ABSTRACT

Title of Dissertation: THREE ESSAYS ON URBAN TRANSPORTATION STUDIES IN WASHINGTON D.C.: SAFETY EFFECT OF ALL-WAY STOP CONTROL, SAFETY EFFECT OF REVERSIBLE LANE AND LOADING ZONE ALLOCATION

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Systematic data-driven and evidence-based urban transportation policy making and evaluation become increasingly important for public agencies to ensure transparent and efficient services. This dissertation, consisting of three essays on urban transportation studies, focuses on two issues (safety and asset management) that are broadly related with urban transportation policy making and evaluation in Washington D.C.

In Chapter One, I evaluate the safety effect of All Way Stop Control (AWSC) conversion with an observational treatment group and a randomly selected control group from stratified samples. Selection bias and time trend are controlled using empirical strategies such as Multiway ANOVA and Difference-in-Differences

analysis. The study reveals statistically significant reductions of right angle crashes upon AWSC conversions. However, for all the other collision types, including right turn, left turn, rear end, sideswipes and bicycle crashes, none of the estimated coefficients were statistically significant. In addition, the study quantified a statistically significant increase of straight hit pedestrian crashes upon AWSC conversion.

In Chapter Two, I study the safety effect of removing reversible lane operations along urban arterials. Taking advantage of the termination of three reversible lane arterials in 2010, the evaluation is performed using the Before-After (BA) study with a control group and the Empirical Bayes (EB) method, respectively. I estimate Crash Modification Factors (CMF) for all crashes, fatal/injury crashes, property damage only (PDO) crashes, rear-end crashes, left turn crashes and sideswipe crashes. My findings suggest a clear tradeoff between safety and the gain of peak direction capacity by operating reversible lanes along urban arterials.

In Chapter Three, I propose an innovative procedure for allocating scarce curbside space for loading zones in an equitable, quantifiable and repeatable manner. Freight Trip Generation (FTG) models are used to estimate the delivery needs for business establishments at a block face level. The current numbers of loading zones per block face are regressed against the Gross FTG (GFTG) per block face and other block face characteristic variables using zero-truncated Negative Binomial models to establish a baseline. Curbside spaces are then assigned as loading zones in an iterative process.

THREE ESSAYS ON URBAN TRANSPORTATION STUDIES IN WASHINGTON D.C.: SAFETY EFFECT OF ALL-WAY STOP CONTROL, SAFETY EFFECT OF REVERSIBLE LANE AND LOADING ZONE ALLOCATION

by

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Preface

Data are essential to planning, delivery and management of transport services and infrastructure. Data analysis is necessary to operate traffic safely, to respond to incidents quickly and to understand crash patterns and trends clearly. In my dissertation, I write three essays that study urban transportation issues in Washington D.C. Each of the issues and resolution approaches are distinct, making each chapter fairly independent of each other. However, these essays are united by the goal of systematic data-driven and evidence-based urban transportation policy making and policy effect evaluation. They also link with each other as real world applications of various empirical strategies for coping with challenges that the District government faces.

Federal legislation has required safety as a critical planning factor in statewide and metropolitan transportation planning processes since the Transportation Equity Act for the 21st Century (TEA-21) (Public Law 105-178) and subsequent legislations, including the Moving Ahead for Progress in the 21st Century Act (MAP-21) (Public Law 112-141) in 2012, and most recently, the Fixing America's Surface Transportation (FAST) Act (Public Law 114-94) in 2015. State departments of transportation (DOTs) and metropolitan planning organizations (MPOs) are required to consider and implement projects, strategies, and services that increase the safety of the transportation system for motorized and non-motorized users (Cambridge Systematics Inc., 2015). Motivated by these federal legislations, my first two essays

are dedicated to the enhance understanding of safety effect of different transportation planning/traffic management tactics.

In the first chapter, I evaluate the safety effect of TWSC to AWSC conversion at roadway intersections using D.C data. AWSC conversion is probably one of the most popular community requests to the District government for safety improvement at un-signalized intersections. People tend to deem AWSC conversion as a low cost solution to reduce intersection related crashes and to reduce travel speed as well as through traffic volumes. Previous studies that analyzed AWSC conversion drew somewhat conflicting conclusions and may be flawed in study design or in lack of statistical significance. I contribute to the literature by analyzing the safety effect of AWSC conversion with staggered crash records spanning ten years (2007 to 2017) at 144 intersections in DC. The study design follows a typical quasi-experimental framework with an observational treatment group and a randomly selected double-sized control group from stratified samples. Selection bias and time trend are well controlled using empirical strategies such as Multiway ANOVA and Difference-in-Differences analysis. The study reveals statistically significant reductions of right angle crashes upon AWSC conversions. However, for all the other collision types, including Right Turn, Left Turn, Rear End, Sideswipes and Bicycle crashes, no statistically significant coefficients are estimated. Aggregately, the AWSC conversion treatment effect to all crashes, fatal/injury crashes and all pedestrian related crashes are not statistically significant, either. Nevertheless, the study quantified a statistically significant increase of Straight Hit Pedestrian crashes upon AWSC conversion.

Additional safety countermeasures rather than merely modifying traffic control signs at intersections need to be considered when implementing AWSC conversions in order to minimize its negative safety effects. The study results are helpful to decision makers in making more informative choices backed by empirical evidences.

In the second chapter, I study the safety effect of removing reversible lane operations along urban arterials using data from Washington, D.C. between 2003 and 2017. Despite the long history and wide geographic spread of reversible lane systems, there have been limited quantitative studies on their safety impact. I contribute to the literature by taking advantage of the termination of three reversible lane urban arterials in D.C. to perform a safety evaluation using the Before-After (BA) study with a control group and the Empirical Bayes (EB) method, respectively. I estimate Crash Modification Factors (CMF) for all crashes, fatal/injury crashes, property damage only (PDO) crashes, Rear End crashes, Left Turn crashes and Sideswipe crashes. My findings suggest a clear safety tradeoff between safety and the gain of peak direction capacity by operating reversible lanes along urban arterials. Generally, all crashes, including both fatal/injury and PDO crashes, are more substantial on reversible roadways. Specifically, left turn crashes caused by lane use confusion and Sideswipe crashes related to lane changing maneuvers appear to be associated with reversible lane operations on urban arterials. The study results provide critical quantitative benefit and cost information for long-term corridor planning project that considers reversible lane system as an operational strategy.

Nevertheless, data-driven analysis is not only applicable in policy effect evaluation, but also instrumental in rule making. In the third chapter, I propose an innovative procedure to allocate scarce curbside spaces for loading zones in an equitable, quantifiable and repeatable manner. Many cities in the U.S., including Washington D.C., allocate curb spaces for commercial loading zones largely at discretion of the agency in charge and are typically initiated by requests from business owners and property managers. I present a demand driven Loading Zone Allocation Model created for the District Department of Transportation (DDOT) to facilitate a proactive decision making process for curbside loading zone space allocation. Freight Trip Generation (FTG) models are used to estimate the delivery needs for business establishments at a block face level. The current numbers of loading zones per block face are regressed against the Gross FTG (GFTG) per block face and other block face characteristic variables using zero-truncated Negative Binomial models to establish the baseline. GFTG is found to be the most significant predictor of the number of loading zones in the District. Curbside spaces are then assigned as loading zones using the selected model based on Akaike's Information Criterion (AIC) in an iterative process. The modeling result shows that the existing curbside allocation regulations are correlated with projected curbside Pickup and Delivery (PUD) activity intensities. Equipped with the model, the agency could take a proactive approach to review existing curbside loading zone regulations and thus address public space allocation issue in a quantifiable and equitable way. I hope this model could potentially inspire other public agencies that are interested in establishing an

equitable, consistent, and repeatable process to evaluate curbside loading zone needs and to manage curbside spaces.

The three related essays in this dissertation contribute to the understanding of emerging urban transportation issues and to developing innovative approach to tackle the challenges that public agencies confront with on a day-to-day basis. Hopefully, the findings and thoughts in this dissertation could shed a little light upon systematic data-driven urban transportation policy making and policy effect evaluations.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AIC	Akaike's Information Criterion
ANC	Advisory Neighborhood Commission
ANOVA	Analysis of Variance
AWSC	All Way Stop Control
B-A	Before-After
CI	Confidence Interval
CMF	Crash Modification Factors
D.C.	District of Columbia
DDOT	District Department of Transportation
DID	Difference-in-Differences
EB	Empirical Bayes
FHWA	Federal Highway Administration
FG	Freight Generation
FTG	Freight Trip Generation
GIS	Geospatial Information System
HSM	Highway Safety Manual
ITE	Institute of Transportation Engineers
LZAM	Loading Zone Allocation Model
MPD	Metropolitan Police Department
MSC	Minor-road-only Stop Control
MUTCD	Manual on Uniform Traffic Control Devices
MVE	Million Vehicles Entering
MWCOG	Metropolitan Washington Council of Governments
NB	Negative Binomial
NCUTCD	National Committee on Uniform Traffic Control Devices
NOI	Notice of Intent
NPS	National Park Services
PDO	Property Damage Only
PUD	Pickup and Delivery
S.D.	Standard Deviation
S.E.	Standard Errors
SIC	Standard Industrial Classification
SPF	Safety Performance Function
STATA	Software for Statistics and Data Science
TARAS	Traffic Accident Reporting and Analysis System
TPB	Transportation Planning Board
TWSC	Two-Way Stop Control
U.S.	United States

Chapter 1: Evaluating the Safety Effect of AWSC Conversion in Washington D.C.

1.1 Introduction

Stop signs are often used in the U.S. to control conflicting traffic movements at intersections that are not busy enough to justify the installation of traffic signals. Stops signs may be installed to control only the minor road or to control all intersecting roads. Currently, out of the 4,685 stop sign controlled intersections in DC, 3,212 are Minor-road-only Stop Controlled (MSC) and 1,473 are All-Way Stop Controlled (AWSC). From here on, to simplify notation and to be consistent with a wider spectrum of literature, Two-Way Stop Control (TWSC) is used interchangeably with MSC.

Converting TWSC intersections into AWSC intersections is one of the most popular requests from local community representatives to the District Department of Transportation (DDOT) as a countermeasure for safety concerns or for traffic calming purposes. AWSC conversion is generally considered as a low cost safety improvement that would reduce crash occurrence at intersections and reduce traveling speed along roadways. Although in residential settings with large numbers of children, speed management appears to offer the greatest potential for injury prevention (Retting et al., 2003a), studies show that stop signs could only influence motorists to slow down approximately 150 feet before and after the stop sign and the mid-block speeds may actually increase as drivers attempt to make up for lost time (Swanson et al., 1998). In fact, FHWA explicitly stated that "*STOP signs should not be used for speed control*" (FHWA, 2009). Therefore AWSC conversion does not seem to be an effective countermeasure to address speeding concerns. Numerous studies show AWSC conversion may reduce the number of

crashes but at the cost of extra roadway user controlled delays (Marek et al., 1997), (Briglia, 1982), (Byrd and Stafford, 1984), (John Lovell and Ezra Hauer, 1986), (Ronald Eck and James Biega, 1988). AWSC may reduce the number of right-angle and left turn with opposing through collisions, however, there is a potential increase in the number of Rear End and Fixed Object collisions (John Lovell and Ezra Hauer, 1986), (Retting et al., 2003b). Nevertheless, safety may be compromised as drivers disregard the all-way stop sign and pedestrians are lured into a false sense of security by the presence of a stop sign because they assume that drivers will stop (Swanson et al., 1998). Moreover, there are concerns of increased exposure time of the pedestrian to vehicles and reduced or eliminated natural gaps in traffic at intersections as a result of increased control delays at AWSC intersections (Noyes, 1994). This general lack of consensus across studies is due to many factors, some related with less robust study design and some related with less significant empirical evidences.

In practice, DDOT evaluates this type of request primarily based on a nationally accepted guideline, the Manual on Uniform Traffic Control Devices (MUTCD). The MUTCD warrants the following (FHWA, 2009):

A. *Where traffic control signals are justified, the multi-way stop is an interim measure that can be installed quickly to control traffic while arrangements are being made for the installation of the traffic control signal.*
B. *Five or more reported crashes in a 12-month period that are susceptible to correction by a multi-way stop installation. Such crashes include* ***right-turn*** *and* ***left-turn*** *collisions as well as* ***right-angle*** *collisions.*
C. *Minimum volumes:*

1. *The vehicular volume entering the intersection from the major street approaches (total of both approaches) averages at least 300 vehicles per hour for any 8 hours of an average day; and*
2. *The combined vehicular, pedestrian, and bicycle volume entering the intersection from the minor street approaches (total of both approaches) averages at least 200 units per hour for the same 8 hours, with an average delay to minor-street vehicular traffic of at least 30 seconds per vehicle during the highest hour; but*
3. *If the 85th-percentile approach speed of the major-street traffic exceeds 40 mph, the minimum vehicular volume warrants are 70 percent of the values provided in Items 1 and 2.*

D. Where no single criterion is satisfied, but where Criteria B, C.1, and C.2 are all satisfied to 80 percent of the minimum values, Criterion C.3 is excluded from this condition.

Option:

05 Other criteria that may be considered in an engineering study include:

A. The need to control left-turn conflicts;

B. The need to control vehicle/pedestrian conflicts near locations that generate high pedestrian volumes;

C. Locations where a road user, after stopping, cannot see conflicting traffic and is not able to negotiate the intersection unless conflicting cross traffic is also required to stop; and

D. An intersection of two residential neighborhood collector (through) streets of similar design and operating characteristics where multi-way stop control would improve traffic operational characteristics of the intersection.

For those familiar with the MUTCD, it is obvious that the above rules generally resemble the signal warrant analysis in MUTCD at large. Like Celniker argued that the MUTCD policy regarding stop sign control is questionable as it seems to be largely derived from signal warrant analysis, they may not necessarily be appropriate for stop control evaluation and the MUTCD policy does not address "mixed" situations with moderate volumes, fewer accidents or less pedestrians (Celniker, 1989).

It has been about ten years since the last version of MUTCD was published in 2009. The National Committee on Uniform Traffic Control Devices (NCUTCD) is working on changing some of the multiway stop control warranty language that are meant to be amended into the forthcoming version of MUTCD. Before the new version of MUTCD rolling out, there is a rising needs to supplement the existing MUTCD guidelines and weigh in local experience into the rationale of assessing AWSC conversion requests. This paper evaluates the safety effect of AWSC conversion comprehensively in order to set a ground for developing a sensible local policy for AWSC conversion analysis using D.C. data. The study results will hopefully clear some ambiguities about the safety effect of AWSC conversion from TWSC and help the decision makers make more informative decisions backed by empirical evidences.

1.2 Literature Review

Numerous studies analyzed the safety effect of AWSC conversion and stop sign controlled intersections in general. The majority body of previous literature suggests that AWSC conversions could potentially have some safety benefits, such as reduction of total number of crashes, number of injury crashes, Right Angle crashes, Left Turn and Right Turn crashes, under certain traffic volume and roadway geometry conditions but at the cost of increased control

delays and potentially increased Rear End or Sideswipe crashes. However, due to lack of empirical evidences, ambiguity still remains in interpreting the relationship between stop sign control and pedestrian crashes at intersections.

A number of researchers assessed the effect of AWSC conversion in terms of crash experience and operational changes. Briglia studied ten rural intersections in Michigan, where traffic controls were changed from TWSC to AWSC, and found that AWSC can be a cost-effective method of intersection control at moderate or low traffic volume junctions. He indicated that the total number of property damage only (PDO) crashes, injury crashes, injuries, fatal crashes and deaths at the ten intersections were reduced after the conversion (Briglia, 1982). Byrd and Stafford opposed to use unwarranted AWSC for speed control under community group's political pressures, as it will result in unnecessary delay and road user costs to the driving public. However, the safety benefit of AWSC depends on individual intersection's characteristics (Byrd and Stafford, 1984). Lovell and Hauer estimated the safety effectiveness of conversion to all-way stop control using crash data obtained from San Francisco, Philadelphia, Michigan and Toronto and found reductions in total, injury, Right Angle and pedestrian crashes after conversion. However, they acknowledge that the accuracy of estimate for less frequent pedestrian accident is not ideal (John Lovell and Ezra Hauer, 1986). Eck and Biega studied three low volume intersections with seasonal alternative two-way and all-way stop controls in West Virginia. They found that four-way stop controls caused unnecessary delays and increased incompliance rate but lowered the 85^{th} percentile mid-block driving speed (Ronald Eck and James Biega, 1988). Marek et al. though, on the contrary, indicated that AWSC could be more operational effective than TWSC or traffic signal under certain traffic volume combinations and the types of upstream and downstream traffic controls will affect safety and efficiency of

selected traffic control type (Marek et al., 1997). Simpson and Hummer found a substantial decrease in total, injury, and frontal-impact crashes after conversion from two-way to all-way stop control using North Carolina data (Simpson and Hummer, 2010). Swanson et al. (Swanson et al., 1998) and Noyes (Noyes, 1994) speculated the negative impacts to pedestrian safety upon AWSC conversion without empirical evidences' support. Ligon et. al identified an increase of crashes after reverse conversion of AWSC to TWSC without controlling for regression-to-the-mean estimation bias (Ligon et al., 1985).

More broadly, researchers also conducted research on the safety performance of stop sign controlled intersections versus uncontrolled, roundabout or signalized intersections. El-Basyouny and Sayed evaluated the Stop-Sign In-Fill program in Canada, where uncontrolled residential intersections are converted to TWSC intersections in an alternating pattern, and found a 51.1% (95% confidence interval: 36.8%~62.3%) reduction of collision frequency using the Full Bayes approach (El-Basyouny and Sayed, 2010). Gårder concluded AWSC is generally safer comparing with TWSC or signalized intersections but without controlling for traffic exposures using Maine data (Gårder, 2004). Persaud et. al deployed an Empirical Bayes study on 23 different intersections in US and found significant reduction of all and injury crashes after conversion from stop sign controlled intersections to modern Roundabouts (Persaud et al., 2001).

One key factor that would affect the safety performance at stop sign controlled intersections is driver compliance. There are concerns regarding the safety effect of unwarranted more rigid intersection control (ie. from no control to TWSC or from TWSC to AWSC), sometimes may allegedly induce aggressive driving behaviors. Jordan and Morgan asserted that the disturbingly poor compliance with Stop signs has implications for critical intersections (where stopping is

vital for safety) and a significant reduction of Stop sign usage lead to greater driver respect for the remaining Stop signs (Jordan and Morgan, 1990). Mounce analyzed driver compliance with Stop sign controlled intersections and concluded that the operational effectiveness of low-volume intersections could be enhanced with no observed safety detriment by the application of no sign control below major-roadway volume of 2000 ADT, yield-sign control at major-roadway volume between 2000 and 5000 ADT, and, depending on minor-roadway volume, stop-sign control or signalization above 5000 ADT (Mounce, 1981). Retting et al. analyzed 1,788 crash reports for intersections with two-way Stop signs during 1996-2000 in four U.S. cities and found angular and rear-end crashes were the most common crashes that involving stop violations. Their study also suggested that most stop sign violation crashes occurred after required stop and are mainly contributable to failure in identifying adequate gaps. They lumped pedestrian crashes into the "other" category due to rare occurrence (Retting et al., 2003b).

Intersection geometry, in terms of the number of approaching legs, seems to play a role in safety performance at Stop sign controlled intersections as well. Bauer and Harwood showed that rural and urban Stop-controlled four legged intersections had twice as many crashes as the three-legged ones (Bauer and Harwood, 1996). David and Norman found that three-legged un-signalized intersections are safer than four-legged un-signalized intersections, with traffic volumes controlled (David and Norman, 1975). Kulmala found that a four-legged intersection is safer than three legged intersections for low minor approach traffic volume, but less safe for high minor approach volume based on Finland data (Kulmala, 1997).

Obviously, traffic volume exposure will substantially affect available critical gaps, number of conflicting vehicles and driver attentiveness and thus the outcome of crash experience at Stop

sign controlled intersections. Thorpe pointed out that unless traffic-exposure measure is known, the relative hazards of various situations cannot be compared (Thorpe, 1963). Hodge and Richardson argued that accident statistics and transport safety evaluation can only be interpreted meaningfully with measure of exposure (Hodge and Richardson, 1985). Satterthwaite found the number of single-vehicle accidents per unit of vehicle distance travelled tends to decrease with increasing traffic, while the number of collisions between two or more vehicles tends to increase, but knowledge about relationships between accidents and traffic volumes at intersections is less extensive (Satterthwaite, 1981).

Although Stop signs are very common traffic control devices widely used in US, there are conflicting views and under-examined areas about the safety effect of AWSC conversion from TWSC. The handful previous study results may be subject to debating due to various methodological and statistical flaws. This study about the safety effect of TWSC to AWSC conversion aims to shed a little more light upon this important but still under explored topic and the main objectives of this research are summarized as follows:

(a) to conduct a before-and-after evaluation, with a quasi-experimental setup, of the safety effect upon AWSC conversion from TWSC;

(b) to investigate the estimated treatment effect under different analysis frameworks;

(c) to fill the critical knowledge gap in understanding the safety impact of AWSC conversion to pedestrians and bicycles; and

(d) to study the importance of matching control sites to treatment sites and its effect on estimation results.

1.3 Study Design

My study design generally follows the framework of a quasi-experimental study with one treatment group (TWSC intersections that are converted to AWSC intersections) and one closely matched control group (TWSC intersections remain as TWSC intersections) that is doubled the size of the treatment group and is randomly selected from stratified samples. Details about the treatment group and the control group formation are described in the following sections.

1.3.1 Treatment Group

As required by the District of Columbia Administrative Procedure Act of 2000 (D.C. Law 13-249), public notice of agency rule making activities and public comment period are mandatory for any changes of D.C. Municipal Regulations. DDOT is required to give a written Notice of Intent (NOI) to modify traffic and/or parking regulations, including the modification of intersection control devices. This letter is made accessible for the purpose of notification and solicitation of comments on the intent to implement modifications within the District. Based on the NOI log, Table 1- shows the total number of NOI for TWSC to AWSC conversions initiated in each year from 2009 to 2014.

Table 1-1 Total Number of NOI's by Year (2009 - 2014)

2009	2010	2011	2012	2013	2014	Total
8	14	15	13	24	8	82

These intersections collectively formed a pool of samples to construct a decent sized treatment group. Upon visual verification against Google and Globespotter Street View, the actual implemented AWSC conversions by NOI year are shown as follows in Table 1-2.

Table 1-2 Total Number of Implemented NOI's by Year (2009 - 2014)

2009	2010	2011	2012	2013	2014	Total
4	8	12	10	17	7	58

In lack of information about the actual AWSC conversion implementation date, a uniform implementation time lag of six months is assumed since the date of NOI initiation based on my knowledge of DDOT internal operation procedures. In addition, a three-month transition period was considered for motorists to adapt to the new traffic control rules. To simplify the data collection process, a staggered three-year before and three-year after study period was defined based on the cut-off NOI dates for each index year as shown in Table 1-3.

Table 1-3 Staggered 3-Year Before-and After Study and NOI Cut-off Dates

Index Year	NOI Cut-off Dates	3-year Before Period	3-year After Period
2010	4/1/2009 – 3/31/2010	1/1/2007 – 12/31/2009	1/1/2011 – 12/31/2013
2011	4/1/2010 – 3/31/2011	1/1/2008 – 12/31/2010	1/1/2012 – 12/31/2014
2012	4/1/2011 – 3/31/2012	1/1/2009 – 12/31/2011	1/1/2013 – 12/31/2015
2013	4/1/2012 – 3/31/2013	1/1/2010 – 12/31/2012	1/1/2014 – 12/31/2016
2014	4/1/2013 – 3/31/2014	1/1/2011– 12/31/2013	1/1/2015 – 12/31/2017

Several intersections with NOI date between 2010 and 2014 are excluded based on cut-off dates. Specifically, the intersections of Q St at Harry Thomas Way, NE and Barnes St at Cassell Pl, NE are excluded from the Treatment group since they are newer constructions with less than three-year before period data available. The intersection of Second Street NW and Kennedy Street NW is excluded from the Treatment group since there was a major geometry improvement, which compounded the safety effect of the AWSC conversion, at the intersection around middle 2017. In addition, one Collector-Minor Arterial intersection (28th Street NW and P Streets NW) and one Collector-Collector intersection (34th Street and Q Street NW), were randomly selected to be dropped off from the Treatment group due to the lack of sufficient suitable Comparison sites. Figure 1-1 shows a flow chart demonstrating the process of including and excluding sample intersections to form the Treatment group.

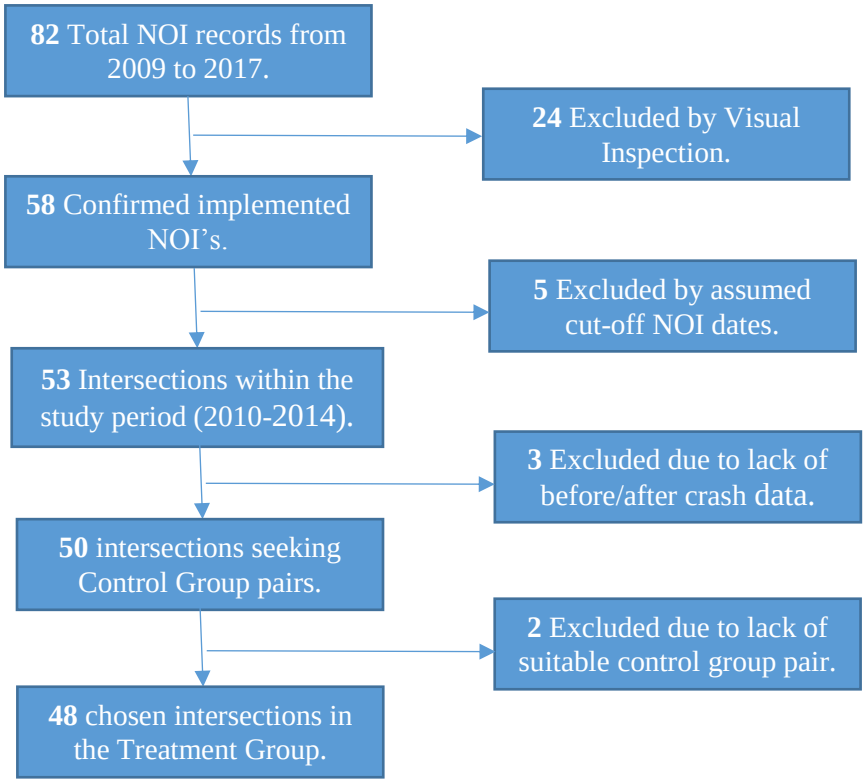


Figure 1-1 Inclusion and Exclusion Criteria for Selecting Treatment Group Intersections

The total number of intersections included in the Treatment group is 48 (as listed in Table A-1 of Appendix) and they distribute spatially in D.C. as shown as the green dots in the following map (Figure 1-2).

