compound symmetry, costs 1degree of freedom to estimate α.

$$[\mathbf{R}_i(\alpha)]_{jk} = Corr(y_{ij}, y_{ik}) = \begin{bmatrix} 1 & \alpha & \alpha & \alpha \\ \alpha & 1 & \alpha & \alpha \\ \alpha & \alpha & 1 & \alpha \\ \alpha & \alpha & \alpha & 1 \end{bmatrix}$$

- Autoregressive

  Only 1 parameter estimated, and decreasing correlation for farther time periods.

$$[\mathbf{R}_i(\alpha)]_{jk} = Corr(y_{ij}, y_{ik}) = \begin{bmatrix} 1 & \alpha & \alpha^2 & \alpha^3 \\ \alpha & 1 & \alpha & \alpha^2 \\ \alpha^2 & \alpha & 1 & \alpha \\ \alpha^3 & \alpha^2 & \alpha & 1 \end{bmatrix}$$

- M-dependent

  For example, 2-dependent (adjacent time periods have 1 correlation coefficient; time periods 2 units of time away have a different correlation coefficient; others are uncorrelated), which needs to estimate 2 parameters.

$$[\mathbf{R}_i(\alpha)]_{jk} = Corr(y_{ij}, y_{ik}) = \begin{bmatrix} 1 & \alpha_1 & \alpha_2 & 0 \\ \alpha_1 & 1 & \alpha_1 & \alpha_2 \\ \alpha_2 & \alpha_1 & 1 & \alpha_1 \\ 0 & \alpha_2 & \alpha_1 & 1 \end{bmatrix}$$

- Unstructured

  This correlation structure assumes different correlation between any two observations taken at the same subject. The correlations need to be estimated separately (here 6).

$$[\mathbf{R}_i(\alpha)]_{jk} = Corr(y_{ij}, y_{ik}) = \begin{bmatrix} 1 & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & 1 & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & 1 & \alpha_{34} \\ \alpha_{42} & \alpha_{42} & \alpha_{43} & 1 \end{bmatrix}$$

SAS/STAT® software's GENMOD procedure can be used to perform GEE analysis by specifying a REPEATED statement. Many correlation structures are available, including independent, exchangeable, autoregressive(1), m-dependent, and unstructured. The generalized linear model estimates (assuming the observations within subjects are independent) are used as the starting values. Then, residuals are calculated from the naive model (observed-predicted) and a working correlation matrix is estimated from these residuals. Then the regression coefficients are refit, correcting for the correlation (iterative process). Both model-based and empirical standard errors of the parameter estimates are produced. Follow is the sample code of the GENMOD procedure in SAS.

```
proc genmod data = datafilename;
class  id;
model y = x1 x2 x3;
repeated subject = id / type=exch;
run; quit;
```

Appendix E: List of Files received from NYCDOT on Safety Countermeasures

Name	File Name	Format	Received Date	Geocoding Output	Notes
Safe Streets NYC: Traffic Safety Improvements in NYC	Safe Street 2008.pdf (report)	Paper	12/2008	Imp_nodes_AJ.shp Imp_segs_AJ.shp	
Speed Reducer	speedreducers.zip SH~Installation~2-april 2006.xls	Shapefile Excel	12/2008		By NYCDOT
Bike Routes	Bike_routes_off_street.zip Bike_routes_on_street.zip upgraded bike facility list.xls	Shapefile Shape file Excel	12/2008 12/2008 12/2010		By NYCDOT
Bus Lanes	Bus_Lanes_New_namejoin.zip Bus_Lanes_New_Dissolve.zip Bus_Lanes_New_only.shp Bus_Lanes.xls	Shapefile Shapefile Shapefile Excel	12/2008 12/2008 12/2009 12/2009		By NYCDOT
Treatment X	Treatment X - to CCNY.xls	Excel	09/2009	tx_nodes_AJ.shp	
Signal Installation	Signalinstallation(FY05-FY09).xls (*5 files*)	Excel	12/2009	SIGNAL_(05-09).shp (*5 shape files*)	
Barnes Dance	Barnes Dance Locations.xls	Excel	12/2009	SIGNAL_BDL2.shp	
Road Diet	RoadDietsOneWays.zip	Shapefile	01/2010		By NYCDOT
One-way Conversion	RoadDietsOneWays.zip	Shapefile	01/2010		By NYCDOT
Split Phase	Split phase locations.xls	Excel	05/2010	split_phase.shp	
Crash	NYSDMV_Crash_db_1989_2007.mdb Region11_2008.accdb	Access Database	12/2008 05/2009		By X,Y Coordinate

Appendix F: Data Fields in the Coding of Safety Countermeasures

Data Field	Description
Borough ID	The ID of the borough where the treatment is implemented (1 – Manhattan, 2 – Bronx, 3 – Brooklyn, 4 – Queens, 5 – Staten Island, 6 – Citywide)
Project ID	The ID (numerical) of the project (There are multiple projects for each borough, the ID is 1, 2, 3, … for projects in each borough)
Project Name	The name of the project in the safe streets report
ImpID	The ID (numerical) of the improvement (There are multiple improvements for each project, the ID is 1, 2, 3, … for improvements for each project)
ImpCode	The code for the improvement (as in Table 2 and the appendix table)
ImpDesc	Description of the improvement
ProjectMon	The month the improvement is implemented
ProjectYear	The year the improvement is implemented
If_Intersection	If the improvement is at intersection or not (1 if at an intersection, 0 if on a segment)
MainSt	The name of the main street where the improvement is implemented
Street/Intersection Info	Some additional information on the street or intersection (For example, improvement is on the service road of the street, then put "service road" in this field)
CrossSt	The name of the cross street (if the improvement is at an intersection)
FromSt	The name of the street where the segment starts (if the improvement is on a segment)
ToSt	The name of the street where the segment ends (if the improvement is on a segment)
Direction	Indicating at which direction of the street the improvement is implemented

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