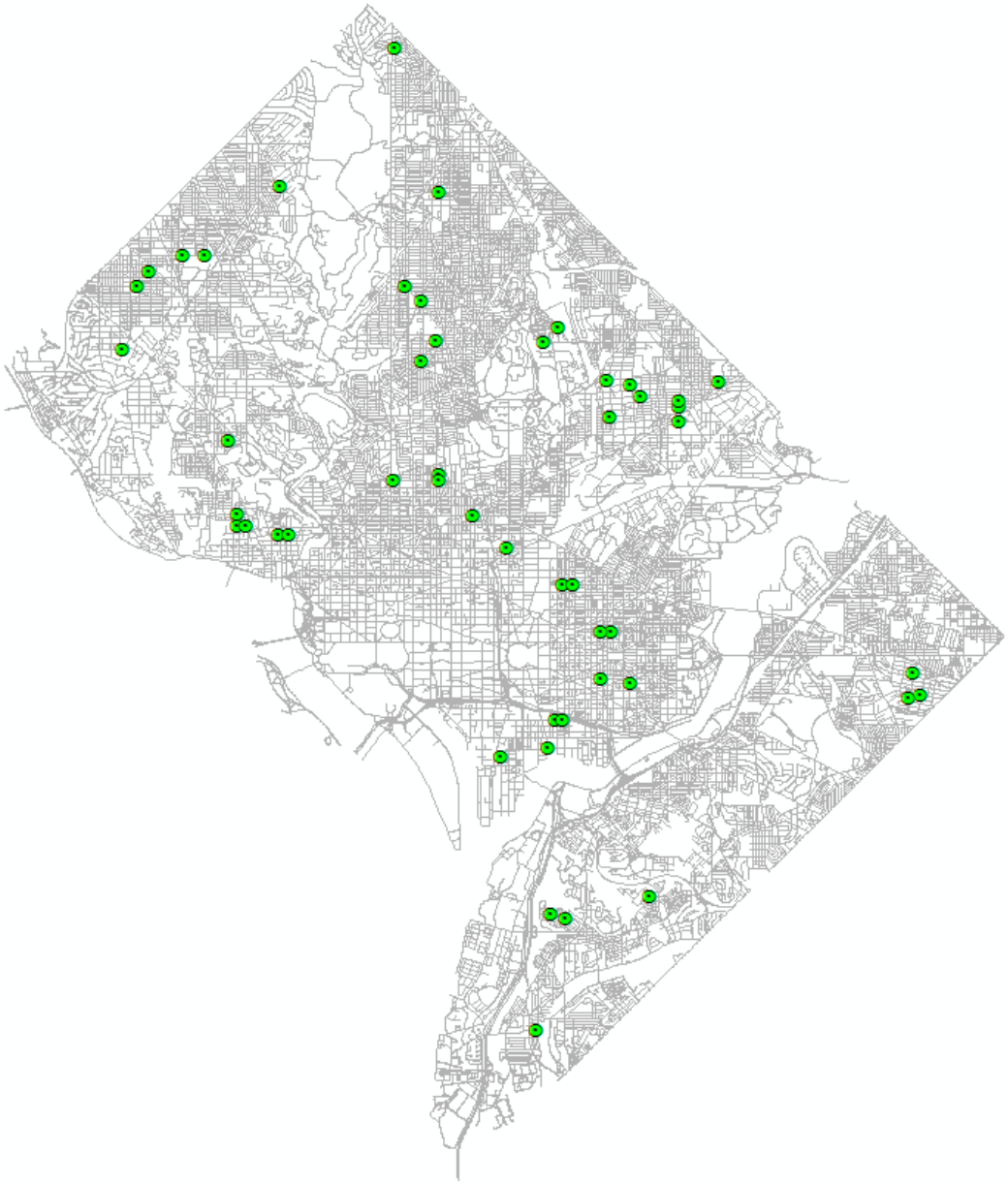


Figure 1-2 Chosen AWSC Intersections in the Treatment Group

1.3.2 Control Group

More than 3,000 unconverted TWSC intersections in D.C. afford a great opportunity for multi-dimensional matching to form a suitable Control group, where the matching scheme is based on

traffic control device type, spatial proximity (by Advisory Neighborhood Commission/ANC), intersecting roads functional classes and intersection geometry. Under certain conditions, matching improves the efficiency of statistical investigation. For instance, a smaller sample size could be used, or the effect of the influential factor could be estimated with a narrower confidence interval (Woodward, 2013). El-Basyouny and Sayed found that incorporating matched yoked comparison groups in collision prediction models may significantly improve the fit, while reducing the need to account for over dispersion (El-Basyouny and Sayed, 2010). The Control group intersection selection procedure aims to reduce selection bias induced confounding factors by having closely matched control group intersections.

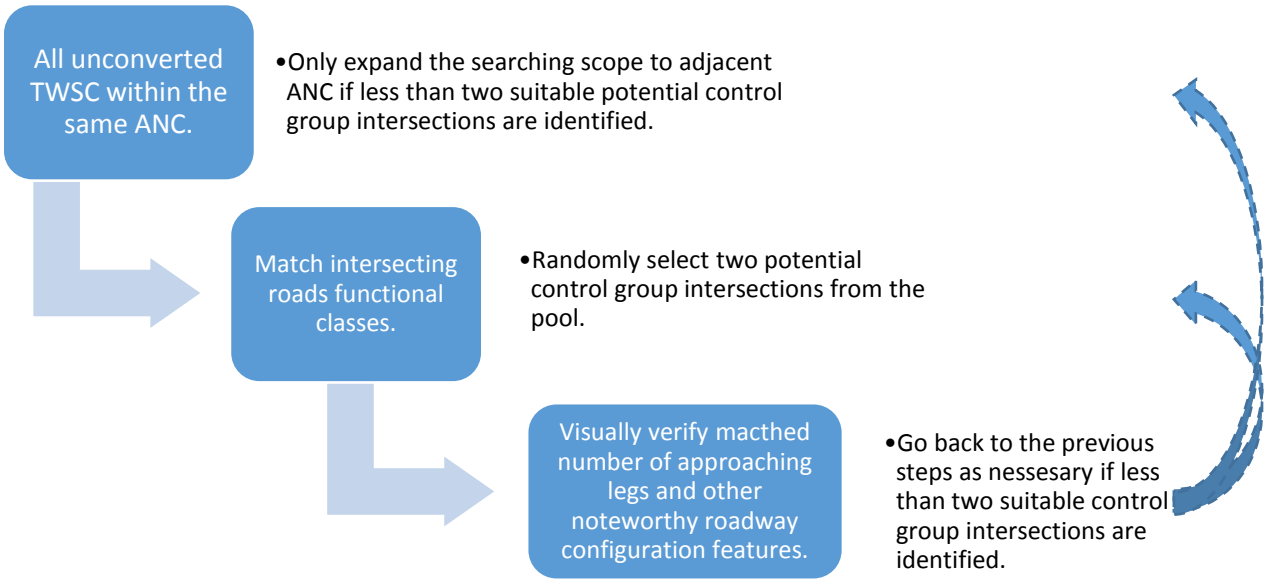


Figure 1-3 The Process of Identifying Control Group Intersections

A Control group with doubled number of comparison intersections is identified to increase the statistical inference power. As illustrated in Figure 1-3, each of the 48 intersections in the Treatment group is matched by location/ANC, by intersecting roadway functional classes, and by number of approaches, to two reference intersections in the TWSC junction population. In other words, two reference intersections are randomly selected from a subset of the unconverted

TWSC intersection population, which contains all unconverted TWSC junctions that are within the same ANC and share the same functional classes of the two intersecting roads for each of the 48 Treatment group intersections as potential control group intersections. Then the two potential control group intersections are visually verified to have the same number of approaches and similar configuration as the target converted AWSC intersection. If any of the potential control intersection did not pass the inspection, it is necessary to go back to previous random selection steps. The searching scope will only be expanded to the adjacent ANC's when suitable matched pairs cannot be identified within the same ANC. Moreover, the year of assumed conversion year as the index year and assigned to the randomly selected referent junctions. At the end, a list of 96 junctions of the Control group with index year labeled is identified as shown in Table A-2 of Appendix.

1.4 Crash Data

Crash records were retrieved from DDOT's Traffic Accident Reporting and Analysis System (TARAS 2.0) during the staggered study periods of three-year before and three-year after for each selected intersection in its index year from 2010 to 2014 (see Table 1-3 for details). Crash records are reviewed based on available narrative descriptions of collisions to eliminate mistakenly assigned crash records and to filter out non-intersection related crash records, parked vehicle crashes for instance, from further analysis. Adjustments to designated collision types are also made as appropriate. The total pooled before and after periods crash records are 317 for the treatment group and 573 for the control group.

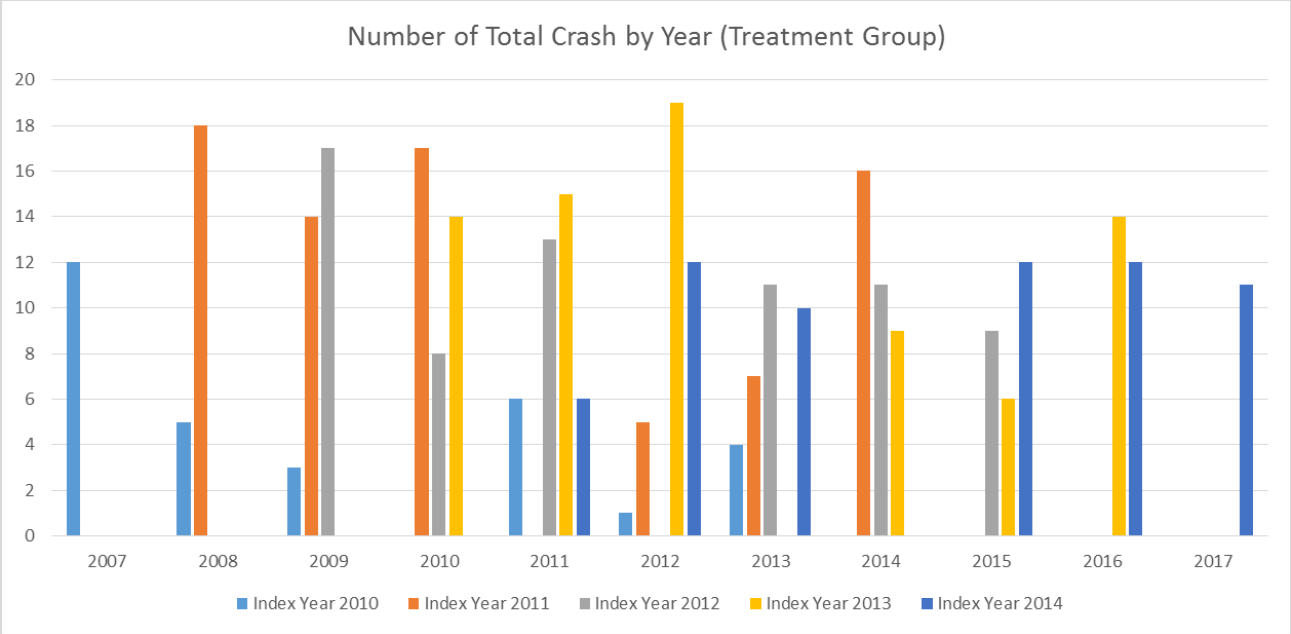


Figure 1-4 Numbers of Total Crashes by Year (Treatment Group)

Table 1-4 Numbers of Total Crashes by Year (Treatment Group)

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Index Year 2010	12	5	3	-	6	1	4				
Index Year 2011		18	14	17	-	5	7	16			
Index Year 2012			17	8	13	-	11	11	9		
Index Year 2013				14	15	19	-	9	6	14	
Index Year 2014					6	12	10	-	12	12	11

Figure 1-4 shows the three-year before and three-year after total numbers of all crashes of the Treatment group by Index Year. It appears that the total numbers of all crashes generally dropped during the after periods comparing with the corresponding before periods, except for Index Year 2014. There are some variations observed within the before or after three-year period.

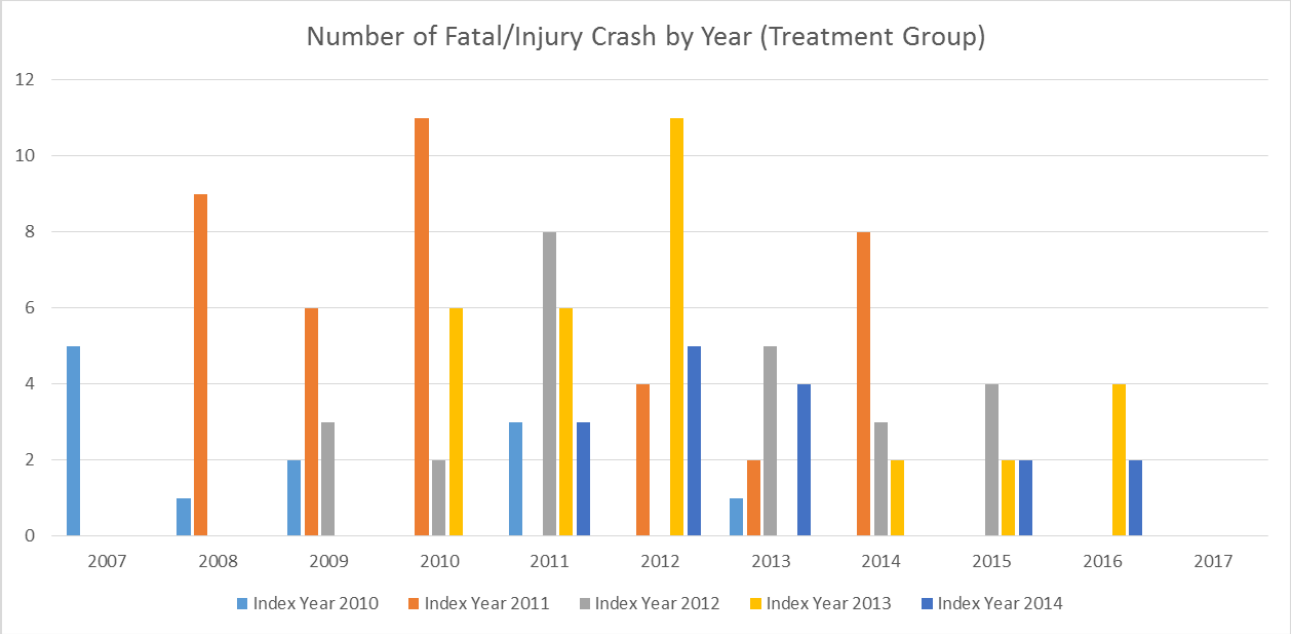


Figure 1-5 Numbers of Fatal/Injury Crashes by Year (Treatment Group)

Table 1-5 Numbers of Fatal/Injury Crashes by Year (Treatment Group)

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Index Year 2010	5	1	2	-	3	0	1				
Index Year 2011		9	6	11	-	4	2	8			
Index Year 2012			3	2	8	-	5	3	4		
Index Year 2013				6	6	11	-	2	2	4	
Index Year 2014					3	5	4	-	2	2	0

Similarly, Figure 1-5 shows the three-year before and three-year after total numbers of fatal/injury crashes of the Treatment group by Index Year. It appears that the total numbers of fatal/injury crashes generally dropped during the after periods comparing with corresponding before periods. It is worth noting that AWSC conversions seem to typically happen right after a major fatal/injury crash uptick, which may indicate the decisions on AWSC conversion may have been influenced by political pressures from the public. Statistically, this phenomenon reveals the problem of regression-to-the-mean issue or selection bias in estimation if not to use longer time series of observational data to estimate the safety effect of AWSC conversions.

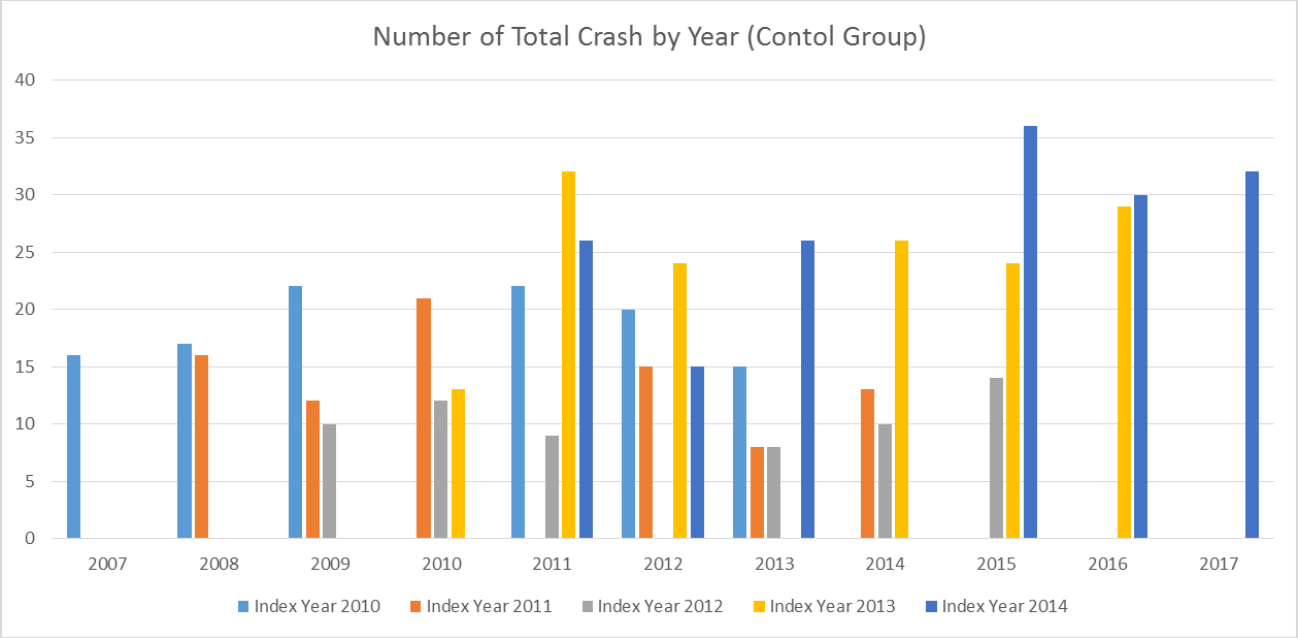


Figure 1-6 Numbers of Total Crashes by Year (Control Group)

Table 1-6 Numbers of Total Crashes by Year (Control Group)

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Index Year 2010	16	17	22	-	22	20	15				
Index Year 2011		16	12	21	-	15	8	13			
Index Year 2012			10	12	9	-	8	10	14		
Index Year 2013				13	32	24	-	26	24	29	
Index Year 2014					26	15	26	-	36	30	32

Figure 1-6 shows the three-year before and three-year after total numbers of all crashes of the Control group by Index Year. The trend of total numbers of crashes shows some volatility during the before/after three-year period. The time trend may exhibit a slightly upward shifting tendency. However, the impression of the upward tendency seems to be largely driven by the Index Year 2014 sub group as the remainder sub groups are generally similar during the before and after periods. This phenomenon could be related to the overhauled changes of the crash reporting system of MPD in late 2015. As only the Index Year 2014 sub group's three-year after period is deep into the post reporting change era.

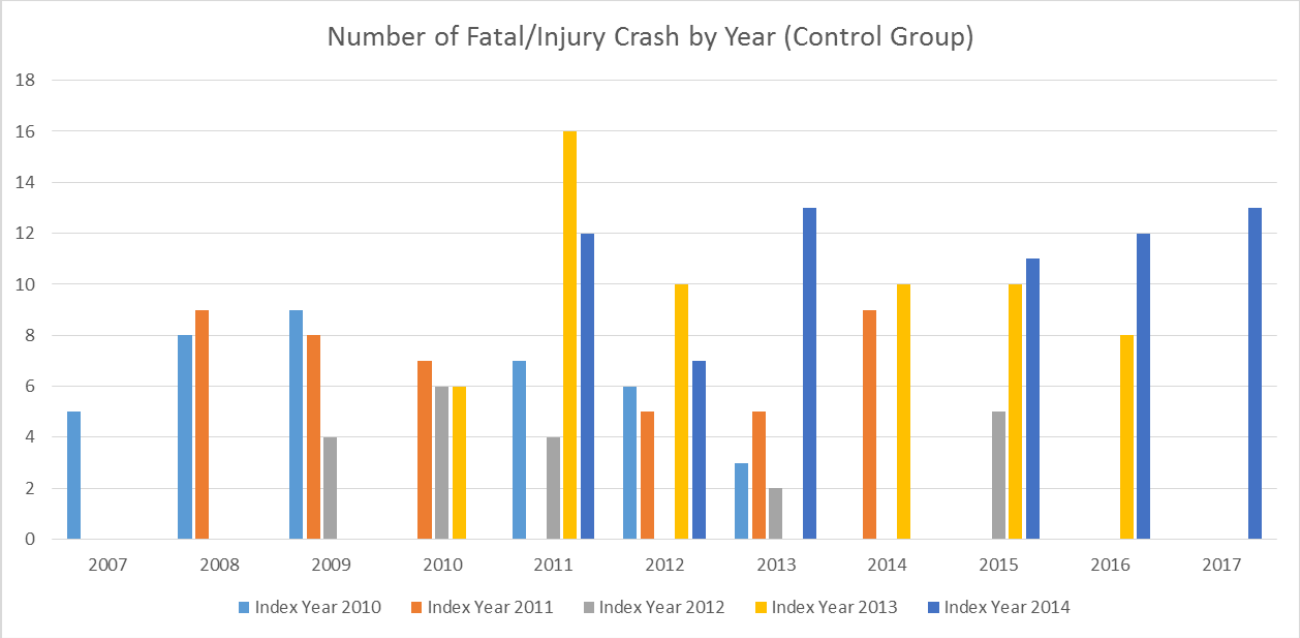
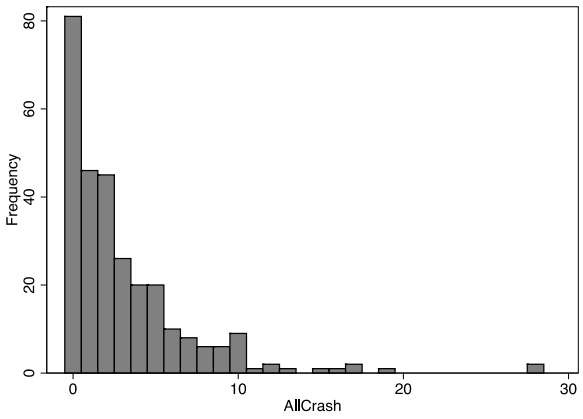


Figure 1-7 Numbers of Fatal/Injury Crashes by Year (Control Group)

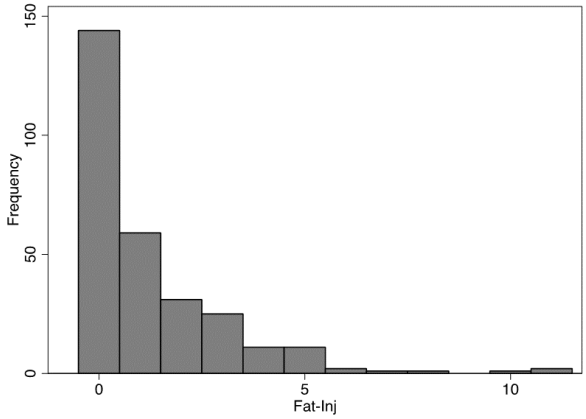
Table 1-7 Number of Fatal/Injury Crashes by Year (Control Group)

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Index Year 2010	5	8	9	-	7	6	3				
Index Year 2011		9	8	7	-	5	5	9			
Index Year 2012			4	6	4	-	2	0	5		
Index Year 2013				6	16	10	-	10	10	8	
Index Year 2014					12	7	13	-	11	12	13

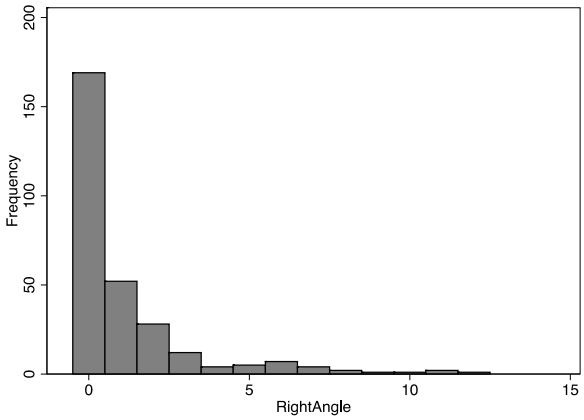
Figure 1-7 shows the three-year before and three-year after total numbers of fatal/injury crashes of the Control group by Index Year. It appears that the total numbers of fatal/injury crashes are generally stable during the before and after periods. It seems justified the aforementioned crash reporting system issue since the reporting of more severe crashes, such as injury and fatal crashes, tends to be more consistent between the reporting system changes.



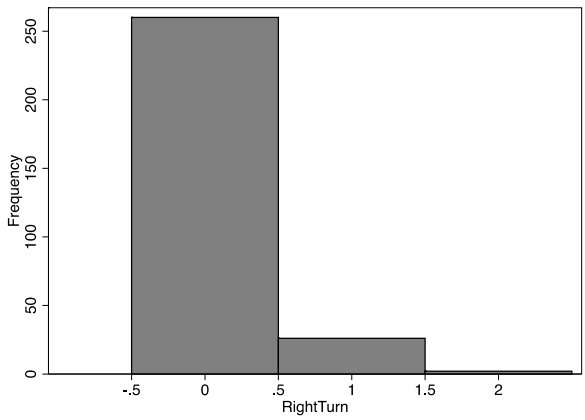
(a) All Crashes



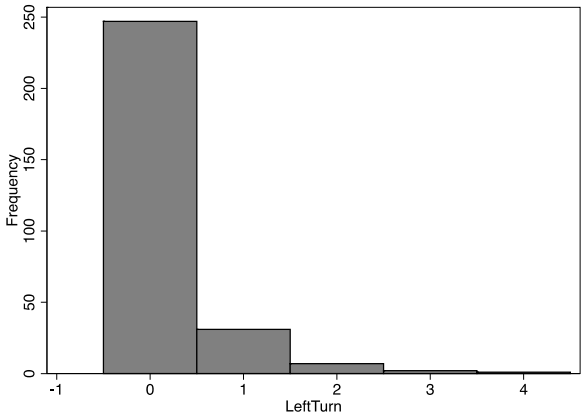
(b) Fatal/Injury Crashes



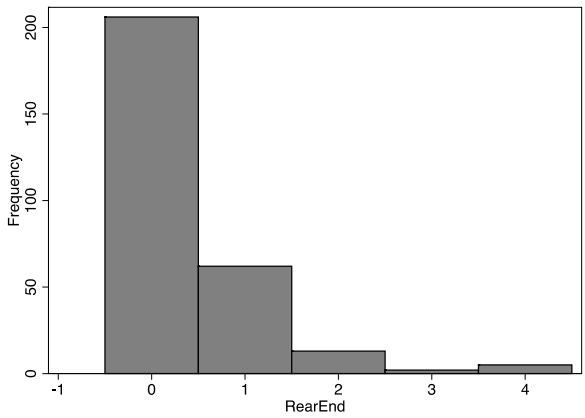
(c) Right Angle Crashes



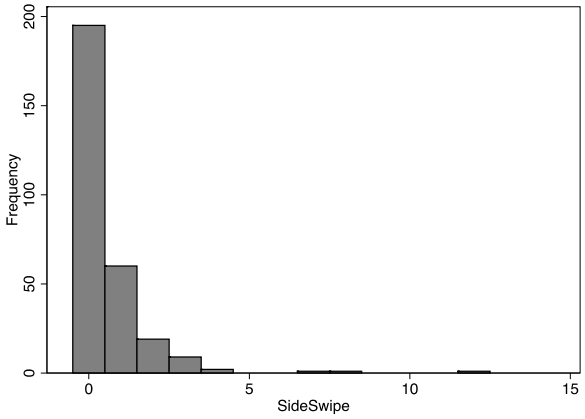
(d) Right Turn Crashes



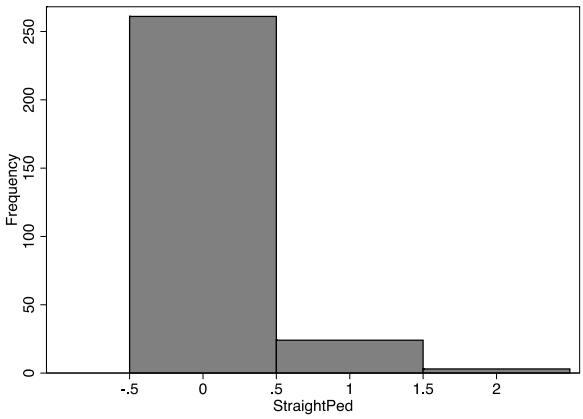
(e) Left Turn Crashes



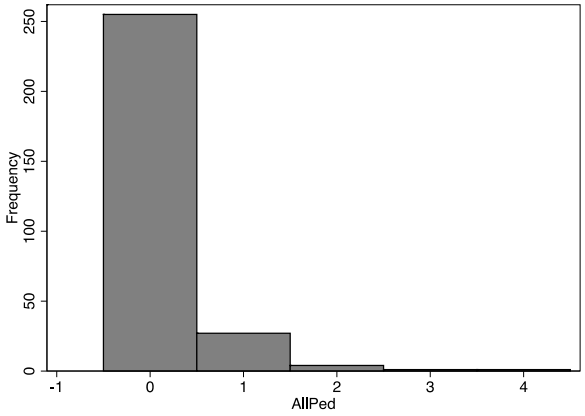
(f) Rear-end Crashes



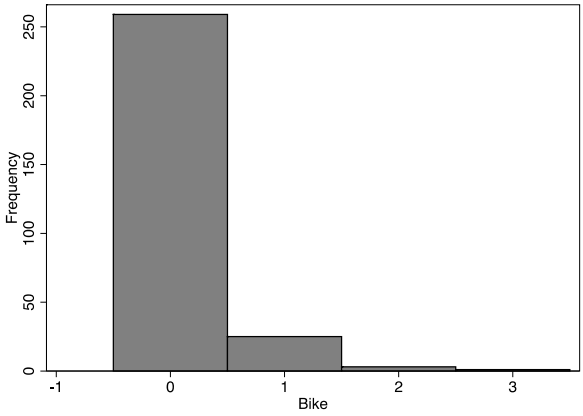
(g) Side Swiped Crashes



(h) Straight Hit Pedestrian Crashes



(i) All Pedestrian Crashes



(j) Bicycle Crashes

Figure 1-8 Histogram of Crash by Type (All Periods)

Figure 1-8 (a) to (j) show before and after period's crash frequency histograms by crash type.

Descriptive statistics for the pooled crash records, in terms of sample mean and standard deviation by collision type, are summarized in Figure 1-9 is included to help illustrate different typical collision types on roadways.

Table 1-8 as follows. The data are broken down by Before/After periods and Treatment/Control groups.

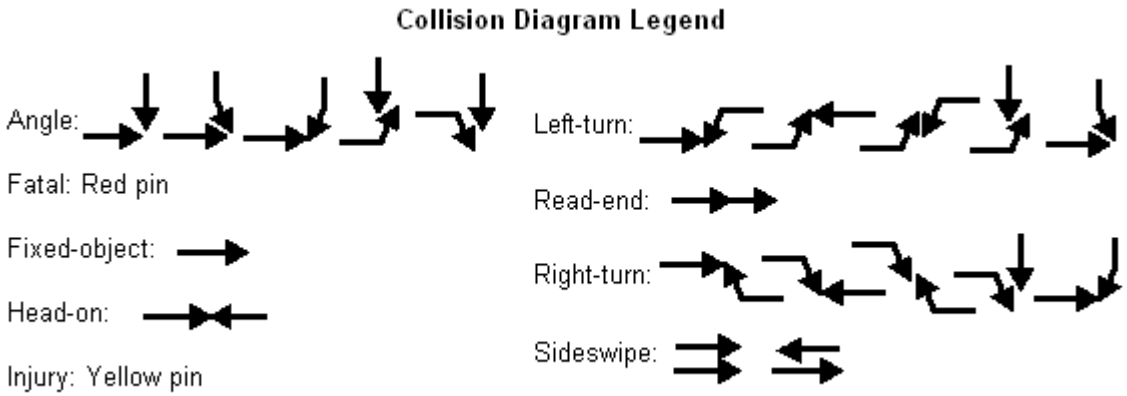


Figure 1-9 Typical Collision Diagram (extracted from AASHTOWare® Safety Analysis Manual)

Figure 1-9 is included to help illustrate different typical collision types on roadways.

Table 1-8 Descriptive Statistics of Pooled Before-and-After 3-year Crash Rate by Collision Type

Collision Type	Period	Treatment Group		Control Group	
		Mean	S.D.	Mean	S.D.
All Crashes	3-yr Before	3.8 ↓	3.76	2.8 ↑	4.16
	3-yr After	2.8	2.87	3.1	4.46
Fatal/Injury	3-yr Before	1.7 ↓	1.95	1.3 ↓	2.13
	3-yr After	0.9	1.25	1.1	1.63
Right Angle	3-yr Before	1.7 ↓	2.31	1.1 ↑	1.89
	3-yr After	0.4	0.76	1.3	2.47
Right Turn	3-yr Before	0.1 -	0.33	0.1 -	0.34
	3-yr After	0.1	0.39	0.1	0.28
Left Turn	3-yr Before	0.2 ↓	0.54	0.2 -	0.58
	3-yr After	0.1	0.33	0.2	0.57
Rear End	3-yr Before	0.4 ↑	0.71	0.3 ↑	0.65
	3-yr After	0.5	0.97	0.4	0.78
Side Swiped	3-yr Before	0.5 ↑	0.85	0.5 -	1.10
	3-yr After	0.8	1.08	0.5	1.49
Straight Hit Pedestrian	3-yr Before	0.1 ↑	0.24	0.1 -	0.29
	3-yr After	0.2	0.52	0.1	0.30
All Pedestrian	3-yr Before	0.1 ↑	0.31	0.1 -	0.49
	3-yr After	0.2	0.52	0.1	0.47
Bicycle	3-yr Before	0.2 ↓	0.59	0.1 -	0.31
	3-yr After	0.1	0.41	0.1	0.28

Note: "↓" – Reduced mean crash rate during the After period; "↑" – Increased mean crash rate during the After period; and "-" – Unchanged mean crash rate during the After period.

As shown in Figure 1-9 is included to help illustrate different typical collision types on roadways.

Table 1-8, the treatment group intersections generally observed decreased or roughly unchanged

3-year crash rate across board except in the Rear End, Sideswipe and Pedestrian crash categories.

In contrast, the control group intersections generally had slightly increased or roughly unchanged 3-year crash rate except in the fatal/injury crash categories, which may suggest that although the frequency of crashes increased, the severity of crashes is alleviated through the advancement of vehicle technologies. The pooled 3-year crash rate trends are mostly consistent with previous literature, where AWSC conversion appears to potentially have the effect of reducing the overall intersection crash rates as well as Right Angle and Turning crashes. Nevertheless, the study may shed some light on the safety impact of AWSC conversion to pedestrian related crashes.

1.5 Conventional Before-and-After Study

A conventional before-and-after study was conducted on the pooled treatment group sites. Observations based on the comparison of pooled before and after crash numbers are highlighted as follows.

The result of the naïve before-and-after study is shown in Table 1-9. Some key findings are:

- There were overall reductions of 27% in total crashes and 49% in fatal/injury crashes following AWSC conversion.
- All combinations of intersecting roadway functional classifications showed reductions in total crashes to some degree.
- All combinations of intersecting roadway functional classifications showed reductions in fatal/injury crashes to some degree.
- Intersections between local and local streets showed the largest reduction in both all and fatal/injury crashes.
- 3-Leg intersections seem not to be ideal candidates for AWSC conversion.

Table 1-9 Comparison of Total and Injury Crashes of the Treatment Group

Category	Total	Total Number of Crash Before	Total Number of Crash After	% Change	Fatal/ Injury Crashes Before	Fatal /Injury Crashes After	% Change
All	48	183	134	-27%	82	42	-49%
Local-Local	18	53	28	-47%	22	7	-68%
Local-Collector	13	40	37	-8%	17	10	-41%
Collector-Collector	5	15	9	-40%	6	5	-17%
Local-Minor Arterial	8	54	46	-15%	29	17	-41%
Collector-Minor Arterial	4	21	14	-33%	8	3	-63%
4 Leg	38	166	107	-36%	75	31	-59%
3 Leg	10	17	27	59%	7	11	57%

Table 1-10 shows a breakdown of before-and-after crashes by collision type amongst the treatment group. Some key findings are:

- There were relatively large reductions in Right Angle crashes for both total crashes (-79%) and fatal/injury crashes (-91%).
- There were reductions in fatal/injury Right Turn crashes (-50%).
- There were relatively large reductions in Left Turn crashes for both total crashes (-40%) and fatal/injury crashes (-100%).
- Increases were observed for Rear End crashes for both total crashes (+30%) and fatal/injury crashes (+50%).
- Large increases of crashes were observed for Straight Hit Pedestrian crashes, for both total crashes (267%) and fatal/injury crashes (350%).

- Large increases of crashes were observed for all Pedestrian collisions, for both total crashes (120%) and fatal/injury crashes (125%).
- There were reductions in all bicycle crashes (-36%) but not in fatal/injury Bicycle crashes.

Table 1-10 Comparison of Total and Injury Crashes of the Treatment Group by Collision Type

Collision Type	All Crashes			Fatal/Injury Crashes		
	Before	After	% Change	Before	After	%Change
All	183	134	-27%	82	42	-49%
Right Angle	82	17	-79%	47	4	-91%
Right Turn	6	6	0%	2	1	-50%
Left Turn	10	6	-40%	6	0	-100%
Rear End	20	26	30%	8	12	50%
Side Swipe	23	36	57%	4	4	0%
Straight Hit Pedestrian	3	11	267%	2	9	350%
All Pedestrian	5	11	120%	4	9	125%
Bike	11	7	-36%	7	7	0%

More rigorous statistical analyses, intended to have selection bias and time trend controlled in estimation, are conducted to test the following hypothesis:

i. AWSC Conversion could potentially reduce the crash rate in the following classes: all crashes, fatal/injury crashes, Right Angle, Left turn and Bicycle crashes;
ii. AWSC conversion may increase the crash rate of Straight Hit Pedestrians, Rear End and All Pedestrian crashes.
iii. AWSC conversion has negligible safety impact to Right Turn crashes.

The statistical analysis results are presented in the following sections.

1.6 Statistical Analysis

1.6.1 Two-Way ANOVA

Analysis of Variance (ANOVA) is a statistical technique for testing if group means are all equal. The two-way ANOVA is an extension of the one-way ANOVA. A two-way ANOVA compares the mean differences between groups that have been split on multiple categorical independent variables.

Say a continuous dependent variable *Y* may be influenced by two categorical independent variables *T* and *G*. The first factor *T* has *I* levels ($i \in \{1, \cdots, I\}$) and the second factor *G* has *J* levels ($j \in \{1, \cdots, J\}$). Each combination of factors *T* and *G* (*i*, *j*) defines a treatment for a total of $I \times J$ treatments. An ANOVA model assumes normality of the dependent variable, specifically:

$$Y_{ijk} | \mu_{ij}, \sigma^2 \underset{\sim}{i.i.d} \mathcal{N}(\mu_{ij}, \sigma^2) \qquad (1\text{-}1)$$

where μ_{ij} is the mean of treatment group (*i*, *j*);

σ^2 is a constant variance.

The F-test is to check whether all μ_{ij}'s are equal. The null hypothesis can be written as:

H_0: $\mu_{11} = \mu_{12} = \cdots = \mu_{ij}$, where $i \in \{1, \cdots, I\}$ and $j \in \{1, \cdots, J\}$.

H_1: $\mu_{ij} \neq \mu_{i'j'}$, for some i, j.

I split the data set into four groups by two independent variables: treatment (treatment=1: Treatment Group; treatment=0: Control Group) and BA (BA=1: After Period; BA=0: Before Period). The main effect for treatment and study period as well as their interaction effect are evaluated under the two-way ANOVA framework.

Table 1-11 Estimated F Value of Each Variable Effect by Crash Type

Collision Type	Group Effect	Time Trend Effect	Treatment Effect
All Crashes	0.40	0.48	1.79
Fatal/Injury	0.17	5.08**	2.03
Right Angle	0.30	4.91**	9.43***
Right Turn	0.58	0.06	0.06
Left Turn	0.29	0.73	0.15
Rear End	1.72	1.45	0.01
Side Swipe	0.34	1.00	0.63
Straight Hit Pedestrian	2.22	3.03*	5.00**
All Pedestrian	0.29	1.16	1.16
Bike	4.81**	1.73	0.19

*Note: *P-value<0.1; **P-value<0.05; ***P-value<0.01*

There was a significant interaction between the effects of treatment and study period on the crash rate of Right Angle ($F_{(1, 284)}$=9.43, p=0.002) and Straight Hit Pedestrian ($F_{(1, 284)}$=5.00, p=0.026) crashes. The insignificant group effect for most collision types seems to suggest the selection bias between the Treatment and Control groups is not significant.

Table 1-12 Predicted Mean Crash Rate by Collision Type

Collision Type	Treatment Group		Control Group	
	Before	After	Before	After
All Crashes	3.81	2.79	2.82	3.15
Fatal/Injury	1.71	0.88	1.29	1.10
Right Angle	1.71 ↓	0.35	1.06	1.28
Right Turn	0.13	0.13	0.10	0.08
Left Turn	0.21	0.13	0.22	0.19
Rear End	0.42	0.45	0.30	0.40
Side Swipe	0.48	0.75	0.51	0.54
Straight Hit Pedestrian	0.06 ↑	0.23	0.09	0.07
All Pedestrian	0.10	0.23	0.14	0.14
Bike	0.23	0.15	0.10	0.06

Table 1-12 shows the linear prediction of mean crash rate by collision type. The treatment group before/after crash means for Right Angle and Straight Hit Pedestrian crashes are highlighted since significant treatment effects are identified. Upon AWSC conversion, the mean reduction of Right Angle crash rate is about 1.36 per year. However, the mean of Straight Hit Pedestrian

crash rate is estimated to increase for about 0.17 crash per year (roughly equivalent to about one crash per five year) after AWSC conversion. This is an alarming issue since the consequence of a straight hit pedestrian crash tends to be more severe as it involves less protected venerable pedestrians. Additional measures need to be taken to offset the negative safety effect to pedestrians upon AWSC conversion.

1.6.2 Difference-in-Differences (DID) Analysis

DID estimation is one of the most important identification strategies in applied microeconomics (Athey and Imbens, 2006), (Andrews et al., 2005), (Derrig and Tennyson, 2011), (Lechner M., 2010). The DID method combines the flawed naïve before vs. after and treatment vs. control group approaches, which could potentially overcome selection bias and time trends in the outcome of interest. Specifically, the DID estimator DD can be expressed as:

$$DD = \bar{Y}_{after}^{treatment} - \bar{Y}_{before}^{treatment} - \left(\bar{Y}_{after}^{control} - \bar{Y}_{before}^{control}\right) \quad (1\text{-}2)$$

The assumption underlying DID estimation is that, in the absence of the treatment program, individual's outcome at time t is given by:

$$E[Y_i|D_i = 0, t = \tau] = \gamma_i + \lambda_\tau \quad (1\text{-}3)$$

The two implicit identifying assumptions are:

- Selection bias relates to fixed characteristics of individuals (γ_i);
- Time trend (λ_τ) is the same for treatment and control groups.

$$DD = \bar{Y}_{after}^{treatment} - \bar{Y}_{before}^{treatment} - \left(\bar{Y}_{after}^{control} - \bar{Y}_{before}^{control}\right)$$

$$= E[Y_{1i}|D_i = 1, t = 2] - E[Y_{0i}|D_i = 1, t = 1]$$

$$- \left(E[Y_{1i}|D_i = 0, t = 2] - E[Y_{0i}|D_i = 0, t = 1]\right)$$

$$= E[\gamma_i|D_i = 1] + \delta + \lambda_2 - (E[\gamma_i|D_i = 1] + \lambda_1)$$
$$- [E[\gamma_i|D_i = 0] + \lambda_2 - (E[\gamma_i|D_i = 0] + \lambda_1)]$$
$$= \delta \quad (1\text{-}4)$$

Denote participation in the Treatment group as

$$I = 1[T = 1, G = 1] = T \times G \quad (1\text{-}5)$$

where $1[\cdot]$ is the indicator function. Equation (1-5) implies that the treatment group (G=1) is treated in period T=1. There is no treatment for the Control group (G=0) in both period and no treatment for either group in period T=0. The observation rule of the outcome variable Y is

$$Y = I \times Y^1 + (1 - I) \times Y^0 \quad (1\text{-}6)$$

In the linear model, the expected outcome Y^0 conditional on T, G and covariate X is specified as

$$E[Y^0|T, G, X] = \alpha T + \beta G + X\theta \quad (1\text{-}7)$$

The Treatment group outcome is observed during the treatment period (T=1):

$$E[Y^1|T = 1, G = 1, X] = \delta + \alpha T + \beta G + X\theta \quad (1\text{-}8)$$

where δ is the treatment effect of interest.

Combine Equations (1-5), (1-6), (1-7) and (1-8), the treatment effect δ can be identified in a linear model:

$$E[Y|T, G, X] = T \times G \times [\delta + \alpha T + \beta G + X\theta] + (1 - T \times G)[\alpha T + \beta G + X\theta]$$
$$= \alpha T + \beta G + \delta T \times G + X\theta \quad (1\text{-}9)$$

In other words, in a linear DID model, the coefficient of interest is simply the estimated parameter for the interaction term of group and time period.

1.6.3 Pooled Data DID Analysis

The first DID estimation utilized all pooled data in a regression framework as specified in Equation (1-10).

$$Y_{i,t} = \mu + \alpha T_t + \beta G_i + \delta(G_i \times T_t) + \varepsilon_{i,t} \quad (1\text{-}10)$$

Where T_t is an indicator equal to 1 if in the Treatment period;

δ is the coefficient of interest (the treatment effect);

$\mu = E[\gamma_i | D_i = 0] + \lambda_1$, which is the before period mean in control group;

$\beta = E[\gamma_i | D_i = 1] - E[\gamma_i | D_i = 0]$, which is the selection bias;

$\alpha = \lambda_2 - \lambda_1$, which is the time trend;

$\varepsilon_{i,t}$ is a random error term.

Given the generally over-dispersed nature of count dependent variables (the crash numbers), Negative Binomial regression is chosen for modeling using STATA's *nbreg* demand. ((Cameron and Trivedi, 1998) and (Cameron and Trivedi, 2009))

Table 1-13 Estimated DID Coefficients and Standard Errors by Collision Type using Pooled Data

Collision Type	Group Effect	Time Trend Effect	Treatment Effect
All Crashes	0.30 (0.217)	0.11 (0.180)	-0.42 (0.310)
Fatal/Injury	0.28 (0.253)	-0.16 (0.218)	-0.51 (0.375)
Right Angle	0.47 (0.305)	0.19 (0.255)	-1.76 (0.481)***
Right Turn	0.18 (0.525)	-0.22 (0.480)	0.22 (0.758)
Left Turn	-0.05 (0.480)	-0.15 (0.398)	-0.36 (0.732)
Rear End	0.32 (0.340)	0.30 (0.284)	-0.03 (0.459)
Side Swipe	-0.06 (0.359)	0.06 (0.280)	0.39 (0.476)
Straight Hit Pedestrian	-0.41 (0.680)	-0.25 (0.516)	1.55 (0.845)*
All Pedestrian	-0.26 (0.603)	0.00 (0.460)	0.79 (0.786)
Bike	0.79 (0.486)	-0.51 (0.545)	0.06 (0.769)

*Note: Coefficient (Standard Error); *P-value<0.1; **P-value<0.05; ***P-value<0.01*

The DID analysis using pooled data revealed a significant treatment effect on the crash rate of Right Angle (z =-3.66, p=0.000) and Straight Hit Pedestrian (z =1.84, p=0.067) crashes. Although, the DID analysis suggests significant reductions of Right Angle crashes by 1.76

crash/year, it appears that the AWSC conversion may induced more Straight Hit Pedestrian crashes by 1.55 crash/year, which is significantly larger that the estimation using ANOVA method. This is an alarming signal that AWSC may cause unexpected side effect which involves vulnerable roadway users and could result in more severe outcomes. No statistically significant group or time trend effect is identified though the DID analysis with pooled data.

1.6.4 Panel Data DID Analysis

Using pooled dataset may encounter the challenge to the homogeneity assumption. Mantel and Haenszel developed a method to calculate a summary measure of the odds ratio across the stratified datasets, which assumes a common true odds ratio for each stratum and the differences in observed odds ratios are due to chance variation (Woodward, 2013). A Mantel-Haenszel test of homogeneity of odds ratios between functional classes is conducted and the assumption of the null hypothesis of no association of stratified dataset, when applied to the observed data, failed to reject the null hypothesis. It is concluded that there is no statistically significant evidence that the association of crash experience with group assignment is different, depending on intersection functional classes. However, since many individual odds ratios are significantly different from one, it makes sense to introduce a fixed effect parameter for each functional class in further estimations.

Table 1-14 Mantel-Haenszel Estimate of Homogeneity of Odds Ratio

Functional Class	**All Crashes**		**Fatal/Injury Crashes**	
	Odds Ratio	**$\chi^2(1)$**	**Odds Ratio**	**$\chi^2(1)$**
Local-Local	1.31	7.28***	1.43	2.97*
Local-Collector	0.98	0.11	0.94	0.35
Collector-Collector	2.40	5.93**	2.82	4.49**
Local-Minor Arterial	1.20	3.59*	1.35	3.29*
Collector-Minor Arterial	0.90	3.22*	0.66	5.01**
M-H Estimate	1.02	0.39	1.04	0.23

*Note: *P-value<0.1; **P-value<0.05; ***P-value<0.01*

Therefore, the second DID estimation utilized a panel data regression framework, where a cross-sectional fixed effect θ_k is introduced to the model, as specified in Equation (1-11).

$$Y_{i,t,k} = \mu + \theta_i + \alpha T_t + \beta G_i + \delta(G_i \times T_t) + \varepsilon_{i,t,k} \quad (1\text{-}11)$$

Where T_t is an indicator equal to 1 if in the Treatment period;

δ is the coefficient of interest (the treatment effect);

θ_k is the cross-sectional fixed effect;

$\mu = E[\gamma_i|D_i = 0] + \lambda_1$, which is the before period mean in control group;

$\beta = E[\gamma_i|D_i = 1] - E[\gamma_i|D_i = 0]$, which is the selection bias;

$\alpha = \lambda_2 - \lambda_1$, which is the time trend;

$\varepsilon_{i,t,k}$ is a random error term.

1.6.4.1 By Intersecting Roads Functional Classes

Table 1-15 Estimated DID Coefficients and Standard Errors by Collision Type using Panel Data per Intersecting Roads Functional Classes

Collision Type	Intersecting Roads Functional Classes Fixed Effect					Group Effect	Time Trend Effect	Treatment Effect
	Local-Local	Local-Collector	Collector-Collector	Local-Minor Arterial	Collector-Minor Arterial			
All Crashes	-	0.81*** (0.165)	0.07 (0.308)	1.24*** (0.184)	1.73*** (0.274)	0.48** (0.198)	0.08 (0.161)	-0.47* (0.277)
Fatal/Injury	-	0.82*** (0.211)	0.14 (0.406)	1.37*** (0.226)	1.64*** (0.324)	0.38* (0.233)	-0.20 (0.198)	-0.52 (0.346)
Right Angle	-	0.88*** (0.256)	-0.67 (0.584)	1.37*** (0.279)	1.92*** (0.397)	0.76**** (0.287)	0.15 (0.236)	-1.80*** (0.456)
Right Turn	-	-0.16 (0.541)	0.36 (0.795)	0.55 (0.518)	1.74*** (0.521)	0.03 (0.522)	-0.22 (0.474)	0.22 (0.747)
Left Turn	-	0.89* (0.517)	1.12 (0.762)	2.01*** (0.492)	2.44*** (0.593)	-0.08 (0.453)	-0.18 (0.378)	-0.38 (0.697)
Rear End	-	1.27*** (0.316)	0.58 (0.552)	1.60*** (0.329)	1.43*** (0.455)	0.40 (0.329)	0.29 (0.272)	-0.09 (0.438)
Side Swipe	-	0.81*** (0.286)	0.43 (0.511)	1.21*** (0.306)	2.12*** (0.392)	-0.00 (0.335)	0.05 (0.264)	0.42 (0.449)
Straight Hit Pedestrian	-	0.28 (0.495)	0.24 (0.815)	0.69 (0.512)	0.80 (0.703)	-0.41 (0.678)	-0.25 (0.511)	1.54* (0.837)
All Pedestrian	-	0.34 (0.489)	0.16 (0.862)	0.86 (0.502)	1.87*** (0.590)	-0.19 (0.597)	0.01 (0.448)	0.70 (0.767)
Bike	-	0.96* (0.558)	0.69 (0.876)	1.59*** (0.558)	1.48** (0.725)	0.81* (0.480)	-0.50 (0.537)	0.07 (0.753)

*Note: Coefficient (Standard Error); *P-value<0.1; **P-value<0.05; ***P-value<0.01*

A DID analysis using panel data classified by intersecting roads functional classes revealed a significant treatment effect on the crash rate of Right Angle (z =-3.95, p=0.000) and Straight Hit Pedestrian (z =1.84, p=0.066) crashes. Again, Negative Binomial regression is chosen for modeling using STATA's *nbreg* demand. The panel data regression introduced a fixed effect for each intersecting roads functional classification combinations. The coefficients of "Local-Local" (Local road intersecting with Local road) type intersections are omitted as the baseline condition.

The positive coefficient signs for higher hierarchy intersections are associated with higher crash rates comparing with the base type of "Local-Local" intersection, which might be associated with higher traffic volume exposures. It appears that the AWSC conversion may induced more Straight Hit Pedestrian crashes across board by 1.54 crash/year. Note there are evidences for significant selection bias in the All Crash, Tatal/Injury Crash, Right Angle Crash and Bicycle Crash estimation, which may indicate that the AWSC conversion sites are not selected through a random process and thus simply comparing the before and after crash rate within the Treatment group will likely exaggerate the safety benefit of the AWSC conversion treatment.

1.3.4.2 By Number of Approaching Legs

Table 1-16 Estimated DID Coefficients and Standard Errors by Collision Type using Panel Data per Number of Approaching Legs

Collision Type	**# of Approaching Legs Fixed Effect**		**Group Effect**	**Time Trend Effect**	**Treatment Effect**
	Three	***Four***			
All Crashes	-	0.78***	0.28	0.10	-0.334
		(0.185)	(0.211)	(0.176)	(0.302)
Fatal/Injury	-	0.71***	0.27	-0.14	-0.46
		(0.234)	(0.248)	(0.213)	(0.370)
Right Angle	-	2.01***	0.47*	0.16	-1.66***
		(0.365)	(0.286)	(0.241)	(0.461)
Right Turn	-	0.32	0.17	-0.22	0.23
		(0.495)	(0.524)	(0.480)	(0.758)
Left Turn	-	-0.10	-0.06	-0.15	-0.35
		(0.395)	(0.480)	(0.398)	(0.731)
Rear End	-	0.61**	0.30	0.30	-0.00
		(0.311)	(0.338)	(0.283)	(0.457)
Side Swipe	-	0.57*	-0.08	0.06	0.41
		(0.299)	(0.347)	(0.278)	(0.473)
Straight Hit Pedestrian	-	0.26	-0.30	-0.13	1.43*
		(0.509)	(0.691)	(0.530)	(0.855)

Collision Type	# of Approaching Legs Fixed Effect		Group Effect	Time Trend Effect	Treatment Effect
	Three	*Four*			
All Pedestrian	-	0.67	-0.20	0.07	0.71
		(0.536)	(0.611)	(0.470)	(0.794)
Bike	-	0.43	0.77	-0.51	0.05
		(0.519)	(0.484)	(0.544)	(0.766)

*Note: Coefficient (Standard Error); *P-value<0.1; **P-value<0.05; ***P-value<0.01*

A DID analysis using panel data classified by the number of approaching legs revealed a significant treatment effect on the crash rate of Right Angle (z =-3.60, p=0.000) and Straight Hit Pedestrian (z =1.67, p=0.094) crashes. Again, Negative Binomial regression is chosen for modeling using STATA's *nbreg* demand. The panel data regression introduced a fixed effect by the number of approaching legs. The coefficients of "3-Leg" intersections are omitted as the baseline condition. The positive coefficient signs for "4-Leg" intersections suggest that "4-Leg" intersections crash rates are generally higher than "3-Leg" intersections, which is consistent with previous literature ((Bauer and Harwood, 1996), (David and Norman, 1975) and (Kulmala, 1997)). It appears that the AWSC conversion may induced more Straight Hit Pedestrian crashes across board by 1.43 crash/year. Note there is somewhat significant selection bias revealed in the Right Angle crash estimation, which indicates that the AWSC conversion sites are not selected through a random process. Simply comparing the before and after crash rate within the Treatment group will likely exaggerate the safety benefit of the AWSC conversion treatment.

1.7 Discussions

As the analysis revealed, Straight Hit Pedestrian crashes are significantly increased upon the conversion of AWSC. It is arguable that the increased Straight Hit Pedestrian crashes may be contributable by more pedestrians chose to cross at converted AWSC intersections as a result of

shifted crossing demands from adjacent intersections. One way to check the above assumption is to review the crash experience of those immediate adjacent intersections around converted sites for "spillover" effect. Therefore all intersections (a total of 192) within 500 feet radius of the converted AWSC intersections are selected as a secondary reference group. Similar to the construction of the reference group, the assumed conversion year of the associated AWSC intersection is assigned as the index year for each chosen secondary reference intersection. Three year before and three year after crash records are collected for all the secondary reference intersections. The collective before-and-after pedestrian related crashes of the secondary reference intersections are shown in Table 1-17.

Table 1-17 Pedestrian Related Crashes at Secondary Reference Intersections

Collision Type	**Three-Year Before**			**T-Test**	**P-Value**	**Three-Year After**		
	Total	**Mean**	**S.D.**			**Total**	**Mean**	**S.D.**
Backing Hit Pedestrian	3	0.02	0.124	0.000	1.000	3	0.02	0.124
Left Turn Hit Pedestrian	22	0.11	0.419	0.602	0.548	18	0.09	0.342
Right Turn Hit Pedestrian	5	0.03	0.160	0.000	1.000	5	0.03	0.160
Straight Hit Pedestrian	22	0.11	0.419	0.437	0.663	19	0.10	0.363
All Pedestrian Related Crashes	52	0.27	1.121	0.615	0.539	45	0.23	0.988

T-Tests are conducted for each pair of three-year before and three-year after pedestrian crash types. The corresponding two-tailed p-values are all greater than 10%. I conclude that the mean differences of three-year before and three-year after pedestrian crashes are not different from zero. Therefore it appears that the before and after crash experience are relatively stable at the secondary reference group, which shows no evidence of systematic shifting of crossing pedestrians towards the converted AWSC intersections.

Utilizing statistical analysis techniques and econometrics identification strategies, such as Multiway ANOVA and DID, I reduced estimation bias induced by selection bias and time trends. The estimation results using different identification strategies are generally consistent and the panel data DID analysis appears to be the most efficient method. Different from the conventional before-and-after study, the regression analysis only reveals statistically significant reductions of Right Angle crashes upon AWSC conversions. However, for all the other collision types, including Right Turn, Left Turn, Rear End, Sideswipes and Bicycle crashes, no statistically significant coefficients are estimated. Aggregately, the AWSC conversion treatment effect to all crashes, fatal/injury crashes and all pedestrian related crashes are not statistically significant, either.

Controversially, the study quantified a significant increase of Straight Hit Pedestrian crashes at the magnitude of 0.17 to 1.54 crash/year upon AWSC conversion using different methods. One possible explanation would be that it is likely contributable to pedestrian's false perception of safety by having AWSC installed at intersections. It is critical to enhance crossing pedestrian visibility at stop sign controlled intersections with countermeasures such as installing high visibility crosswalk markings and pedestrian crossing warning signs, eliminating parking spots close to crosswalks, installing bulb-outs or raised crosswalks, etc. Since pedestrians are always the more vulnerable party involved in a Straight Hit Pedestrian crash, educational campaigns that encourage pedestrians to diligently checking oncoming traffic before stepping off the curb would be helpful. The last but not the least, improving Stop sign compliance through enhanced enforcement programs will definitely help reduce such tragedies.

One caveat of the study is due to lack of complete traffic exposure information, especially on local roads. In retrospect, the study could be more robust if historical traffic exposure information was available. It would help the public agencies to make more informative decisions if consistent traffic data collection program could be implemented to gather multi modal traffic data information.

However, it is not a straightforward task to plausibly incorporate traffic volume exposures into analytical framework at intersections. For example, whether the sum, the product or some other function form of the major road traffic volume and the minor road traffic volume more representable as the appropriate measure of traffic exposure is not a trivial question (Satterthwaite, 1981). It is at risk to have incorrect right hand function form if traffic exposures were to be incorporated into estimation. On the other hand, with the quasi-experimental study design, traffic volume exposure changes associated with time trend has been addressed to some degree and the recent year overall traffic growth is minimal in D.C. area anyway (according to MWCOG TPB, the 2015total vehicle-miles traveled on area roads was just 1% higher than in 2007[1].). Therefore, not including traffic volume exposure information may not necessarily undermine the creditability of the study.

[1] TPB News, Population up, but area travel holding steady, https://www.mwcog.org/about-us/newsroom/2016/04/26/population-up-but-area-travel-holding-steady, *accessed on 1/11/2019*

Chapter 2: Evaluating the Safety Effect of Removing Reversible Arterial Roadways in Washington D.C.

2.1 Introduction

A reversible lane is a lane in which traffic may travel in either direction depending on regulations. Typically, a reversible lane system is used to improve traffic throughput by allocating lane(s) to accommodate peak period traffic flow without the need for expanding roadway cross sections. The direction of travel in the shared lane varies by time of day or day of week (Wolshon and Pande, 2016). It is deemed to be one of the most cost effective methods to maximize the utility of existing infrastructure capacity to cope with congestions caused by unbalanced tidal traffic flows (Wolshon and Lambert, 2004). However, due to its unconventional setup, a reversible lane operation may induce operational challenges and safety concerns. Moreover, increased throughput capacity is not always favorable from a local community's perspective. As Banister stated, a certain level of congestion on roads is "desirable" in many locations (e.g. residential streets and around schools) (Banister, 2008). People may potentially consider stop for shopping or dining before heading directly back to home from work in order to avoid peak congestions and thus bring more revenue to local businesses. Additionally, reversible lane systems could potentially impose challenges to crossing pedestrians (Dey et al., 2011).

For about 90 years, different forms of reversible roadways have been utilized throughout the world involving reversible/convertible lanes, managed lanes and contraflow operations. Within the U.S., at least 21 states have reversible lane systems in operation[2]. The existing reversible lane systems are implemented using a wide variety of strategies. Guidelines for design and control of

[2] "Reversible lane", Wikipedia, accessed on July 26th, 2017.

reversible lane systems in terms of geometry layout, traffic control devices (signals, signs) and pavement markings are highlighted in both the *A Policy on Geometric Design of Highways and Streets* (*a.k.a* the *Green Book*) (AASHTO, 2011) and the Manual on Uniform Traffic Control Devices (MUTCD) (FHWA, 2009). Generally, pavement markings, signs and overhead signals are deployed to inform the roadway users regarding the effective lane usage assignment. However, road users may be afraid of "driving on the wrong side" and exhibit erratic driving behaviors, especially along the transitional sections where the reversible lane system connecting with regular roadways. As a result, more frequent rear-end, sideswipe and even head-on crashes may be observed. Additionally, left turning movements either from the main street or from the side streets may find the movements more challenging (Markovetz et al., 1995).

Despite the long history and wide geographic spread of reversible lane systems, there have been limited quantitative studies on their safety impacts. Wolshon (Wolshon and Lambert, 2004) synthesized several safety studies ((Markovetz et al., 1995), (DeRose et al., 1996), (Upchurch, 1975), (Agent and Clark, 1982)) that have identified higher Left Turn and Head-on crash rates associated with reversible lane operations. A before-after analysis with shorter time-span (one to two years) data is typically used in these studies. Wolshon also pointed out the lack of studied safety effects to pedestrian activities along reversible lanes (Wolshon and Lambert, 2004). Contrary to the popular sentiment of perceived unsafe reversible lane systems, Golub found the crash rate along reversible lanes in the City of Phoenix was not significantly different from comparable streets (Golub, 2012). Given the limited studies with mixed results, this paper aims to fill the knowledge gap of safety impact due to the use of the reversible lane systems using data collected in D.C.

2.2 Background

In D.C., reversible lane systems are implemented to improve traffic flow and reduce congestions during rush hours in corridors that accommodate predominately commuter traffic (Dey et al., 2011). As shown in Table 2-, D.C. operated eleven roadway segments with reversible lanes, while three of them were terminated in 2010 upon evaluation. The total length of the currently operated reversible lane system is about 8.5 miles, which is less than one percent of the total length of roadways under the D.C.'s jurisdiction.

The existing reversible lane systems in D.C. vary by roadway functional classification, lane split, length, operation duration and traffic control strategy. On the Theodore Roosevelt Bridge, which is a part of Interstate 66, movable concrete barriers separate directional traffics. Rock Creek and Potomac Parkway and a part of Canal Road are converted to full one-way operation along peak directions with limited access. Due to aesthetics concerns, overhead signage or signal controllers are precluded as viable traffic control devices for reversible lane systems in D.C. (Dey et al., 2011). As a result, all the remaining reversible lane systems in D.C. are implemented in their most simplistic form with only pavement markings (as shown in Figure 2-1) and roadside signage (static or dynamic, as shown in Figure 2-2). Pavement markings typically include dashed double yellow lines and transition arrows. Roadside signage specifies in a graphic or descriptive text format the lane use configurations during certain time periods.

Figure 2-1 Typical Reversible Lane Roadway Pavement Marking

Figure 2-2 Typical Static and Dynamic Reversible Signs used in D.C.

During peak periods, on-street parking is restricted along the reversible principal arterials to maximize the available paved surface for traffic thoroughfare usage. Turning restrictions may be imposed on some side streets to avoid the conflicts of certain movements.

Dey et al. identified anecdotally a higher propensity of Head-on and Sideswipe crashes along reversible Connecticut Avenue compared with conventional non-reversible Wisconsin Avenue and Massachusetts Avenue (Dey et al., 2011). Nevertheless, the termination of reversible lane operations along Constitution Avenue, NE, Pennsylvania Avenue, SE and Fifteenth Street, NW in 2010 provides a good opportunity to assess the safety impact of reversible lane systems using more rigorous quantitative methods.

Table 2-1 Reversible Lane System in DC

Road Name	Start	End	Lane Split	Duration	Length (feet)	Traffic Control Device	Functional Class
Canal Road, NW	Chain Bridge	Arizona Ave, NW	2:1	6:15 – 10:00 am 2:45 – 7: 15 pm	2,500	Sign, VMS, Pavement Marking	Expressway
Canal Road, NW	Arizona Road, NW	Foxhall Road, NW	2:0	6:15 – 10:00 am 2:45 – 7: 15 pm	3,000	Sign, Pavement Marking	Principal Arterial
Chain Bridge	Canal Road, NW	DC Line	2:1	6:15 – 10:00 am 2:45 – 7: 15 pm	1,500	Sign, Pavement Marking	Principal Arterial
Connecticut Ave, NW	Legion Street, NW	Woodley Road, NW	4:2	7:00 – 9:30 am 4:00 – 6:30 pm	14,600	Sign, Pavement Marking	Principal Arterial
Independence Ave, SW	Washington Ave SW	2nd St, SE	3:1	4:00 – 6:30 pm	2,900	Sign, VMS, Pavement Marking	Principal Arterial
16th St, NW	Arkansas Ave, NW	Irving St, NW	3:2	7:00 – 9:30 am 4:00 – 6:30 pm	3,900	Sign, VMS, Pavement Marking	Principal Arterial
Rock Creek and Potomac Pkwy (NPS)	Connecticut Ave, NW	I-66	4:0	6:45 – 9:30 am 3:45 – 6: 30 pm	13,500	Sign, Pavement Marking, Enforcement	Principal Arterial
Theodore Roosevelt Bridge	Rock Creek and Potomac Pkwy	George Washington Memorial Pkwy	4:3	6:00 – 11:00 am	3,000	Sign, Pavement Marking, Movable Barriers	Interstate
Constitution Avenue, NE[a]	N. Carolina Ave, NE	3rd St, NE	2:0	7:00 – 9:30 am	4,900	Sign, Pavement Marking	Minor Arterial
Pennsylvania Avenue, SE[a]	Branch Ave, SE	27th St, SE	3:2	4:00 – 6:30 pm	2,700	Sign, Pavement Marking	Principal Arterial
15th Street, NW[a]	K St, NW	Massachusetts Ave, NW	6:0	4:00 – 6:30 pm	1,500	Sign, Pavement Marking	Principal Arterial

a. Eliminated reversible lane operation in 2010

2.3 Crash Modification Factor

A crash modification factor (CMF) is used to calculate the expected number of crashes after implementing a safety countermeasure on roadways (AASHTO, 2010). Or, CMF can be computed as the ratio of the expected number of crashes with implementing a safety countermeasure to the expected number of crashes without implementing that safety countermeasure. Several attributes can be used to associate a CMF with a given scenario including safety countermeasure type, roadway type, area type, road segment or intersection geometry, road segment or intersection traffic control, traffic volume, and the locality from which the CMF was developed (AASHTO, 2010). However, estimating the expected number of crashes before/after or with/without implementing a safety countermeasure is not a trivial task. Carefully designed studies are necessary to properly estimate CMF's.

To estimate crashes with treatment (assuming the countermeasure of interest is implemented) using CMF, the safety performance without treatment has to be estimated. The Highway Safety Manual (HSM) presents several methods for estimating the safety performance of a roadway or an intersection (AASHTO, 2010). The most straightforward method for estimating crashes without treatment is to compute the long-term (i.e., 5+ years) average crash frequency before treatment. More rigorously, the number of crashes without treatment could be estimated using an untreated control group of sites similar to the treated ones to account for irrelevant changes to the treatment such as traffic volume, technology and demographic changes. Alternatively, the Empirical Bayes (EB) method, as described in the HSM (AASHTO, 2010), is a rigorous method for estimating crashes without treatment as the method combines information from the site of

interest with information from other comparable sites and the method could potentially address the regression-to-the-mean issue (Gross et al., 2010).

2.4 Methodology

2.4.1 Before-After Study with a Control Group

A control group is used to calculate the ratio of observed crash frequency in the after period to that in the before period. The observed crash frequency in the before period at a treatment site group is multiplied by this comparison ratio to estimate expected crashes had no treatment been implemented. This is then compared to the observed crashes in the after period at the treatment site group to estimate the safety effects of the treatment. (Gross et al., 2010)

The expected number of crashes for the treatment group had no treatment been implemented during the after period is estimated from Equation (2-1):

$$N_{exp,T,a} = N_{obs,T,b}\left(N_{obs,C,a}/N_{obs,C,b}\right) \quad (2\text{-}1)$$

where,

$N_{exp,T,a}$= the expected number of crashes for the treatment group had no treatment been implemented during the after period,

$N_{obs,T,b}$= the observed number of crashes of the treatment group during the before period,

$N_{obs,C,a}$= the observed number of crashes of the control group during the after period,

$N_{obs,C,b}$= the observed number of crashes of the control group during the before period (AASHTO, 2010).

Crashes are stochastic and relatively rare events (thankfully). The total number of crashes at a site is expected to change with or without the implementation of a safety treatment, the regression-to-the-mean issue persists if there is site selection bias. A Before-After (BA) study with a control group does not account for regression-to-the-mean unless treatment and control sites are matched on the basis of crash occurrence besides sharing similar physical traits. A perfect control group is one where the ratios of expected crash counts in the after period to the expected crash counts in the before period are equal to the treatment group, had no treatment been implemented (Gross et al., 2010). Unfortunately, such ratios would not been known since the treatment has been implemented. Therefore, it is critical to determine whether a control group is considered suitable.

The suitability of a control group can be gauged by checking the time series of the historical crash rate of the treatment group and candidate control group, with similar trend lines indicating more suitable control groups. Hauer proposed a quantitative approach, the odds ratio test, to check the suitability of candidate control groups (Hauer, 1997).

$$sample\ odds\ ratio_{i,j} = \frac{n_{T,i}n_{C,j}/n_{T,j}n_{C,i}}{1+\frac{1}{n_{T,j}}+\frac{1}{n_{C,i}}} \quad (2\text{-}2)$$

where,

$n_{T,i}$=number of crashes of the treatment group in year *i*,

$n_{T,j}$=number of crashes of the treatment group in year *j*,

$n_{C,i}$=number of crashes of the control group in year *i*,

$n_{C,j}$=number of crashes of the control group in year *j*.

The sample odds ratios are computed for each treatment-control pair in the time series before the treatment is implemented. From this sequence of sample odds ratios, the sample mean and standard error are determined. If this sample mean is sufficiently close to 1.0, the candidate control group is deemed suitable.

Additional requirements for a suitable control group, as outlined by Hauer, include:

- Symmetric before and after time periods for the treatment and control groups;
- The changes in factors other than the treatment under study (e.g., changes in traffic volume, technology and demographic) are similar in the treatment and control groups; and
- Sufficiently large sample size of observed crashes. (Hauer, 1997)

It is worth noting though that suitable control groups may not easy to be identified in reality.

Assuming the control group is suitable, the variance of $N_{exp,T,a}$ can be estimated approximately by Equation (2-3).

$$Var(N_{exp,T,a}) = {N_{exp,T,a}}^2 \left(\frac{1}{N_{obs,T,b}} + \frac{1}{N_{obs,C,b}} + \frac{1}{N_{obs,T,a}}\right) \quad (2\text{-}3)$$

where,

$N_{obs,T,a}$= the observed number of crashes of the treatment group during the after period (Hauer, 1997).

Consequently, the CMF and its variance, which are adjusted by the estimation dispersion, can be estimated from Equations (2-4) and (2-5) (Hauer, 1997).

$$CMF = \frac{N_{obs,T,a}/N_{exp,T,a}}{1+\frac{Var(N_{exp,T,a})}{N^2_{exp,T,a}}} \quad (2\text{-}4)$$

$$Var(CMF) = \frac{CMF^2\left(\frac{1}{N_{obs,T,a}}+\frac{Var(N_{exp,T,a})}{N^2_{exp,T,a}}\right)}{\left(1+\frac{Var(N_{exp,T,a})}{N^2_{exp,T,a}}\right)^2} \quad (2\text{-}5)$$

2.4.2 Empirical Bayes Method

The Empirical Bayes (EB) method is used to combine the estimation from a predictive model with observed crash data to obtain a more reliable estimation of the expected average crash frequency (AASHTO, 2010). The objective of the EB method is to more precisely estimate the number of crashes that would have occurred at a treated site during the after period had a treatment not been implemented (Gross et al., 2010). Details about the development of the EB method are summarized by Hauer (Hauer, 1997).

The EB method produces an estimate of the expected average crash frequency that combines the model prediction and the site-specific crash data in proportion to the level of certainty that can be attached to each (AASHTO, 2010). Due to the stochastic nature of crashes, if in one year a particular site experienced a disproportionally higher crash rate, in the following year this site's crash rate is expected to be lower even without the implementation of any safety treatments. This issue in statistics is called regression-to-the-mean. The safety effect of a treatment countermeasure may be random rather than fixed if heterogeneity (over time, space, or individuals) exists in the unobserved factors that are related to the treatment countermeasure (Mannering et al., 2016). The advantage of the EB approach is that it accounts for observed

changes in crash frequencies before and after a treatment that may be due to regression-to-the-mean or unobserved heterogeneity (Gross et al., 2010).

Similarly to the BA study method, a control group comparable to the treatment group are required for the EB method. However, the data from the control group are first used to estimate a safety performance function (SPF) that relates crash experience of the sites to their traffic and physical characteristics. One typical SPF for roadway segments is as specified in Equation (2-6).

$$Crashes\ per\ year = L \times \exp(\alpha + \beta \times ln[c \times AADT \times f_R]) \quad (2\text{-}6)$$

where,

L = the length of the roadway segment,

AADT = the Average Annual Daily Traffic volume along the roadway segment,

f_R = AADT adjusted factor accounting for actual reversible lane operation time,

c = AADT scale coefficient, typically equals to 0.001,

α and β are parameters to be estimated.

To account for regression-to-the-mean, the number of crashes expected in the before period without the treatment ($N_{exp,T,b}$) is a weighted average of the number of crashes observed in the before period at the treated sites ($N_{obs,T,b}$) and the number of crashes predicted at the treated sites ($N_{pre,T,b}$). Specifically,

$$N_{exp,T,b} = W_{SPF}\left(N_{pre,T,b}\right) + (1 - W_{SPF})\left(N_{obs,T,b}\right) \quad (2\text{-}7)$$

where,

W_{SPF} is the weight of SPF estimation, which is derived by the over-dispersion parameter from the SPF calibration process (Hauer, 1997). The weight also depends on the number of years of crash record in the before period. In general, the SPF weight is reduced if many years of crash records are used. W_{SPF} can be calculated using Equation (2-8).

$$W_{SPF} = \frac{1}{1+k\times\sum_Y N_{pre,T,b}} \quad (2\text{-}8)$$

where,

k = overdispersion parameter from the associated SPF function,

Y = all study years (AASHTO, 2010).

The expected number of crashes for the treatment group had no treatment been implemented during the after period using the EB method is estimated from Equation (2-9):

$$N_{exp,T,a} = N_{exp,T,b}\left(N_{pre,T,a}/N_{pre,T,b}\right) \quad (2\text{-}9)$$

where,

$N_{exp,T,a}$= the expected number of crashes for the treatment group had no treatment been implemented during the after period,

$N_{exp,T,b}$= the expected number of crashes of the treatment group during the before period,

$N_{pre,C,a}$= the predicted number of crashes by the SPF of the treatment group during the after period,

$N_{pre,C,b}$= the predicted number of crashes by the SPF of the treatment group during the before period (Gross et al., 2010).

The variance of $N_{exp,T,b}$ can be estimated by Equation (3-10) (AASHTO, 2010).

$$Var(N_{exp,T,a}) = N_{exp,T,a}(1 - W_{SPF}) \quad (2\text{-}10)$$

Equations (2-4) and (2-5) remain applicable for CMF using the EB method (Gross et al., 2010).

2.5 Data

Three reversible lane arterials in D.C., including Constitution Avenue, NE (between North Carolina Ave, NE and Third St, NE), Pennsylvania Avenue, SE (between Branch Ave, SE and 27th St, SE) and Fifteenth Street, NW (between K St, NW and Massachusetts Ave, NW), were terminated in 2010 upon evaluation. Since the aforementioned three roadway segments are all urban arterials, facilities that can potentially be considered as candidate control group subjects are limited within Connecticut Ave, NW (between Legion Street, NW and Woodley Road, NW), Independence Ave, SW (between Washington Ave SW and Second St, SE) and Sixteenth St, NW (between Arkansas Ave, NW and Irving St, NW). Rock Creek and Potomac Pkwy (between Connecticut Ave, NW and I-66) was excluded from consideration as a candidate control group subject since it operates as a one-way road rather than two-way like the others during reversal operation, its surrounding land use is significantly different from the other facilities and it is operated under the jurisdiction of National Park Services (NPS) rather than DDOT.

Crash records were retrieved from DDOT's Traffic Accident Reporting and Analysis System (TARAS 2.0) Crash Management System between January 1st, 2003 and December 30th, 2017. So the before and after study periods were balanced at 2010, the year when the treatment of eliminating reversible lane operation was implemented.

Recognizing the spillover effect of reversible lane operations, the crash experience may be affected by reversible lane operation during the transitional shoulder periods as well. However, it is arbitrary to define a clear-cut transitional shoulder period for analysis purposes. Therefore, the crash records used for analysis were limited within just the official reversible operation hours only for consistency. Table 2 shows the total number of crashes occurred during the reversible lane operation periods on each of the above six facilities per year from 2003 to 2017. Traffic volumes were obtained from DDOT's published Annual Average Daily Traffic (AADT) maps. The annual crash rates were calculated per the FHWA's recommended equation by dividing the number of crashes by the measure of traffic exposure, as shown in Equation (2-11).

$$Annual\ Crash\ Rate = \frac{Number\ of\ Crashes}{AADT \times f_R \times segment\ length \times 365/1{,}000{,}000} \quad (2\text{-}11)$$

where f_R is an AADT adjusted factor, ranging from 0.15 to 0.35, which is calculated based on available 15-minute interval traffic volume count and the actual reversible lane operation schedule on each facility.

Figure 2-3 shows the time series of annual crash rate per facility of the six roadway segments in D.C. The crash rates generally decreased on Constitution Avenue, NE and Pennsylvania Avenue, SE right after the treatment year of 2010. The crash rates on the other facilities exhibit some volatilities throughout the study time, without a generally upward or downward trend.

Obviously, the Fifteenth Street, NW, which tends to have a significantly higher crash rate than the others, is an outlier in the cohort. The Fifteenth Street, NW (between K St, NW and

Massachusetts Ave, NW) is a relatively short roadway segment, about 1500 feet in total length. A significant portion of this roadway segment can be considered as transitional areas, where the operational characteristics and crash experiences would likely be drastically different from the regular reversible lanes (Lathrop, 1972). The Constitution Avenue, NE (between North Carolina Ave, NE and Third St, NE) segment is classified as a minor arterial road which operated in one-way during reversal operation, unlike all the control group subjects that are operated in two-way. For the above reasons, the Fifteenth Street, NW and Constitution Avenue, NE segments were excluded from the treatment group for further analysis. As a result, only the Pennsylvania Avenue, SE segment was left in the treatment group. The study was then precisely focused on the safety effectiveness of removing split reversible lane operation along urban principal arterials.

Table 2-2 Numbers of Crashes during Reversible Lane Operation Periods by Facility (2003-2009)

Facility	Years Before Treatment						
	2003	2004	2005	2006	2007	2008	2009
Connecticut Ave, NW	74	105	126	116	114	98	99
Independence Ave, SW	0	17	11	9	7	10	5
16th St, NW	32	39	28	35	25	32	27
Constitution Ave, NE	4	7	13	6	14	12	13
Pennsylvania Ave, SE	12	19	30	20	16	25	22
15th St NW, NW	7	12	12	9	11	6	7

Table 2-3 Numbers of Crashes after Reversible Lane Removal Periods by Facility (2011-2017)

Facility	Years After Treatment						
	2011	2012	2013	2014	2015	2016	2017
Connecticut Ave, NW	93	103	87	95	114	107	132
Independence Ave, SW	0	7	0	0	6	11	13
16th St, NW	41	38	41	39	42	41	38
Constitution Ave, NE	7	1	4	3	2	7	5
Pennsylvania Ave, SE	9	10	11	5	11	7	10
15th St NW, NW	4	12	7	16	9	4	3

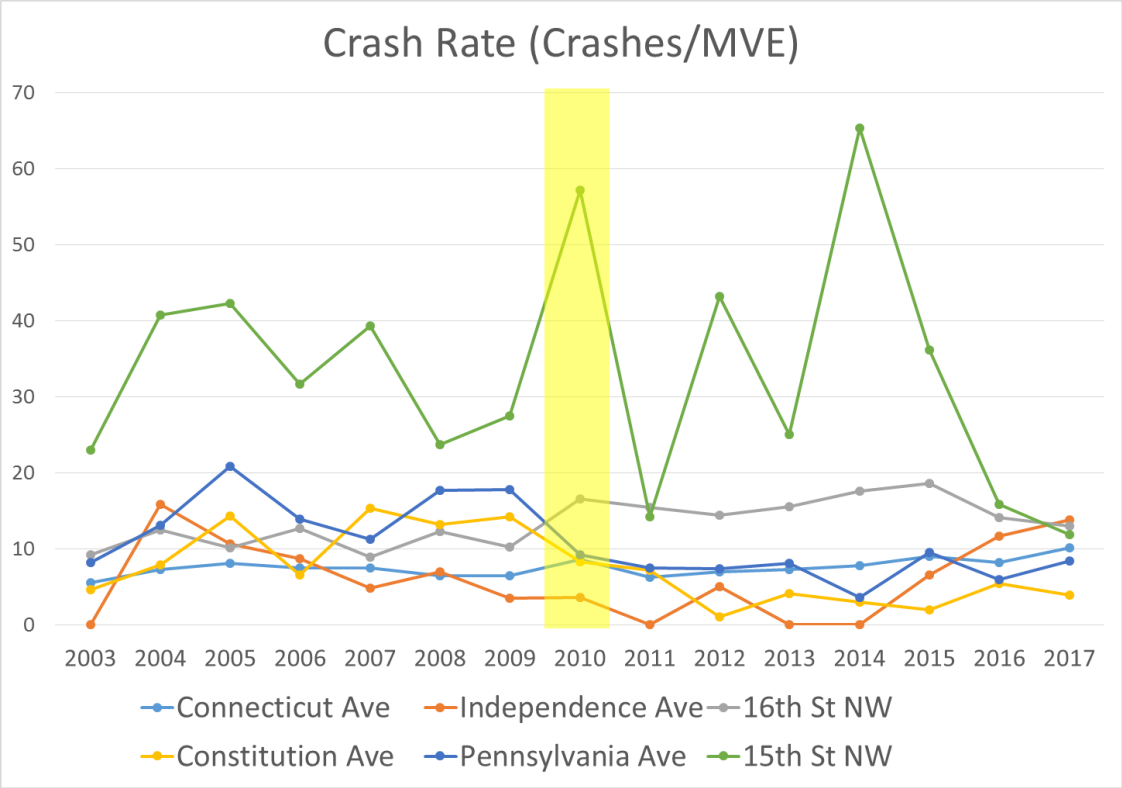


Figure 2-3 Crash Rate (Crashes/MVE) by Facility (2003 - 2017)

Figure 2-4 shows the average crash rate of the treatment group (excluding Fifteenth Street, NW and Constitution Avenue, NE data) versus the control group from 2003 to 2017. It appears that the crash rates of the treatment group are generally higher than these of the control group before the treatment year of 2010. Following 2010, the crash rates of the treatment group seems to become lower than these of the treatment group.

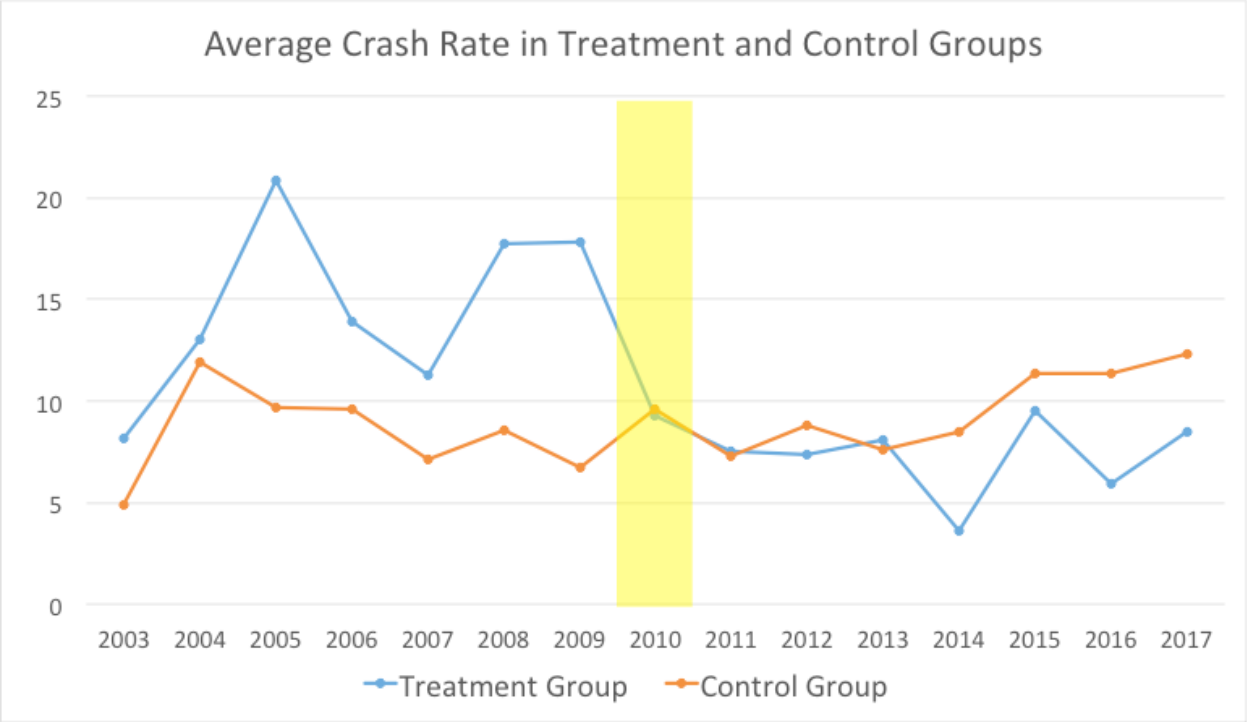


Figure 2-4 Average Crash Rate in Treatment and Control Groups

The sample odds ratios testing results are shown in Table 2-4. It appears the chosen control group is suitable according to Hauer's guideline (Hauer, 1997).

Table 2-4 Sample Odds Ratio Tests before the Treatment Year

Year	2003	2004	2005	2006	2007	2008	2009	Mean	S.E.	95% CI	
Odds Ratio	1.18	0.45	1.27	0.76	0.64	0.67	2.18	1.02	0.22	0.58	1.46

Table 2-5 shows the descriptive statistics of annual crashes by severity for each of the six reversible lane systems in D.C. based on crash records from 2003 to 2017.

Table 2-5 Descriptive Statistics of Annual Crashes by Severity (2003 – 2017)

Facility	All		Fatal/Injury		PDO	
	Mean	S.E	Mean	S.E	Mean	S.E
Connecticut Ave NW	106	3.99	30	2.34	76	3.60
Independence Ave SW	7	2.29	1	1.03	6	2.12
16th St NW	36	2.41	11	1.80	25	2.13
Constitution Ave NE	7	2.05	3	1.77	4	1.50
Pennsylvania Ave SE	15	2.68	5	1.85	10	2.16
15th St NW	9	1.97	3	1.38	6	1.77

Due to a substantial change of the Metropolitan Police Department (MPD) of D.C. crash-reporting format, not all previously available crash types are reported after 2015. To maintain the consistency and symmetry of data, two before year data (2003 and 2004) are dropped from some crash type specific analysis accordingly. Table 2-5 shows the descriptive statistics of the crashes by type for each of the six reversible lane systems in D.C. based on crash records between 2005 and 2015.

Figure 2-5 shows a radar chart of the percentage of crashes during reversible operation periods by crash type between 2005 and 2015. It is found that the consolidated Back-up, Rear-end, Sideswipe and Left Turn crashes are the mostly pronounced crash types observed on these reversible lane systems in D.C. This phenomenon seems to be explainable by anticipated driving behaviors along reversible lane systems. For example, drivers entering wrong lanes may take corrective measures, such as backup, to cause backup crashes. Drivers who are confused about lane use configuration may slow down abruptly and increase the chances of rear-end crashes. Drivers concerned about moving violations along reversible lanes tend to stay away from the problematic lanes (Dey et al., 2011), which will cause imbalanced lane utilization ratio and may induce a surge of same direction Sideswipe crashes due to frequent and inattentive lane changing. Left Turn crashes involving reversible lane systems are elaborated in detail in Markovetz's study (Markovetz et al., 1995). A further in-depth review of narratives on MPD's PD-10 Traffic Crash Reports eliminated the alleged causality between backup crashes and reversible lane operations as most backup crashes occurred on adjacent parking lots or parking lanes. Furthermore, the crash narratives suggest that a number of left turn crashes are attributable to reversible lane operation since at-fault drivers turned from the middle lane rather than the

leftmost lane when reversible lane operation was in effect. Moreover, sideswipe crashes are mostly contributable to lane changing maneuvers.

Table 2-6 Descriptive Statistics of Annual Crashes during Reversible Operation Periods by Type (2005-2015)

	Connecticut Ave		Independence Ave		16th St		Constitution Ave		Pennsylvania Ave		15th ST	
Crash Type	**Mean**	**S.E.**	**Mean**	**S.E.**	**Mean**	**S.E.**	**Mean**	**S.E.**	**Mean**	**S.E.**	**Mean**	**S.E.**
Back Hit Moving Veh.	3	1.89	1	0.00	2	0.98	0	0.00	2	0.82	2	0.71
Back Hit Parked Veh.	5	1.56	1	0.00	1	0.52	1	0.50	2	0.71	2	1.32
Back Hit Ped.	2	0.92	0	0.00	1	0.00	1	0.00	1	0.00	2	0.00
Back Hit Stopped Veh.	1	0.00	2	0.00	1	0.00	0	0.00	1	0.58	1	0.58
Fixed Object	3	1.70	3	1.41	2	0.71	1	0.53	3	1.75	1	0.79
Head On	4	1.66	2	0.71	2	0.79	2	1.17	2	1.57	2	0.52
Left Turn Hit Ped.	4	2.50	2	0.71	2	0.88	1	0.00	1	0.00	2	1.03
Left Turn Hit Veh.	43	11.82	2	1.19	8	4.00	3	2.48	8	5.48	5	3.10
Non-Collision Accident	1	0.82	1	0.00	2	0.71	1	0.00	1	0.00	1	0.00
Other	16	10.20	2	1.00	2	1.01	3	2.43	3	2.42	3	1.27
Parked Vehicle	8	3.38	1	0.50	5	2.41	2	0.82	1	0.00	2	0.88
Ran Off Roadway	1	0.45	1	0.00	1	0.00	1	0.00	2	1.06	1	0.00
Rear End	54	11.86	8	5.87	25	7.95	5	1.59	2	0.58	9	2.26
Right Angle	22	7.34	2	0.79	10	5.72	10	7.33	20	6.08	4	2.40
Right Turn Hit Ped.	2	0.71	0	0.00	1	0.38	1	0.00	8	5.06	1	0.82
Right Turn Hit Veh.	6	1.55	3	1.94	4	1.79	1	0.00	1	0.00	4	1.56
Side Swiped	53	13.49	8	3.67	27	7.37	4	2.29	2	0.92	10	3.94
Straight Hit Ped.	4	2.39	2	1.10	3	1.64	2	0.82	18	6.33	1	0.73
Unknown	8	16.09	1	3.01	4	5.88	1	0.86	3	2.85	3	2.85

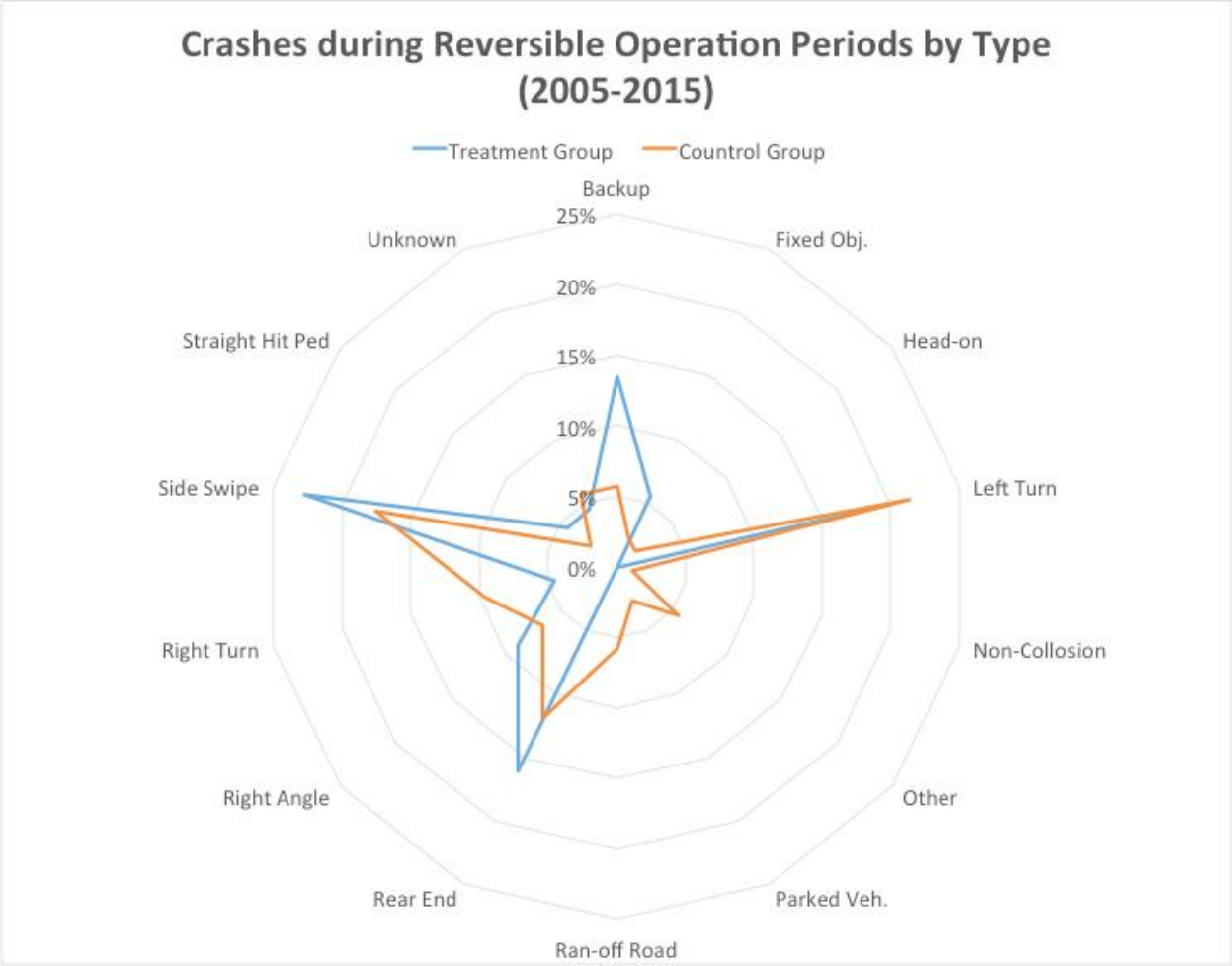


Figure 2-5 Radar Chart of Crash Percentage during Reversible Operation Periods by Type (2005-2015)

2.6 Results

Since the treatment group experienced, thankfully, too few Head-on and pedestrian/bicycle related crashes to support meaningful statistical inference analysis, only Left turn, Rear-end and Sideswipe crashes were analyzed individually in addition to crash counts by severity. Table 2-7 shows the estimated CMF's by crash type. Note that crashes were consolidated (i.e., only those potentially attributable to reversible lane operations were include), and therefore, more pronounced changes were observed along the selected roadway segments than described previously.

The results of the BA study with a control group showed an overall crash reduction of 46% after eliminating the reversible lane operation. Similarly, a reduction of 57% of fatal and injury crashes and a reduction of 43% of PDO crashes were found after eliminating the reversible lane operation. All above reductions are statistically significant at the 95% confidence level. The results revealed that Left Turn and Sideswipe crashes would be significantly reduced without the reversible lane operation. However, the safety effect for Rear-end crashes upon the termination of reversible lane operation remained inconclusive since one is within the estimated bounds of 90% or 95% CI of its CMF.

Table 2-7 CMF by Crash Type using Before-After Study with a Control Group

Crash Type	CMF	S.E. (CMF)	95% CI		90% CI	
All	0.54	0.13	0.29	0.79	0.33	0.75
Fatal/Injury	0.43	0.17	0.09	0.77	0.15	0.72
PDO	0.57	0.16	0.26	0.87	0.31	0.82
Left Turn[b]	0.02	0.02	-0.02	0.07	-0.01	0.06
Rear-End[b]	0.62	0.30	0.04	1.20	0.13	1.11
Side Swipe	0.50	0.20	0.11	0.90	0.17	0.84

b. Because of MPD crash data reporting issue, only crashes in 05-09 as before period and 11-15 as after period are used for calculation

Due to the stochastic nature of crashes, the issue of regression-to-the-mean persists in the BA study with a control group method. Rather, the EB approach can account for observed changes in crash frequencies before and after a treatment that may be due to regression-to-the-mean.

As the first step of the EB method, SPF's were estimated using the control group data. Table shows the estimation results of SPF's using STATA (Long and Freese, 2014). The estimated coefficients, standard errors and z-test values as well as log-likelihood value are reported for all crashes and PDO crashes only. Based on the SPF estimation results, the weights W_{SPF} used to calculate EB crash estimate were calculated from the over-dispersion parameter. Implicitly, the

SPF for Fatal/Injury crashes is the difference between the SPF's of all crashes and PDO crashes. SPF's for all the other specific crash types were estimated by multiplying their respective long-term proportion to all crashes and the SPF of all crashes. The long term proportions of Left Turn, Rear-end and Sideswipe crashes, in the control group, are 24.8%, 17.0% and 26.7%, respectively.

Table 2-8 SPF Estimation Results by Crash Type[c]

Crash Type	Para.	Coef.	S.E.	Z	P>|Z|	95% CI		Log Likelihood	W_{SPF}
All	α	0.99	0.54	1.84	0.07	-0.06	2.04	-192.14	0.25
	β	1.09	0.23	4.68	0.00	0.63	1.55		
PDO	α	1.09	0.46	2.34	0.02	0.18	2.00	-174.72	0.16
	β	0.90	0.20	4.53	0.00	0.51	1.30		

c. Coefficients are estimated using STATA's Negative Binomial Regression Model "nbreg" function (Long and Freese, 2014).

Essentially, the EB estimate is a weighted combination of the observed crashes during the before period at the treated sites and the predicted number of crashes at the treated sites based on information obtained from the control group with similar characteristics. In this way, estimating the crash for before period at the treatment sites is less susceptible to site selection bias and thus, the risk of overstating the safety benefit of a particular safety countermeasure would be mitigated.

According to Table 2-9, the results of the EB study showed an overall crash reduction of 45% after eliminating the reversible lane operation. Similarly, a reduction of 49% of fatal and injury crashes and a 46% reduction of PDO crashes were found after eliminating the reversible lane operation. All of the above reductions are statistically significant at the 95% confidence level. The results revealed that Left Turn and Sideswipe crashes would be significantly reduced without the reversible lane operation. However, the safety effect for Rear-end crashes upon the termination of reversible lane operation remained inconclusive.

Table 2-9 CMF by Crash Type using EB Method

Crash Type	CMF	S.E. (CMF)	95% CI		90% CI	
All	0.55	0.08	0.40	0.69	0.42	0.67
Fatal/Injury	0.51	0.13	0.26	0.76	0.30	0.72
PDO	0.54	0.09	0.36	0.71	0.39	0.68
Left Turn[b]	0.04	0.04	-0.04	0.13	-0.03	0.11
Rear-End[b]	1.05	0.35	0.38	1.73	0.49	1.62
Side Swipe	0.53	0.14	0.26	0.79	0.31	0.75

b. Because of MPD crash data reporting issue, only crashes in 05-09 as before period and 11-15 as after period are used for calculation

Note a CMF is supposed to be a non-negative factor. The negative lower bound of a confidence interval for left turn CMF is due to minimal observed number of left turn crashes during the after period and it only has statistical significance, but no factual connections with reality.

Overall, the EB estimations are consistent with the BA study with control group, but are more statistically significant with narrower confidence intervals.

2.7 Summary

The safety effect of removing reversible lane operation in its most simplistic form (i.e., with only pavement marking and roadside signage) along urban principal arterials has been assessed using a BA study with a control group method as well as with the EB method.

Based on the historical crash records and traffic data from 2003 to 2017 in D.C., the BA study with a control group showed after eliminating the reversible lane operation an overall crash reduction of 46%, a reduction of 57% of fatal and injury crashes and a reduction of 43% PDO crashes. The EB study showed an overall crash reduction of 45%, a reduction of 49% of fatal and

injury crashes and a 46% reduction of PDO crashes after eliminating the reversible lane operation. All of the above reductions are statistically significant at the 95% confidence level. However, the safety effects for Rear-end crashes upon the termination of reversible lane operation remain inconclusive according to either method. Yet the study results revealed that Left Turn and Sideswipe crashes would be significantly reduced without the reversible lane operation. Nevertheless, it is worth noting that the reduction of Left Turn crashes is not only attributable to the elimination of reversible lane operation but also contributable to enhanced left turn storage lane and exclusive left turn signal phasing. Therefore, the estimated CMF should be interpreted with caution, and probably needs to be adjusted on a case-by-case basis.

As described earlier, the roadway segments in the treatment group were not chosen as a result of random selection, but rather through an evaluation process. However, the EB method smoothed out the regression-to-the-mean issue. Moreover, the suitability of the control group selection seems to be justified through the odds ratio test. The safety effect of removing reversible lane operation appears to be statistically significant, taking regression-to-the-mean and heterogeneity into considerations.

This empirical study quantified the safety effect of removing reversible arterial roadways. The findings suggest a clear tradeoff between safety and the gain of peak direction capacity by operating reversible lanes along urban arterials. Generally, all crashes, including both PDO and fatal/injury crashes, are more substantial along reversible roadways. Moreover, Left Turn crashes caused by lane confusion and Sideswipe crashes related to lane changing maneuvers appear to be associated with reversible lane operations. The research results could be used for cost-benefit

analysis in planning studies for implementing reversible lane operations as a strategy to cope with imbalanced directional peak period traffics. Further studies on understanding the safety impacts of different traffic control devices and the safety performance in different zones along a reversible lane system (ie, approaching zone, switch-in zone, regular reversed lane zone, switch-out zone and departing zone, etc.) (Lathrop, 1972) are recommended.

Chapter 3: Developing an Equitable Approach for Curbside Loading Zone Allocation in Washington D.C.

3.1 Introduction

Many cities[3] in the U.S., including Washington D.C. (the District), allocate curb spaces for commercial loading zones largely at the discretion of the agency in charge and typically initiated by the requests from business owners and property managers. As the District continues its development sparked by the increase of city population, confronting the growing demand of freight trips and commercial vehicle pickup and delivery (PUD) activities in the District becomes one of the key issues. The District Department of Transportation (DDOT) attempts to develop a more proactive approach to allocate curbside loading spaces by creating a Loading Zone Allocation Model (LZAM) which incorporates detailed urban truck-trip generation methodology using business characteristics and delivery pattern data. The LZAM is used to analyze freight demand on a block-by-block basis, which leads to a comprehensive evaluation of the PUD demand against the amount of curbside commercial loading space available in the District. The

[3] City of Chicago, *Loading Zones*, http://www.cityofchicago.org/city/en/depts/bacp/sbc/loading_zones.html accessed July 18th, 2014;

Seattle Department of Transportation, *Loading Zones*, http://www.seattle.gov/transportation/parking/parkingload.htm accessed July 18th, 2014;

San Antonio-Bexar Metropolitan Planning Organization, *Downtown San Antonio On-Street Space Management Plan*. San Antonio , 2000;

DDOT, *Curbside Management Study*. Washington, D.C. 2014

model will be used to evaluate each loading zone request from a business owner or a developer or to proactively review existing curbside loading zone assignment and ultimately to establish an equitable, consistent, and repeatable process to uniformly evaluate curbside loading zone needs. This paper explains in details about how the demand driven LZAM is established for the District.

This chapter is structured as follows: in the Introduction section, the motivation of creating a quantitative LZAM for the District is outlined; in the Estimating Truck Trips Demand section, a literature review of Freight Trip Generation (FTG) methods is conducted and a series of formulas to quantify the truck demands are staged; in the Data section, the source of data, the ArcGIS tool for data management and post-processing and details about variables used in regression analysis are described; in the Regression Analysis section, the structure of a zero-truncated Negative Binomial (NB) model is introduced, the estimation results and the selection of the best fit model are shown; in the Application section, two numerical examples about how the model could be used to inform decision processes are illustrated and finally, in the Conclusion and Recommendation section, a summary of findings, limitation of the model and remarks of recommendations for further studies are presented to close the study out.

3.2 Estimating Truck Trip Demand

3.2.1 Freight Trip Generation Models

In general, truck models could be categorized into two groups: vehicle-based and commodity-based (Fischer et al., 2001). A vehicle-based FTG method usually involves regressing the number of truck trips per type on explanatory variables such as land use class, building floor area, employment data, etc. In contrast, a commodity-based FTG method usually starts from an estimation of economic activities including production and consumption of goods and then

converts the tonnage of shipments into number of truck trips. Holguín-Veras et. al (Holguín-Veras et al., 2011) distinguished these two types of truck models as FTG model for vehicle-based model and Freight Generation (FG) model for commodity based model. Under the context of on-street PUD activities, truck trip generation could be directly linked with FTG as no other freight modes are in consideration. Hereafter, I will use the terms truck model and FTG model interchangeably.

Each type of truck model has its own advantages and limitations. A vehicle-based FTG method, as its name suggests, is centered on vehicles and trucks. The term *truck* is a broad concept that covers many different types of commercial vehicles involved in freight movements, such as single-unit trucks, 18-wheelers and cargo vans, etc. The essence of a vehicle-based FTG method is the estimation of trip rates, which is a concept consistent with the ITE Trip Generation Manual (Institute of Transportation Engineers., 2012) method that is widely accepted in the Transportation Engineering/Planning field. Truck trip generation rates are estimated based on field observations of truck traffic flows and relevant land-use/employment data. Hence the estimated trip generation rates would statistically match with the empirical data. However, the estimated trip rates tend to be specific and may be case sensitive. Therefore, the estimation requires disaggregated data in detail that is usually difficult to retrieve and the estimated results may not necessarily be transferable to other situations.

Unlike a vehicle-based FTG method, a commodity-based FG method interpret economic activities related with the production and consumption of goods and retroactively uses conversion factors such as value-to-weight ratio, freight mode split and payload factors. In other

words, commodity-based FG methods take an indirect approach to forecast truck trip demands. It effectively integrates economic activities into the prediction process. However, it lacks proper mechanisms to take account of truck movement unrelated with good movements, linked trips with multiple deliveries and local pick-up and delivery trips that consist of a significant portion of truck trips within urban areas (Fischer et al., 2001).

These above mentioned attributes primarily determined the application of corresponding truck models: the vehicle-based FTG method is widely adopted in both engineering and planning applications, but the commodity-based FG method seems to limit its application within the regime of macroscopic planning studies. The allocation of curb space for PUD activities is a typical local planning application and therefore commodity-based FG methods are precluded from further consideration for the study.

Cherrett et. al. (Cherrett T. et al., 2012) found that smaller, specialized establishments generate more freight activity since larger establishments are more likely to have streamlined operations using larger delivery vehicles. Holguín-Veras et. al (Holguín-Veras et al., 2011) reviewed a large body of literature concerning FTG methods and found that the most frequently used model is a constant FTG rate as a function of a single independent variable (e.g. employment and floor space). However, they also found that many firms of different sizes in the same line of business seemingly require the same number of inputs from different vendors. In other words, businesses of the same type, regardless of establishment size, tend to attract similar number of delivery trucks. Therefore, it may be problematic for using constant FTG rates as a function of establishment size indicators, such as employment and floor space. Holguín-Veras et. al

(Holguín-Veras et al., 2012) proposed three types of FTG formulas depending on establishment classifications.

Type A. FTG is proportional to employment level as shown in Equation 3-1:

$$f_i = \beta E_i \tag{3-1}$$

Type B. FTG is constant per establish as shown in Equation 3-2:

$$f_i = \alpha \tag{3-2}$$

Type C. FTG is a combination of a constant and a term proportional to employment level as shown in Equation 3-3:

$$f_i = \alpha + \beta E_i \tag{3-3}$$

where $f_i$is the FTG by establishment *i* and E_i is the number of employees at establish *i*.

Holguín-Veras et. al also investigated the transferability of their FTG models. With data from a national furniture chain and grocery stores in New York City and Seattle, they found that the geographic variables are statistically insignificant in most cases and therefore indicated that their proposed FTG models may be applicable to different geographic regions (Hyeon-Shic Shin et al., 2013). With this in mind, the parameters estimated in Holguín-Veras et. al's studies could serve as a reasonable starting point for FTG estimations in the District until better local data sources are available.

3.2.2 Truck Trip Generation

Based on discussions in the previous section, three types of FTG models, Type A, B and C, are proposed to predict the daily truck demands either by the number of employees per business establishment, by a constant or by both. However, it is worth noting that Type A and B models

could be consolidated as Type C by forcing its parameters α or β to be zero. Therefore, I do not differentiate the three types of model in the following sections.

Parameters α and β for each Standard Industrial Classification (SIC) code are adopted from Holguin-Veras, et al (Holguín-Veras et al., 2011) and NCHRP Synthesis 298 (Fischer et al., 2001) as shown in Table 3-1. Refer to Table C-1 in Appendix for a full list of Standard Industrial Classification (SIC) code breakdown.

Since the study in NCHRP Synthesis 298 (Fischer et al., 2001) does not differentiate between attraction trips and production trips, without loss of generality, I lump trip generation rates for SIC Code between 60 and 99 into attractions only. Since I consider both attraction and production trips in FTG calculation equivalently, this generalization will not affect the calculation results fundamentally.

Table 3-1 Adopted FTG Model Parameters

SIC	Attraction		Production		
Code	α	β	α	β	Source
15	0	0.125	2.16	0	Tables 2 and 3[1]
16	2.467	0	2.16	0	Tables 2 and 3[1]
17	2.508	0	2.067	0	Tables 2 and 3[1]
20	1.609	0.01	1.444	0	Tables 2 and 3[1]
21-23	3.377	0	1.611	0	Tables 2 and 3[1]
24	0	0.061	1.611	0	Tables 2 and 3[1]
25	1.434	0.027	1.611	0	Tables 2 and 3[1]
26-33	3.377	0	1.611	0	Tables 2 and 3[1]
34	2.875	0	1.611	0	Tables 2 and 3[1]
35-38	3.377	0	1.611	0	Tables 2 and 3[1]
39	0	0.139	1.611	0	Tables 2 and 3[1]
40-41	0	0	2.216	0.072	Tables 2 and 3[1]
42	0	0	2.151	0.077	Tables 2 and 3[1]
43-46	0	0	2.216	0.072	Tables 2 and 3[1]
47	0	0	3.917	0	Tables 2 and 3[1]

SIC Code	Attraction α	Attraction β	Production α	Production β	Source
48-49	0	0	2.216	0.072	Tables 2 and 3[1]
50	4.931	0	1.554	0.04	Tables 2 and 3[1]
51	1.813	0.074	0	0.089	Tables 2 and 3[1]
52	0	0.408	1.72	0	Tables 2 and 3[1]
53	2.899	0	1.72	0	Tables 2 and 3[1]
54	4.155	0	1.444	0	Tables 2 and 3[1]
55	2.899	0	1.72	0	Tables 2 and 3[1]
56	1.314	0.032	1.72	0	Tables 2 and 3[1]
57	3.714	0	1.72	0	Tables 2 and 3[1]
58	2.017	0.034	1.444	0	Tables 2 and 3[1]
59	2.902	0	1.72	0	Tables 2 and 3[1]
60-88	0	0.329	0	0	Table D-1d[2]
89-99	0	0.006	0	0	Table D-1e [2]

1. (Holguín-Veras et al., 2011); 2. (Fischer et al., 2001)

3.3 Data

3.3.1 Data Sources

The primary data sources for this study are the D.C. Geospatial Information System (DCGIS) and the InfoUSA® Database (updated in July, 2013).

3.3.1.1 GIS Database

Business information and curbside loading zone inventory information are all geocoded as point features in ArcMap. Street shapefile, block shapefile and all other auxiliary shapefiles are retrieved from DCGIS. A GIS database, as shown in Figure 3-1 Loading Zone Analysis GIS Database, is formed as the ground for further analysis. In Figure 3-1, red dots represent existing curbside loading zones and green dots represent existing business establishments in D.C.

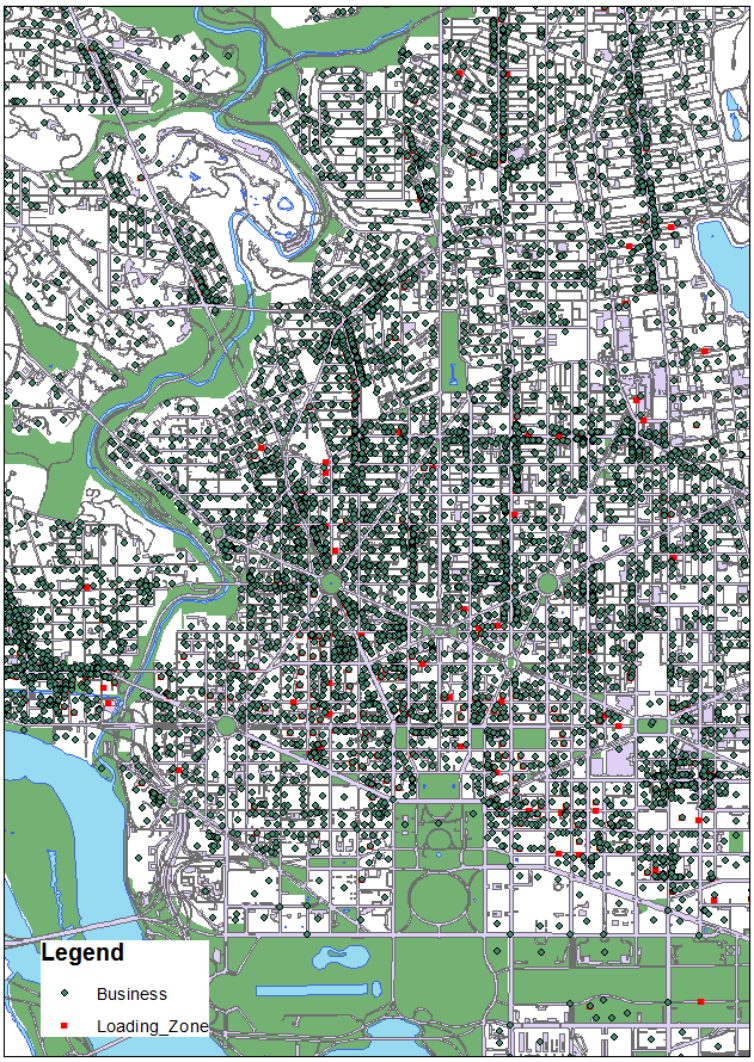


Figure 3-1 Loading Zone Analysis GIS Database

3.1.1.2 InfoUSA® Database

Business establishment data in the District are obtained from the InfoUSA® Database (updated in July, 2013). A total of 59,730 business establishments are listed in the data set across 79 two-digit SIC classes and 174 zip code area within the District. The numbers of employees in each establishment range from 1 to 9,200, with a mean of 11 and standard deviation of 94. Table 3-2 shows a breakdown of the number of establishments and number of employees by each SIC division in details.

Table 3-2 Breakdown of InfoUSA® Data by SIC Divisions

Division	SIC Code Range	Description	Number of Establishments	Number of Employees
A	01-09	Agriculture, Forestry, And Fishing	175	1,149
B	10-14	Mining	24	289
C	15-17	Construction	1,165	13,523
D	20-39	Manufacturing	654	15,883
E	40-49	Transportation, Communication, Electric, Gas, and Sanitary Services	1,226	24,129
F	50-51	Wholesale Trade	548	7,178
G	52-59	Retail Trade	6,196	70,008
H	60-67	Finance, Insurance and Real Estate	3,687	38,755
I	70-89	Services	37,417	390,065
J	91-99	Public Administration	8,638	105,965
All	01-99	All Divisions	59,730	666,944

However, the InfoUSA® Database contains redundant information of business establishments due to coding issues (ie. seemingly identical business establishes with minor variation in name or address likely caused by human errors are found in the original database; for example, Mc Kenna Long & Aldridge LLP vs. Mc Kenna Long & ALDRIDGE Llp, etc). Google® Refine is found to be a useful tool to clean up large data set efficiently and automatically. Google® Refine's clustering operations, which means "finding groups of different values that might be alternative representations of the same thing"[4], are used to identify seemingly identical entries. The refined InfoUSA® data with consolidated business information remains 47,931 unique business records (about 80% of the raw data) as shown in Table 3-3. It is worth noting that the refined total number of businesses within the District is consistent with the Esri® Business Analyst

[4] Google® Refine Online Help Files. https://github.com/OpenRefine/OpenRefine/wiki/Clustering-In-Depth, accessed July 28th, 2014

estimation of a total 48,833 business establishments within the District in 2013 based on information from Dun & Bradstreet, Inc.

Table 3-3 Breakdown of Refined InfoUSA® Data by SIC Divisions

Division	SIC Code Range	Description	Number of Establishments	Number of Employees
A	01-09	Agriculture, Forestry, And Fishing	152	1,054
B	10-14	Mining	24	289
C	15-17	Construction	1,163	13,358
D	20-39	Manufacturing	654	15,883
E	40-49	Transportation, Communication, Electric, Gas, and Sanitary Services	1,224	23,823
F	50-51	Wholesale Trade	548	7,178
G	52-59	Retail Trade	6,184	69,673
H	60-67	Finance, Insurance and Real Estate	3,637	38,613
I	70-89	Services	25,725	317,568
J	91-99	Public Administration	8,620	105,861
All	01-99	All Divisions	47,931	593,300

3.3.2 ArcGIS Model

A substantial body of literature that explores the role and potential of GIS to support various forms of urban analysis and planning has accumulated in the last twenty years, and in fact, GIS is used routinely in many aspects of urban research (Páez and Scott, 2004). Using the Data Management Toolbox in ArcMAP®, a GIS model is developed. The dependent variable and the potential explanatory variables are aggregated to block face level. Basically, a block face, with the number of loading zones from one to eight, is tied with FTG, the number of business establishments, the number of buildings, the average building roof area and the existence of alleys on either side of it. A total of 742 block faces associated with at least one designated curbside loading zone are found within the District. Figure 3-2 shows a flow chart of the entire analysis process.

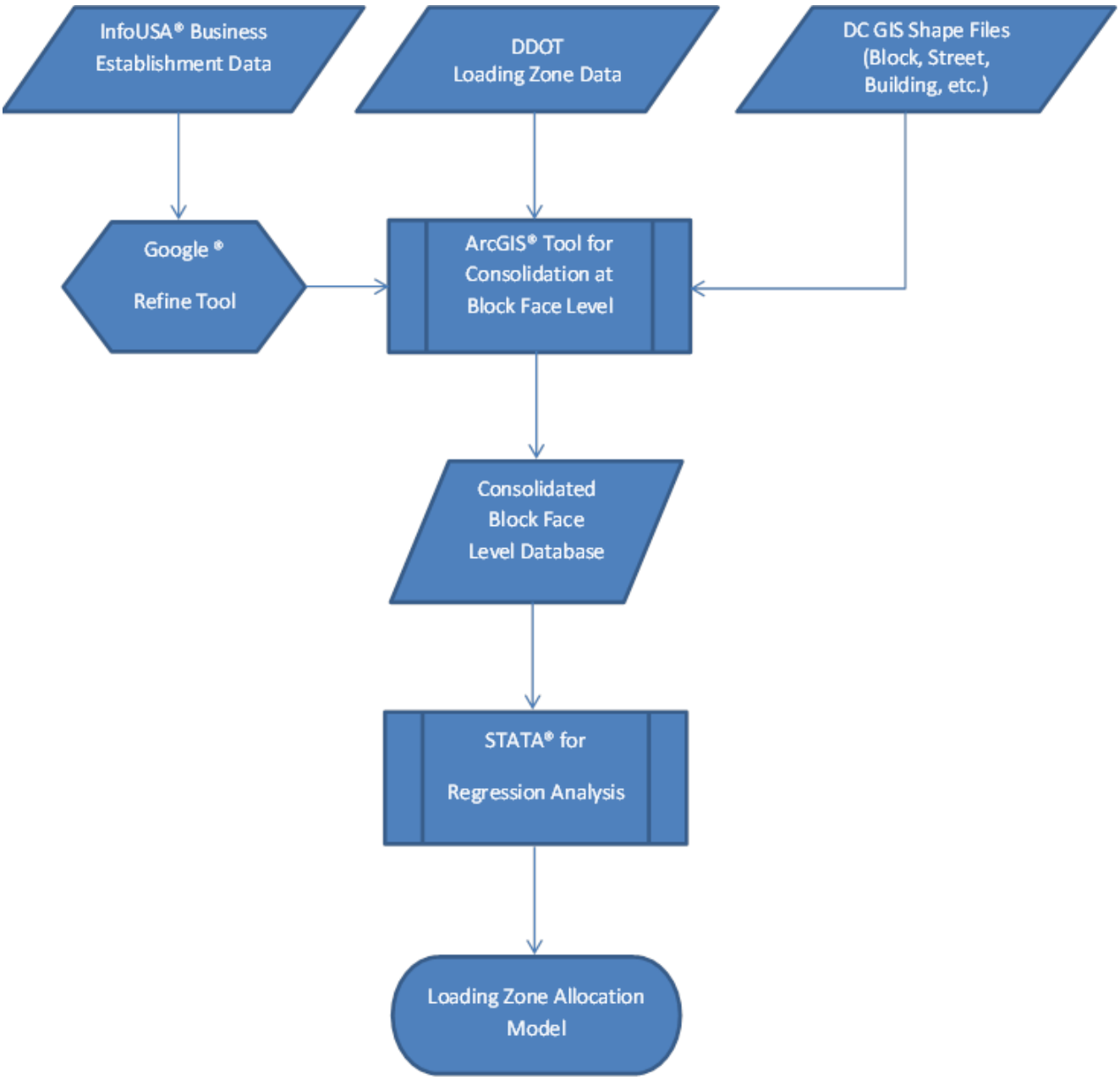


Figure 3-2 A Flow Chart of the Analysis Process

Figure 3-3 shows a flow chart of the ArcGIS model, blue means input files, green means output files and yellow indicates tools in use. A total of five GIS shapefiles (including loading zones, business establishments, blocks, buildings and streets) obtained from DCGIS and InfoUSA are processed using the ArcGIS modeling tool. A point feature (the centroid of each selected Block Face polyline) class is generated as the end product of this ArcGIS model.

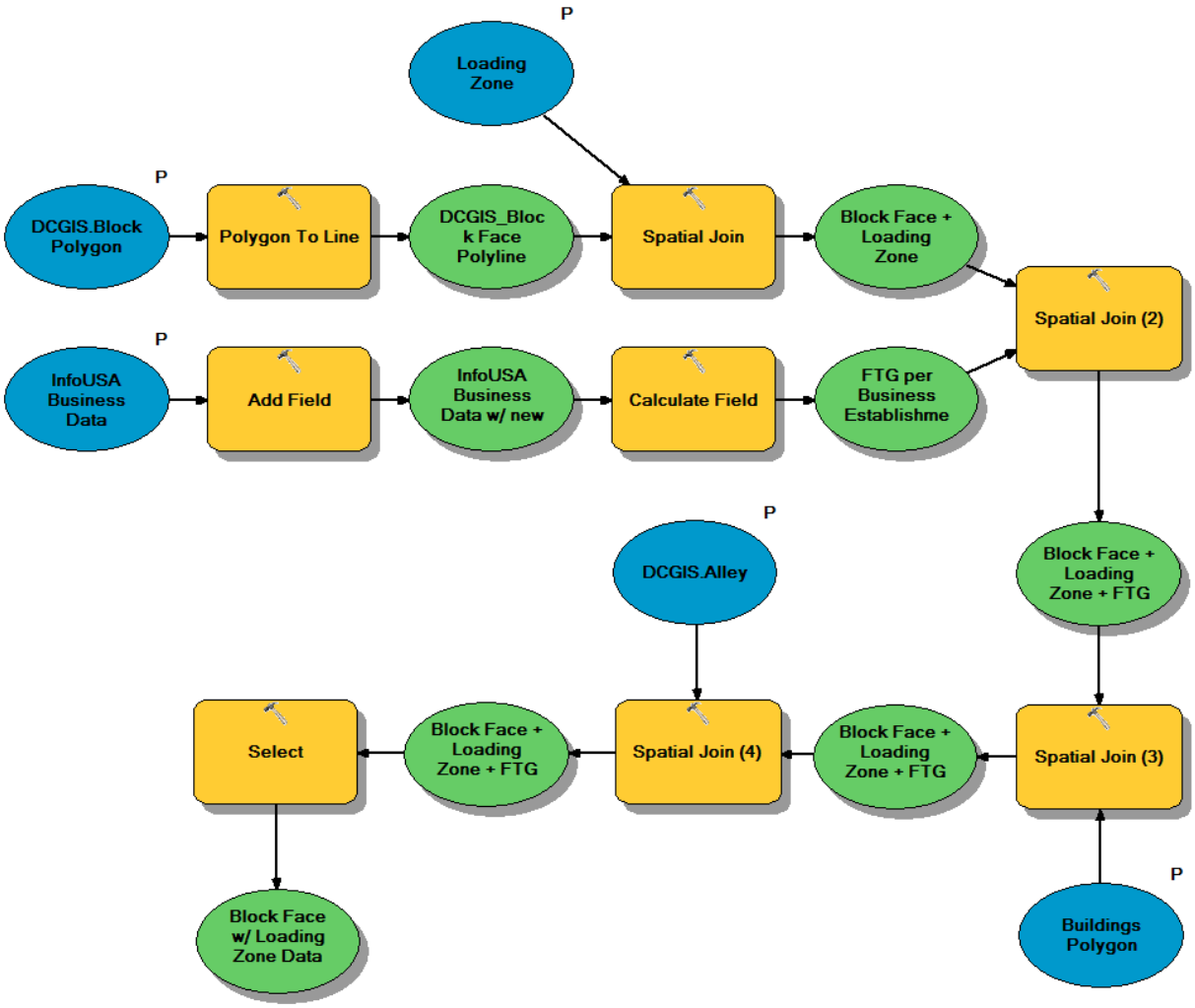


Figure 3-3 A Flow Chart of the Developed GIS LZAM Tool

3.3.3 Dependent and Explanatory Variables

3.3.3.1 Loading Zone (LZ)

LZ, the dependent variable, is the total number of designated curbside loading zones within 30 meters of reach from a block face. A 30-meter wide buffer band width is chosen based on Habib and Crowley's study (Habib and Crowley, 1976) of parking patterns of PUD vehicles in Brooklyn, New York. They find that 98 percent of all PUD vehicles are parked within 30 meters of the destination establishment regardless of curb space availabilities and regulations. If the

drivers cannot find a proper curb parking space within 30 meters, they would double park to PUD. Consistently, Alho and Silva (Alho and de Abreu e Silva, 2014) indicate the maximum distance that delivery drivers are willing to walk to conduct PUD activities is between 25 to 50 meters.

3.3.3.2 GFTG (Gross FTG)

GFTG is the total FTG per block face, which represents the total curbside truck trip demand, generated by business establishments sitting within a 30 meters wide buffer zone of a block face. Therefore, one business establishment could be assigned to multiple block faces. It is expected that the number of loading zones will increase as GFTG increases.

Note that FTG is not only driven by the business needs from the receivers, it is also affected by the logistics operation of the carriers. When I aggregate the FTG's to GFTG, one unit of GFTG does not necessarily translate into one truck trip to the particular block. For example, carriers such as FedEx and UPS could do multiple PUD activities with just one truck trip. In another example, Holguín-Veras and Patil estimate two to three deliveries per stop based on interviews with carrier companies (excluding express parcel carriers) using Denver data (Holguín-Veras and Patil, 2005). Therefore, GFTG should be understood as a measure of relative intensity of delivery needs rather than the number of truck trips at an aggregate level.

Based on the FTG formulas in Section 4.2.2, the calculated FTG's range from 0 to 3026.8 PUD per day (PUD/day), from the set of refined InfoUSA® database with 47,931 data entries. This range is too wide to be reasonable in the District: when curbside PUD is in concern, it is hard to

believe or even physically possible that a particular business establishment will have thousands of delivery trucks making curbside PUD in a single day. Therefore, this specific range might indicate that some parameters based on the New York Metropolitan data are not necessarily applicable to the District. However, the scope of this research did not lend resources to conduct a full scale calibration of the FTG models. An ad-hoc solution is proposed to use a statistic method to identify outliers and exclude them from further consideration. Outliers of the estimated FTG's are identified using a Box-and-Whisker plot as shown in Figure 3-4. The lower quartile of Q1 = 0.658 (PUD/day), the upper quartile of Q3 = 3.290 (PUD/day), and the interquartile range IQR is 2.632 (PUD/day). Hence, the lower inner fence of LIF = 0 (PUD/day) and upper inner fence of UIF = 7.238 (PUD/day). Any estimated FTG's lager than 7.238 (PUD/day) are outliers.

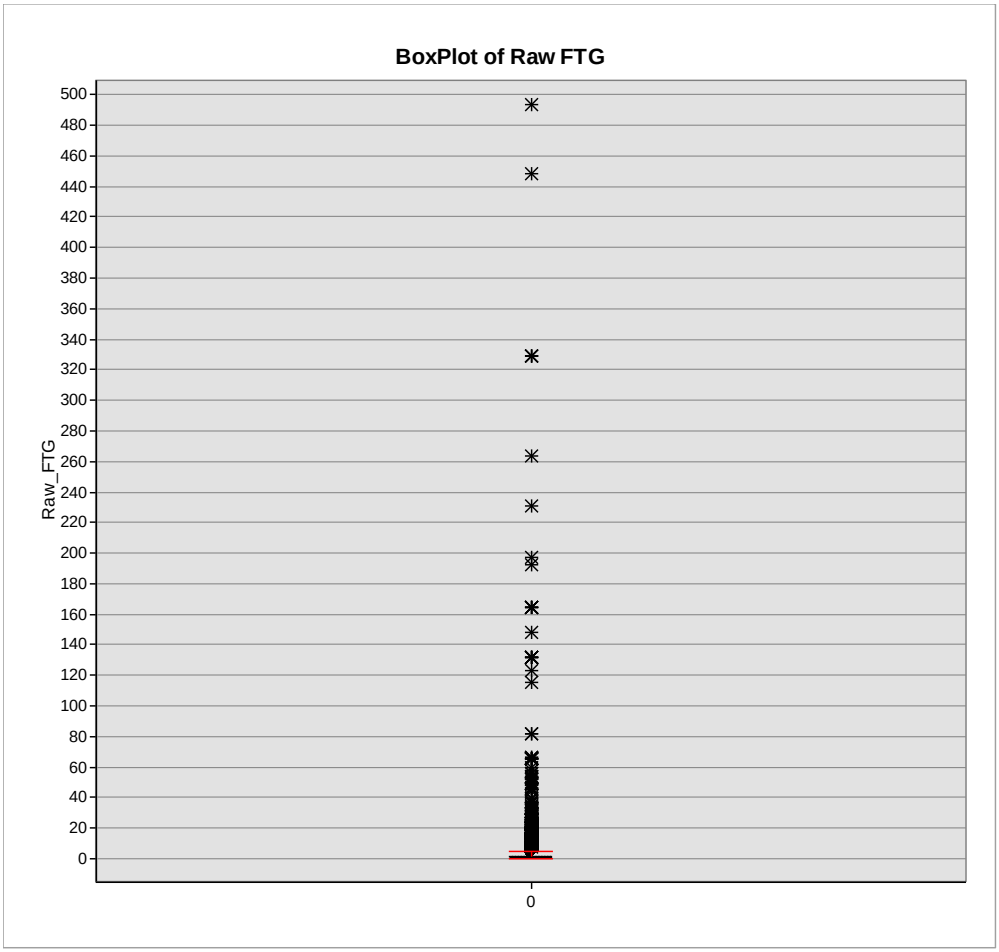


Figure 3-4 Box-and-Whisker plot of FTG

Furthermore, the District zoning requirements[5] for office building loading berths are one berth for 20,000-50,000 square feet gross floor area; two berths for 50,000-200,000 square feet gross floor area; and three for 200,000 square feet gross floor area and above. Similar regulations are imposed for other types of establishments including grocery and drug stores, retail and service establishments, etc.

As shown in Table 3-4, the InfoUSA® database categorized business establishments into four classes based on gross floor area.

Table 3-4 InfoUSA® Business Size Classifications

Class	Gross Floor Area Range (Square Feet)
A	0 – 2,500
B	2,500 – 10,000
C	10,000 – 40,000
D	40,000 and above

Since the main concern of the study is about on-street PUD activities, larger business establishments falling under categories C (10,000 – 40,000 square feet) and D (40,000 square feet and above) in the InfoUSA® Database are excluded from FTG calculations assuming that off-street loading spaces are available for them.

3.3.3.3 Business Establishment (BIZ)

BIZ is the total number of business establishments associated with the closest block face. In a way, FTG is a weighted measurement of BIZ by freight trip demands. It is expected that FTG

[5] The Zoning Commission for the District of Columbia, D.C. Municipal Regulations Rule 11-2201: Schedule of Requirements for Loading Berths, Loading Platforms, and Service/Delivery Loading Spaces, Washington D.C., 2005

and BIZ are highly positively correlated. BIZ is introduced as a potential explanatory variable to confirm the prediction power of FTG on the number of loading zones.

3.3.3.4 Building (BLDG)

BLDG is the total number of buildings sitting within a 30 meters wide buffer zone of a block face. It is expected that FTG and BLDG may be somewhat positively correlated. BLDG is introduced as another potential explanatory variable to confirm the prediction power of FTG on the number of loading zones.

3.3.3.5 Average Building Footage (AVGR)

AVGR is the average building roof cut area, as a proxy of a building's footage, buildings sitting within a 30 meters wide buffer zone of a block face. As mentioned earlier, the larger the floor area of a building, the more likely that it will have off street loading facilities. It is expected that the number of loading zones will decrease as the AVGR increases.

3.3.3.6 Alley

Alley is a dummy variable that indicates whether alleys are attached to a block face. It is an index to feature the potential availability of off-street loading area. Similar to AVGR, it is expected that the number of loading zones will decrease as Alleys present.

3.3.3.7 Descriptive Statistics and Expected Coefficient Signs

Table 3-5 shows some basic descriptive statistics and the expected coefficient signs of all variables.

Table 3-5 Descriptive Statistics and Expected Coefficient Sign of all Variables[1]

Variable	Unit	Mean	Standard Deviation	Min	Max	Expected Coefficient Sign
LZ	unit	1.38	0.768	1	8	not applicable
GFTG[2]	PUD/day	28.93	36.028	0	276.18	+
BIZ[3]	unit	16.12	22.676	0	213	+
BLDG	unit	18.09	14.237	1	103	+
AVGR	m^2	933.75	1367.493	39.36	11312	-
Alley	not applicable	0.29	0.454	0	1	-

Note:
[1.] Based on a total of 742 observations or block faces with at least one associated loading zone in the District.
[2.] Due to the FTG calculation method, it is possible that zero truck trips are generated per block face.
[3.] Businesses are coded as point features in ArcGIS and usually sit on the centroid of its building, therefore these point features may not necessarily spatially related with block face that their entrances are facing to.

3.4 Regression Analysis

3.4.1 Modeling Method

One of the primary reasons of this study is to standardize the procedure of curbside loading zone allocation. It is critical to understand the current practice and to form a baseline condition before proceeding to the creation of a new procedure. Regression models are used to quantify the underlying relationships between the number of existing loading zones and site specific characteristics at block face level. Previous field observations found that PUD could occur on either side of a street but may not be further than 30 meters from the place where a truck is parked. Therefore an analysis at a block face level is appropriate for curbside loading zone related issues. The hypothesis is that the total truck trip demand per block face, GFTG, is a significant factor in determining the allocation of commercial loading zones in the District under

the existing conditions. If the hypothesis is failed to be rejected, GFTG could be adopted as a critical instrument to guide the process of allocating curbside loading zones in an equitable, consistent, and repeatable manner and to uniformly evaluate curbside loading needs throughout the District in the future.

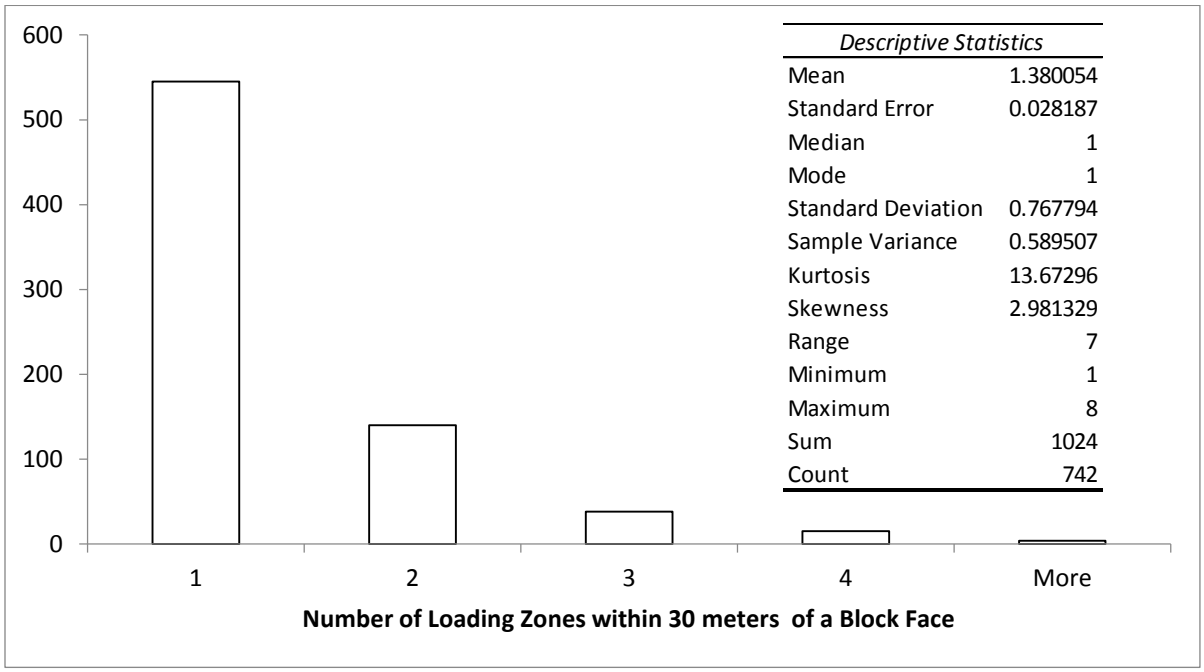


Figure 3-5 Histogram of Number of Loading Zones per Block Face

I exclude block faces without existing loading zones (19,081 out of 19,823 or 96%) from our dataset for regression because I have no effective mechanisms to differentiate locations with zero associated loading zones for no sufficient curbside PUD activity demands or for other various reasons, such as nobody filed a request to initiate the investigation, the availability of alternative off-street loading facilities, space limitations or conflicting interests, etc. After all, I am trying to model the decision rule, therefore I have to make sure that the decisions have been made. However, the best way to tell a decision has been made in certain is the existence of active loading zones.

Figure 3-5 shows a histogram of the number of loading zones per block face in the District, which represents non-negative count data. It seems that the distribution of the number of loading zones per block face is skewed to the right (its median is smaller than its mean) and dispersed (its variance is greater than its mean). This effort does not attempt to model the number of loading zones per block face using Ordinary Least Squared (OLS) regression that is embedded with the assumption of a normal distribution on the dependent variable. Instead, I estimated zero-truncated NB models that could potentially represent the available data statistically better. Thus I could use observations of positive LZ's to extrapolate attributes of zero LZ's, assuming the number of LZ's follow an NB distribution.

The Poisson distribution and NB distribution are typical distributions used to model count data in statistical analysis (Cameron and Trivedi, 1998). An NB distribution is more suitable for over-dispersed data than a Poisson distribution that assumes the mean equals to the variance. However, since zero counts (block faces without loading zones) are excluded from our dataset, the dependent variable in our model, the number of loading zones per block face, is truncated at zero, taking only positive values (from 1 to 8 in our sample). I will use the truncated NB regression model as specified by Grogger and Carson (Grogger and Carson, 1991) for regression. The model for truncated counts from an NB distribution can be written as:

$$\Pr(Y_i = j | Y_i > 0) = \frac{\Gamma\left(j+\frac{1}{\alpha}\right)}{\Gamma(j+1)\Gamma\left(\frac{1}{\alpha}\right)}(\alpha\lambda_i)^j[1+\alpha\lambda_i]^{-\left(j+\frac{1}{\alpha}\right)}[1-F_{NB}(0)]^{-1} \quad (3\text{-}4)$$

The log-likelihood is

$$\ln(L) = \sum_{i=1}^{N} ln\left(\Gamma\left(j + \frac{1}{\alpha}\right)\right) - \ln\left(\Gamma(j+1)\right) - \ln\left(\Gamma\left(\frac{1}{\alpha}\right)\right) + jln(\alpha) + j\beta X_i - \left(j + \frac{1}{\alpha}\right)\ln[1 + \alpha\lambda_i] - \ln[1 - (1 + \alpha\lambda_i)^{-1/\alpha}]$$

(3-5)

The conditional mean and variance of this model are given by

$$E(Y_i|X_i, Y_i > 0) = \lambda_i[1 - F_{NB}(0)]^{-1} \quad (3\text{-}6)$$

and

$$var(Y_i|X_i, Y_i > 0) = \frac{E(Y_i|X_i, Y_i > 0)}{F_{NB}(0)^{\alpha}}\{1 - [F_{NB}(0)]^{1+\alpha}E(Y_i|X_i, Y_i > 0)\} \quad (3\text{-}7)$$

The reduced form of the model is given by

$$\lambda_i = e^{\beta_0 + \sum_{k=1}^{K}\beta_k X_{ki}} \quad (3\text{-}8)$$

where Y_i is the number of loading zones at block face i;

$\Pr(Y_i = j|Y_i > 0)$ is the conditional probability mass function (pmf) of the zero-truncated NB distribution;

L is the likelihood function;

$\Gamma()$ is the gamma function defined for any $r>0$ by $\Gamma(r) = \int_0^{\infty} z^{r-1}e^{-z}dz$;

$F_{NB}(0)$ is the cumulative distribution (cdf) function of the NB distribution at zero;

$E(Y_i|X_i, Y_i > 0)$ is the conditional expectation of the zero-truncated NB distribution;

$var(Y_i|X_i, Y_i > 0)$ is the conditional variance of the zero-truncated NB distribution;

α is the over –dispersion parameter the zero-truncated NB distribution that needs to be estimated;

$\beta = (\beta_0 \quad \beta_1 \quad \ldots \quad \beta_K)$ is the parameter vector that needs to be estimated; and

$X_i = (1 \quad X_{1i} \quad \ldots \quad X_{Ki})^T$ is the i^{th} observation of explanatory variables.

3.4.2 Model Selection

The Akaike's Information Criterion (AIC) is adopted for choosing a regression model that can better fit with observations. AIC is defined using the following formula:

$$AIC = -2ln\left[L\left(\hat{\theta}\right)\right] + 2K \quad (3\text{-}9)$$

where $L\left(\hat{\theta}\right)$ is the likelihood function of the estimated model and *K* is the number of estimated parameters in the model. A model with a smaller AIC value is deemed as a better model statistically (Greene, 2012).

3.4.3 Multicollinearity Detection

A pairwise correlation matrix (as shown in Table 3-6) are calculated using STATA® in order to detect correlations between independent variables. If multicollinearity presents, we may get unstable regression parameters. I found that the GFTG and BIZ are highly correlated. Therefore these two variables should not be included in a same regression model simultaneously.

Table 3-6 Pairwise Correlation Matrix of Variables

	LZ	GFTG	BIZ	BLDG	AVGR	Alley
LZ	1.0000					
GFTG	0.3201	1.0000				
BIZ	0.2802	**0.9083**	1.0000			
BLDG	0.0392	0.1334	0.0451	1.0000		
AVGR	0.0154	-0.0330	0.0457	-0.4198	1.0000	
Alley	0.0321	0.0971	0.0844	0.3563	-0.1494	1.0000

3.4.4 Model Estimation

Regression models are estimated using the *tnbreg* command in STATA® based on a data set of 742 block faces with existing designated loading zones in the District. The zero-truncated NB model estimation results are presented in Table 3-7. From Models *A1* to *A5*, only one explanatory variable is added to the model to identify the most significant explanatory variable. In this case, GFTG is the most significant explanatory variable. In Model *B1*, all other

explanatory variables, except BIZ due to collinearity, are added into regression. From Models *B2* to *B3*, the most insignificant explanatory variable is dropped off from regression at each time. The α's, measurements of over-dispersion, are statistically significant in all models and therefore confirm that NB regressions are more appropriate than Poisson regressions for the dataset. Based on the AIC, Model *A1* is chosen as the best model, which takes the following form:

$$\widehat{LZ} = e^{(-1.3515+0.011617\times GFTG)} \quad (3\text{-}10)$$

where $\widehat{LZ}$ is the estimated conditional expectation of number of loading zones per block face and GFTG is the total truck trip demands generated by the specific block face. Since $\widehat{LZ}$ is the conditional expectation of the number of loading zones per block face for a given GFTG, it is possible for it to take non-integer values. Intuitively, an estimated $\widehat{LZ}$ of 1.3 means, given the GFTG amount, it is more likely for the particular block face to have one designated loading zone rather than two in the District. The model is in line with our expectation of a positive coefficient for GFTG (with its p-value less than 1%). I fail to reject the hypothesis of GFTG is a significant prediction factor in determining the allocation of commercial loading zones in the District.

Table 3-7 Truncated Negative Binomial Model Estimation Results

	Model[1]							
Variable	A1	A2	A3	A4	A5	B1	B2	B3
Constant	-1.3515**	-1.5679**	-1.6192**	-1.5505**	-1.5518**	-1.4428**	-1.3545**	-1.3696**
	(0.296)	(0.423)	(0.642)	(0.646)	(0.632)	(0.342)	(0.308)	(0.300
GFTG	1.1617×10^{-2}**	-	-	-	-	1.1602×10^{-2}**	1.1613×10^{-2}**	1.1565×10^{-2}**
	(1.901×10^{-3})					(1.944×10^{-3})	(1.915×10^{-3})	(1.898×10^{-3})
BIZ	-	1.8672×10^{-2}**	-	-	-	-	-	-
		(3.938×10^{-3})						
BLDG	-	-	6.0619×10^{-3}	-	-	7.922×10^{-4}	-1.1247×10^{-3}	-
			(5.488×10^{-3})			(6.095×10^{-3})	(5.491×10^{-3})	
AVGR	-	-	-	2.75×10^{-5}	-	4.46×10^{-5}	-	-
				(6.01×10^{-5})		(6.22×10^{-5})		
Alley	-	-	-	-	0.1446	0.07614	0.07538	0.06548
					(0.165)	(0.162)	(0.161)	(0.154)
ln(α)	-0.1463	0.4184	0.9535	0.9798	0.9558	-0.1176	-0.1442	-0.1463
	(0.597)	(0.665)	(0.916)	(0.931)	(0.918)	(0.600)	(0.597)	(0.5967)
α	0.8639*	1.5196*	2.5949*	2.6639*	2.6009*	0.8891*	0.8657*	0.8639*
	(0.516)	(1.010)	(2.378)	(2.480)	(2.388)	(0.534)	(0.517)	(0.515)
Degree of Freedom	739	739	739	739	739	736	737	738
Number of Parameters (K+1)	3	3	3	3	3	6	5	4
LR χ^2(K-1)	54.06**	42.68**	1.22	0.21	0.76	54.79**	54.29**	54.24**
Log-Likelihood	-574.752	-580.442	-601.173	-601.679	-601.403	-574.389	-574.641	-574.662
AIC	**1155.504**	1166.884	1208.345	1209.358	1208.807	1160.777	1159.281	1157.323

Note: [1]Estimated coefficient and standard error in () are given for each variable

*Significant at the 95% confidence level

**Significant at the 99% confidence level

3.4.5 Interpretation of the Modeling Results

It turns out that the estimated coefficients for most potential explanatory variables, except for GFTG and BIZ, are statistically insignificant in regression. Furthermore, GFTG appears to be a better explanatory variable than BIZ, which suggests GFTG characterized the true truck trip demands to some extend and the allocation of curbside commercial loading zones in practice may be implicitly demand driven in the District. In a sense, the estimated model describes the status quo of the curbside loading zone allocation rule in the District. The model can only be as "rational" as the existing data appear to be. By no means, it should be claimed as the best practice guideline for the District or for the other areas. However, the model does provide a tangible approach to connect the PUD demand with the rule for loading zone allocation at a block face level. As the decisions of loading zone allocation become more responsive to PUD needs in the District, the model will evolve to be more "rational" through re-estimation of parameters.

Different from coefficients estimated from an OLS regression, the coefficients estimated from a zero-truncated NB model actually reflect the change rate of log transformed count of loading zones per block face. Figure 3-6 shows how the predicted conditional mean of loading zones and its corresponding 95% confidence intervals (CI's) will change along with GFTG's in the chosen best model (Model *A1*).

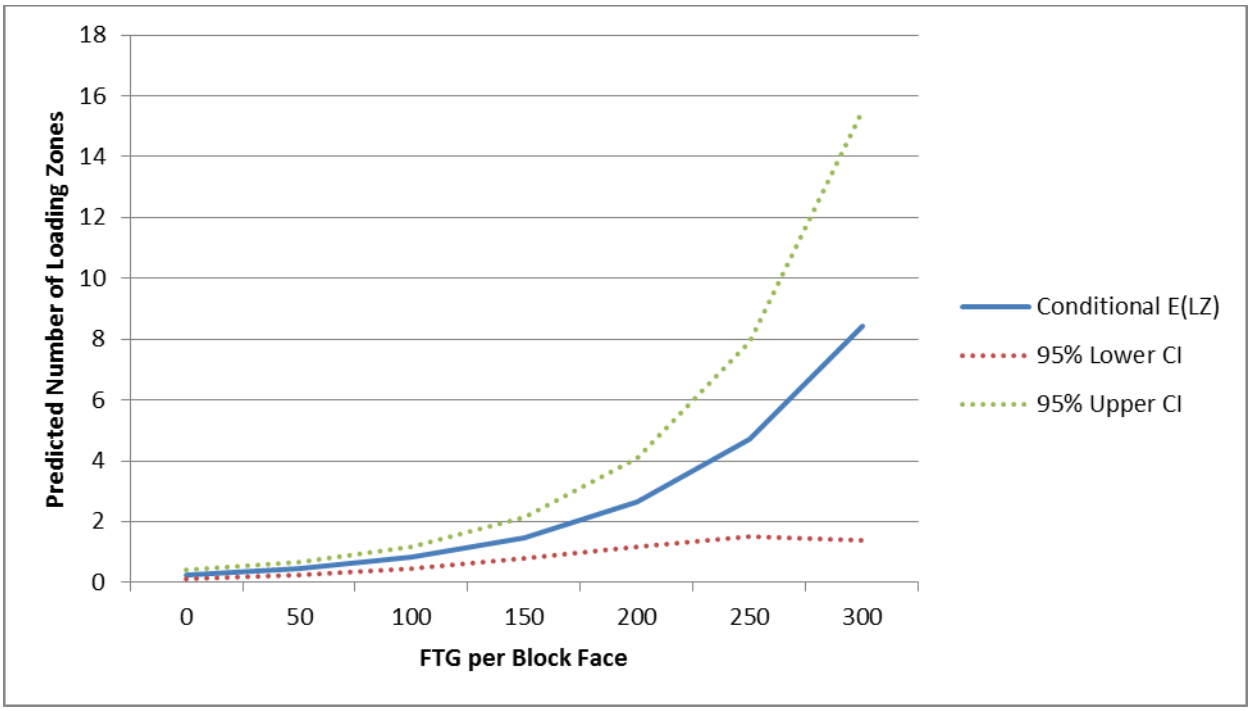


Figure 3-6 The Predicted Number of Loading Zones per Block Face.

In general, the conditional mean of loading zone numbers would increase as GFTG increases. However, the span of CI would be expanded as the GFTG increases, too. This result is consistent with our expectations, since the relationship between GFTG and the number of loading zones is not exactly monotonically increasing. For example, as the demand of PUD activities increases to a certain level, off-street loading portals may be necessary to sustain day-to-day operations.

3.5 Application of the Model

3.5.1 Existing Condition Screening

Figure 3-7 Block Face Screening

With the LZAM, I may plot the discrepancies between the predicated conditional expectation of loading zones and the actual allocated number of loading zones in color schemes. So the potentially under/over designated block faces will be highlighted (as shown in the red/green dots on Figure 3-7) using a GIS map. Further investigations on these block faces may be conducted to determine the actual needs of adding/removing loading zones.

3.5.2 Development Evaluation

Table 3-8 Cut-off FTG Values

Number of Loading Zone per Block Face	Cut-off GFTG (PUD/day)
1	116.3381
2	176.0047
3	210.9075
4	235.6714

Another usage of the model may be the referencing cut-off (threshold) GFTG values as shown in Table 3-8. If I have new development or change of land use on a block, I may compare the changed FTG values against these threshold FTG values to preliminarily justify the needs of adding/removing loading zones. For instance, if the existing FTG at a block face is 150 PUD/day and only one curbside loading zone is available. Several new businesses with additional FTG of 50 PUD/day may warrant a study for whether an additional loading zone is required for the block. Again, as mentioned earlier, the referencing thresholds are not meant to be the best practice guideline. However, it provides an objective measure that would facilitate a consistent and equitable decision process.

3.6 Conclusion and Recommendation

With the LZAM, an equitable, consistent, and repeatable process to uniformly evaluate curbside loading zone needs could be established for the District and for the other jurisdictions that are interested in quantitative driven approaches in decision makings. The establishment of the LZAM is an iterative process and the model needs

to be recalibrated periodically as newer information become available to ensure fairness in the procedure.

Although the methodology presented in this chapter is innovative to make the decision rule of curbside loading zone allocation correspond to the actual curbside truck trip demand, admittedly, there are still many limitations with the explanatory variable GFTG (or FTG):

- First, the curbside truck trip demand is estimated using a vehicle-based FTG method with employment data as predictors. Therefore it inherits all the critics against the FTG method, such as: it requires considerably disaggregated industry/land-use categories that are difficult to retrieve in reality and using employment data to predict FTG tend to underestimate the future demand of truck trips since the labor productivity tends to improve overtime, etc (Fischer et al., 2001);
- Second, smaller business establishments may share a common commercial building with off-street loading docks available and therefore have no contribution to curbside FTG. On the contrary, some larger buildings maybe exempted from the zoning requirements due to historical reasons, etc. and therefore need curbside PUD; and
- Third, most of the FTG model parameters are adopted from studies in the New York Metropolitan area without calibration and validation against the local conditions in the District. I am not sure about the accuracy and prediction

power of the FTG models, since the true truck generation data in the District are unavailable and it is impossible to validate estimated FTG's.

Other limitations are related with the assumption about decision rules: the underline assumption of our analysis is that the existing curbside loading zone designations in the District are based on a rational decision process implicitly. However, the rational assumption is a contentious concept in the contemporary planning theory. The traditional rational model assumes that decision makers have full knowledge about the problem, alternative solutions, as well as unlimited resources, but in reality, decision makers face 'bounded' conditions that are imposed by cognitive limits, social differentiations, pluralist conflicts and structural distortions (Forester, 1999).

Overall, many factors need to be considered in the process of deciding how to allocate curbside spaces for commercial deliveries other than merely the truck trip demand. Nevertheless, a demand driven analysis would be a reasonable initial point for a jurisdiction to justify the need for facilities that support truck PUD needs.

Moreover, the LZAM primarily focuses on business needs from a receiver's perspective. The occupancy of curbside loading spaces are not only related with the frequency of deliveries but also related with the operation of carriers (ie, service time, logistics planning, etc.) (Jaller et al., 2013). Future studies are needed to better understand the needs of loading zones weigh in the operation attributes of carriers in regards of dwell time, vehicle characteristics, the means of getting goods off the vehicle and transporting from the vehicle to premises and the extent to which delivery

person has to communicate with the receiver, etc (Allen and University of Westminster. Transport Studies Group., 2000).

Finally, curbside spaces are public spaces, the allocation of curbside spaces involves conflicting interests from different parties. The interactions between different land-uses and urban forms in related with curbside space allocation are also interesting topics worth further explorations.

Chapter 4: Remarks

The three related essays in this dissertation contribute to the understanding of urban transportation issues and to the exploration of innovative approach to tackle the challenges that public agencies confront while managing scarce public goods. Using D.C. data, significant safety effects of AWSC conversion from TWSC are identified, the safety improvement of eliminating reversible lane operation on urban arterial roadways is quantified and an innovative approach to allocate curbside space for loading zone in response to the actual loading activity demands is explored.

The first essay in Chapter 1 assesses the safety effect of converting TWSC intersections to AWSC intersections. Converting TWSC intersections into AWSC intersections is a popular request from local community representatives to DDOT and many other public agencies as a countermeasure for safety concerns or for traffic calming purposes. AWSC conversion is generally considered as a low cost safety improvement that would reduce crash occurrence at intersections and reduce traveling speed along roadways. Several different identification strategies are employed, including conventional Before-and-After study, multi-way ANOVA and DID analysis, using before and after crash data for the treatment group and matched control group. It is found that the safety improvement in terms of crash rate reduction only applies to a particular crash type, which is Right Angle crash. Nevertheless, it is estimated that the crash rate of Straight Hit Pedestrians is expected to increase upon AWSC conversion. Caution is needed if AWSC conversion would be considered as a

blanket treatment for local communities. Additionally, AWSC conversion should be implemented with enhanced visibility of crossing pedestrians at intersections. Potential countermeasures include the installation of high visibility crosswalk markings, installation of bulb-outs, installation of advanced pedestrian crossing warning signs, eliminating near side parking spots and installation of raised crosswalks and other techniques.

The second essay in Chapter 2 studies the safety effect of removing reversible lane operations along urban arterials using data from Washington, D.C. between 2003 and 2017. Taking advantage of the termination of three reversible lane arterials in 2010, the safety evaluation was performed using the Before-After (BA) study with a control group and the Empirical Bayes (EB) method, respectively. The Crash Modification Factors (CMF) for all crashes, fatal/injury crashes, property damage only (PDO) crashes, Rear End crashes, Left Turn crashes and Sideswipe crashes were estimated. The findings suggest a clear safety tradeoff between safety and the gain of peak direction capacity by operating reversible lanes along urban arterials. Generally, all crashes, including both fatal/injury and PDO crashes, are more frequent on reversible roadways. Specifically, Left Turn crashes caused by lane use confusion and sideswipe crashes related to lane changing maneuvers appear to be associated with reversible lane operations on urban arterials. These findings provide strong policy implications that the throughput capacity gain of reversible lane operation comes at the cost of increased crashes. Planners and policy makers should evaluate reversible lane operation proposals comprehensively while taking account of their costs and benefits.

The third essay in Chapter 3 finds that the current practices of allocating curb spaces for commercial loading zones in many U.S. cities are largely at the discretion of the agency in charge and are typically initiated by the requests from business owners and property managers. A demand-driven Loading Zone Allocation Model is created for the District Department of Transportation to facilitate the decision making process for curbside loading zone space allocation. Freight Trip Generation (FTG) models are used to estimate the delivery needs for business establishments at a block face level. The current numbers of loading zones per block face are regressed against the Gross FTG (GFTG) per block face and other block face characteristic variables using zero-truncated negative binomial models. GFTG is found to be the most significant predictor of the number of loading zones per block face in the District. Curbside spaces are then assigned as loading zones using the selected model based on Akaike's Information Criterion (AIC) in an iterative process. It is worth noting that the model is not meant to justify that the existing loading zone allocation in D.C. is advantageous. However, the model does appear to reveal that the loading zone allocation result is significantly correlated with one of the Pickup and Delivery (PUD) activity intensity indicators, which shows its linkage with true curb side space demand for PUD activities. This model is useful to establish an equitable, consistent, and repeatable process to uniformly evaluate curbside loading zone needs. Any public agencies that are interested in incorporating a quantitative approach into their loading zone allocation program may be enlightened by the approach presented in this essay.

Appendices

Table A-1 List of Treatment Group Intersections (for Chapter 1 Study)

Intersection	ANC	Road One Functional Class	Road Two Functional Class	Number of Legs	Assumed Conversion Year
10th ST NE and C ST NE	6A	Local	Local	4	2011
10th ST SE and C ST SE	6B	Local	Local	4	2014
10th ST NW and V ST NW	1B	Local	Local	4	2012
10th ST NW and W ST NW	1B	Local	Local	4	2012
12th ST NE and C ST NE	6A	Local	Local	4	2011
12th ST NE and IRVING ST NE	5B	Minor Arterial	Local	4	2011
12th ST NE and OTIS ST NE	5B	Minor Arterial	Local	4	2013
13th ST NW and CRITTENDEN ST NW	4C	Minor Arterial	Local	3	2014
13th ST and QUINCY ST NW	4C	Minor Arterial	Local	4	2014
14th ST and NEWTON ST NE	5B	Collector	Local	4	2011
14th ST NW (IOWA AVE NW) and EMERSON ST NW	4C	Minor Arterial	Local	4	2012
15th ST NE and LAWRENCE ST NE	5B	Local	Local	4	2010
15th ST SE and BRUCE PL SE	8E	Local	Local	3	2012
1st ST SE and CHESAPEAKE ST SE	8D	Collector	Local	3	2014
1st ST NW and N ST NW	5E	Collector	Local	4	2012
20th ST NW and HAMLIN ST NE	5C	Collector	Local	4	2013
20th ST NE and JACKSON ST NE	5C	Collector	Local	4	2014
20th ST NE and KEARNY ST NE	5C	Collector	Local	4	2014
28th ST NE and NEWTON ST NE	5C	Local	Local	4	2010
2nd ST NE and TAYLOR ST NE	5A	Local	Minor Arterial	3	2012
30th ST NW and P ST NW	2E	Collector	Minor Arterial	4	2010
33rd ST NW and Q ST NW	2E	Collector	Collector	4	2010
34th ST NW and RESERVOIR RD NW	2E	Collector	Minor Arterial	4	2010
35th ST NW and EDMUNDS ST NW	3C	Local	Local	3	2011
38th ST NW and FESSENDEN ST NW	3E	Local	Collector	3	2013

Intersection	ANC	Road One Functional Class	Road Two Functional Class	Number of Legs	Assumed Conversion Year
3rd ST SE and I ST SE	6D	Local	Local	4	2013
44th ST NW and DAVENPORT ST NW	3E	Local	Local	4	2013
45th ST NW and BRANDYWINE ST NW	3E	Local	Local	4	2012
4th ST NE and I ST NE	6C	Collector	Local	4	2013
4th ST SE and I ST SE	6D	Collector	Local	4	2013
4th ST SE and NEWCOMB ST SE	8C	Local	Local	4	2014
51st ST SE and ASTOR PL SE	7E	Collector	Local	4	2014
51st ST SE and QUEENS STROLL PL SE	7E	Collector	Local	4	2014
53rd ST SE and D ST SE	7E	Local	Local	4	2014
5th ST SE and MELLON ST SE	8C	Local	Local	4	2013
5th ST NW and R ST NW	6E	Local	Minor Arterial	4	2011
6th ST and I ST NE	6C	Collector	Local	4	2013
DELAWARE AVE SW and CANAL ST SW	6D	Collector	Collector	3	2010
FESSENDEN ST NW and BELT RD NW	3E	Collector	Local	4	2013
HAWAII AVE NE and VARNUM ST NE	5A	Collector	Local	4	2012
KANSAS AVE NW and TAYLOR ST NW	4C	Minor Arterial	Local	4	2011
KENTUCKY ST SE and C ST SE	6B	Collector	Local	4	2014
N ST SE (TINGEY ST SE) and NEW JERSEY AVE SE	6D	Local	Local	4	2012
NEW HAMPSHIRE AVE NW and V STREET NW	1B	Minor Arterial	Collector	4	2013
NORTHAMPTON ST NW and UTAH AVE NW	3G	Local	Collector	4	2013
NORTHGATE RD NW and PRIMROASE RD NW	4A	Local	Local	3	2013
RITTENHOUSE ST NW and 9TH ST NW	4B	Local	Local	4	2013
UNIVERSITY AVE NW and RODMAN ST NW	3D	Local	Local	3	2012

Table A-2 List of Control Group Intersections (for Chapter 1 Study)

Intersection	ANC	Road One Functional Class	Road Two Functional Class	Number of Legs	Index Year
SOUTH CAROLINA AVE SE and 14th ST NE	6A	Local	Local	4	2011
E ST NE and TENNESSEE AVE NE	6A	Local	Local	4	2011
10th ST SE and SOUTH CAROLINA AVE SE	6B	Local	Local	4	2014
D ST SE and 5th ST SE	6B	Local	Local	4	2014
5th ST NE and V ST NE	1B	Local	Local	4	2012
V ST NE and 3rd ST NE	1B	Local	Local	4	2012
8th ST NW and O ST NW	1B	Local	Local	4	2012
SUMMIT PL NE and TODD PL NE	1B	Local	Local	4	2012
16th ST NE and CONSTITUTION AVE NE	6A	Local	Local	4	2011
A ST SE and 14th ST SE	6A	Local	Local	4	2011
MICHIGAN AVE NE and WEBSTER ST NE	5B	Minor Arterial	Local	4	2011
NEWTON ST NE and 13th ST NE	5B	Minor Arterial	Local	4	2011
12th ST NE and UPSHUR ST NE	5B	Minor Arterial	Local	4	2013
16th ST NE and MONROE ST NE	5B	Minor Arterial	Local	4	2013
14th ST NW and CRITTENDEN ST NW	4C	Minor Arterial	Local	3	2014
TAYLOR ST NW and ARKANSAS AVE NW	4C	Minor Arterial	Local	3	2014
13th ST NW and INGRAHAM ST NW	4C	Minor Arterial	Local	4	2014
JEFFERSON ST NW and 13th ST NW	4C	Minor Arterial	Local	4	2014
14th ST NE and LAWRENCE ST NE	5B	Collector	Local	4	2011
20th ST NE and SHEPHERD ST NE	5B	Collector	Local	4	2011
ARKANSAS AVE NW and FARRAGUT ST NW	4C	Minor Arterial	Local	4	2012
EMERSON ST NW and ARKANSAS AVE NW	4C	Minor Arterial	Local	4	2012
16th ST NE and GIRARD ST NE	5B	Local	Local	4	2010
TAYLOR ST NE and 22nd ST NE	5B	Local	Local	4	2010
9th ST SE and YUMA ST SE	8E	Local	Local	3	2012
CONDON TER SE and YUMA ST SE	8E	Local	Local	3	2012
ELMIRA ST SE and 6th ST SE	8D	Collector	Local	3	2014

Intersection	ANC	Road One Functional Class	Road Two Functional Class	Number of Legs	Index Year
MARTIN LUTHER KING JR AVE SW and 1st PL SW	8D	Collector	Local	3	2014
BATES ST NW and 1st ST NW	5E	Collector	Local	4	2012
SEATON PL NE and 3rd ST NE	5E	Collector	Local	4	2012
DOWNING ST NE (DOUGLAS ST NE) and MONTANA AVE NE	5C	Collector	Local	4	2013
SARATOGA AVE NE and MONTANA AVE NE	5C	Collector	Local	4	2013
17th ST NE and FRANKLIN ST NE	5C	Collector	Local	4	2014
26th ST NE and FRANKLIN ST NE	5C	Collector	Local	4	2014
14th ST NE and GIRARD ST NE	5C	Collector	Local	4	2014
BRYANT ST NE and 18th ST NE	5C	Collector	Local	4	2014
26th ST NE and IRVING ST NE	5C	Local	Local	4	2010
31st ST NE and ADAMS ST NE	5C	Local	Local	4	2010
EASTERN AVE NE and HAMILTON ST NE	5A	Local	Minor Arterial	3	2012
SARGENT RD NE and DELAFIELD PL NE	5A	Local	Minor Arterial	3	2012
44th ST NE and SHERIFF RD NE	2E	Collector	Minor Arterial	4	2010
BUCHANAN ST NE and SARGENT RD NE	2E	Collector	Minor Arterial	4	2010
BUNKER HILL RD NE and 18th ST NE	2E	Collector	Collector	4	2010
G ST NW and 24th ST NW	2E	Collector	Collector	4	2010
8th ST NE and WEST VIRGINIA AVE NE	2E	Collector	Minor Arterial	4	2010
H ST NW and 8th ST NW	2E	Collector	Minor Arterial	4	2010
27th ST NW and WOODLEY RD NW	3C	Local	Local	3	2011
35th ST NW and RODMAN ST NW	3C	Local	Local	3	2011
BUTTERWORTH PL NW and 42nd ST NW	3E	Local	Collector	3	2013
FESSENDEN ST NW and 43rd ST NW	3E	Local	Collector	3	2013
6th ST SE and I ST SE	6D	Local	Local	3	2013
POTOMAC AVE SE and 9th ST SE	6D	Local	Local	4	2013
47th ST NW and DAVENPORT ST NW	3E	Local	Local	4	2013
WINDOM PL NW and 45th ST NW	3E	Local	Local	4	2013
45th ST NW and ELLICOTT ST NW	3E	Local	Local	4	2012

Intersection	ANC	Road One Functional Class	Road Two Functional Class	Number of Legs	Index Year
BRANDYWINE ST NW and 43rd PL NW	3E	Local	Local	4	2012
A ST NE and 15th ST NE	6C	Collector	Local	4	2013
CONSTITUTION AVE NE and 19th ST NE	6C	Collector	Local	4	2013
14th ST NE and A ST NE	6D	Collector	Local	4	2013
8th ST SE and D ST SE	6D	Collector	Local	4	2013
11TH PL SE & CONGRESS ST SE	8C	Local	Local	4	2014
BROTHERS PL SE and TRENTON PL SE	8C	Local	Local	4	2014
AYERS PL SE and 51st ST SE	7E	Collector	Local	4	2014
KIMI GRAY CT SE and 51st ST SE	7E	Collector	Local	4	2014
A ST SE and 51st ST SE	7E	Collector	Local	4	2014
BASS PL SE and 51st ST SE	7E	Collector	Local	4	2014
ASTOR PL SE and 50th ST SE	7E	Local	Local	4	2014
BOWEN RD SE and BURNS ST SE	7E	Local	Local	4	2014
14th PL SE and SAVANNAH ST SE	8C	Local	Local	3	2013
SAVANNAH ST SE and 5th ST SE	8C	Local	Local	4	2013
8th ST NW and Q ST NW	6E	Local	Minor Arterial	4	2011
8th ST NW and R ST NW	6E	Local	Minor Arterial	4	2011
15th ST NE and DUNCAN ST NE	6C	Collector	Local	4	2013
CONSTITUTION AVE NE and 15th ST NE	6C	Collector	Local	4	2013
20th ST NE and EASTERN AVE NE	6D	Collector	Collector	3	2010
R ST NE and 2nd ST NE	6D	Collector	Collector	3	2010
46th ST NW and DAVENPORT ST NW	3E	Collector	Local	4	2013
BUTTERWORTH PL NW and 46th ST NW	3E	Collector	Local	4	2013
8TH ST NE & GALLATIN ST NE	5A	Collector	Local	4	2012
GALLATIN ST NE and 12th ST NE	5A	Collector	Local	3	2012
13th ST NW and HAMILTON ST NW	4C	Minor Arterial	Local	4	2011
14th ST NW and ALLISON ST NW	4C	Minor Arterial	Local	4	2011
16th ST SE and MASSACHUSETTS AVE SE	6B	Collector	Local	4	2014
A ST SE and 8th ST SE	6B	Collector	Local	4	2014

Intersection	ANC	Road One Functional Class	Road Two Functional Class	Number of Legs	Index Year
CARROLLSBURG PL SW and O ST SW	6D	Local	Local	3	2012
4TH PL SW & G ST SW	6D	Local	Local	4	2012
4th ST NW and Q ST NW	1B	Minor Arterial	Collector	4	2013
V ST NE and LINCOLN RD NE	1B	Minor Arterial	Collector	4	2013
BELT RD NW and MCKINLEY ST NW	3G	Local	Collector	4	2013
QUESADA ST NW and NEVADA AVE NW	3G	Local	Collector	4	2013
NORTHGATE RD NW and ROXANNA RD NW	4A	Local	Local	3	2013
ROCK CREEK FORD RD NW and FORT STEVENS DR NW	4A	Local	Local	3	2013
GERANIUM ST NW and 8th ST NW	4B	Local	Local	4	2013
HEMLOCK ST NW and 9th ST NW	4B	Local	Local	4	2013
51st PL NW and CATHEDRAL AVE NW	3D	Local	Local	3	2012
SALEM LN NW and 45th ST NW	3D	Local	Local	3	2012

Table C-1 Full List of SIC (by NAICS Association, LLC, for Chapter 3 Study)

Division	Code	Industry Title
A	**01-09**	**Agriculture, Forestry, And Fishing**
	01	Agricultural Production - Crops
	02	Agricultural Production - Livestock and Animal Specialties
	07	Agricultural Services
	08	Forestry
	09	Fishing, Hunting and Trapping
B	**10-14**	**Mining**
	10	Metal Mining
	12	Coal Mining
	13	Oil and Gas Extraction
	14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels
C	**15-17**	**Construction**
	15	Building Construction - General Contractors & Operative Builders
	16	Heavy Construction, Except Building Construction - Contractors
	17	Construction - Special Trade Contractors
D	**20-39**	**Manufacturing**
	20	Food and Kindred Products
	21	Tobacco Products
	22	Textile Mill Products
	23	Apparel, Finished Products from Fabrics & Similar Materials
	24	Lumber and Wood Products, Except Furniture
	25	Furniture and Fixtures
	26	Paper and Allied Products
	27	Printing, Publishing and Allied Industries
	28	Chemicals and Allied Products
	29	Petroleum Refining and Related Industries
	30	Rubber and Miscellaneous Plastic Products
	31	Leather and Leather Products
	32	Stone, Clay, Glass, and Concrete Products
	33	Primary Metal Industries
	34	Fabricated Metal Products, Except Machinery & Transport Equipment
	35	Industrial and Commercial Machinery and Computer Equipment
	36	Electronic, Electric Equipment & Components, Except Computer Equipment
	37	Transportation Equipment
	38	Measure/Analyze/Control Instruments; Photo/Medical/Optical Goods; Watches/Clocks
	39	Miscellaneous Manufacturing Industries

Division	Code	Industry Title
E	**40-49**	**Transportation, Communications, Electric, Gas, And Sanitary Services**
	40	Railroad Transportation
	41	Local, Suburban Transit & Interurban Highway Passenger Transport
	42	Motor Freight Transportation
	43	United States Postal Service
	44	Water Transportation
	45	Transportation by Air
	46	Pipelines, Except Natural Gas
	47	Transportation Services
	48	Communications
	49	Electric, Gas and Sanitary Services
F	**50-51**	**Wholesale Trade**
	50	Wholesale Trade - Durable Goods
	51	Wholesale Trade - Nondurable Goods
G	**52-59**	**Retail Trade**
	52	Building Materials, Hardware, Garden Supply & Mobile Home Dealers
	53	General Merchandise Stores
	54	Food Stores
	55	Automotive Dealers and Gasoline Service Stations
	56	Apparel and Accessory Stores
	57	Home Furniture, Furnishings and Equipment Stores
	58	Eating and Drinking Places
	59	Miscellaneous Retail
H	**60-67**	**Finance, Insurance, And Real Estate**
	60	Depository Institutions
	61	Nondepository Credit Institutions
	62	Security & Commodity Brokers, Dealers, Exchanges & Services
	63	Insurance Carriers
	64	Insurance Agents, Brokers and Service
	65	Real Estate
	67	Holding and Other Investment Offices
I	**70-89**	**Services**
	70	Hotels, Rooming Houses, Camps, and Other Lodging Places
	72	Personal Services
	73	Business Services
	75	Automotive Repair, Services and Parking
	76	Miscellaneous Repair Services
	78	Motion Pictures
	79	Amusement and Recreation Services

Division	Code	Industry Title
	80	Health Services
	81	Legal Services
	82	Educational Services
	83	Social Services
	84	Museums, Art Galleries and Botanical and Zoological Gardens
	86	Membership Organizations
	87	Engineering, Accounting, Research, Management & Related Services
	89	Services, Not Elsewhere Classified
J	**90-99**	**Public Administration**
	91	Executive, Legislative & General Government, Except Finance
	92	Justice, Public Order and Safety
	93	Public Finance, Taxation and Monetary Policy
	94	Administration of Human Resource Programs
	95	Administration of Environmental Quality and Housing Programs
	96	Administration of Economic Programs
	97	National Security and International Affairs
	99	Nonclassifiable Establishments

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