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The Influences of Intersection Roadway Characteristics on Pedestrian-Vehicle Collisions

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The Influences of Intersection Roadway Characteristics on Pedestrian-Vehicle Collisions

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Master of Urban and Regional Planning

by

Jasmin Y. Kim

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ABSTRACT OF THE THESIS

The Influences of Intersection Roadway Characteristics on

Pedestrian-Vehicle Collisions

by

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Master of Urban and Regional Planning

University of California, Los Angeles, 2016

Professor Martin Wachs, Chair

In dense urban areas, collisions involving pedestrians and vehicles present a significant challenge for public health. Achieving pedestrian safety is complicated because countless intersection roadway characteristics—traffic control devices, roadway geometry, and sociodemographic and behavioral decision-making—can influence pedestrian-vehicle collisions (PVCs). In the past, studies have examined influences of multiple roadways, sociodemographic, and built environment factors on PVCs. Few studies, however, specifically examine relationships, 'at' or 'near' intersections, where pedestrian collisions frequently occur. This study measures the influences of multiple intersection roadway characteristics—including various built environment, traffic control devices, and sociodemographic descriptors of neighborhoods surrounding the intersection sites—on pedestrian-vehicle collisions (PVCs) in Washington D.C. from 2010 to 2014.

Using collision and roadway attribute data sets obtained from the Metropolitan Police Department of the District of Columbia, the District Department of Transportation, and the U.S. Census, this study consisted of four stages of analysis: 1. archival review of all PVCs, 2. spatial mapping, 3. negative binomial regression modeling, and 4. field observations of seven intersections with the highest number of PVCs over pedestrian demand index (PDI). Findings include some significant relationships between multiple intersection roadway characteristics and PVCs. Based on the findings of this analysis, some countermeasures—such as updating the PDI annually, extending the sidewalks, and increasing the number of streetlights, area of sidewalk, and raised crosswalks—are recommended to enhance pedestrian safety at roadway intersections.

Keywords**:** *pedestrians, safety, contributing factors, pedestrian-vehicle collisions, GIS, geo-coded crashes, pedestrian crash zones, pedestrian crossings, mid-block crashes, intersection site characteristics, countermeasures, built environment, pedestrian exposure.*

The thesis of Jasmin Youngeun Kim is approved.

Michael C. Lens

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University of California, Los Angeles

2016

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GLOSSARY

1. “ArcGIS”: “a geographic information system (GIS) for working with maps and geographic information”(“ArcGIS,” 2016).
2. “Area-Wide Level”: refers to a broader level of spatial boundary (than site-specific level) examined to analyze the response variable. In this specific study, area-wide level refers to examining PVCs at census tracts or wider scale of spatial boundaries (e.g., wards and police districts).
3. “DDOT” or District Department of Transportation: District of Columbia government’s Department of Transportation manages and maintains planning, designing, construction, and maintenance for the District’s streets, alleys, sidewalks, bridges, traffic signals and streetlights (District of Columbia, Department of Transportation, 2015).
4. “Explanatory Variable” or “Independent Variable”: Explains for the changes in a response variable when statistically significant.
5. “MPDC” or “Metropolitan Police Department of the District of Columbia”: Primary law enforcement agency for the District of Columbia.
6. “MUTCD” or “Manual on Uniform Traffic Control Devices on Streets and Highways”: A compilation of national standards provided by the Federal Highway Administration’s (FHWA) for all traffic control devices, including road marking, highway signs, and traffic signals. This manual is “updated periodically to accommodate the nation’s changing transportation needs and address new safety technologies, traffic control tools and traffic management techniques”(The Federal Highway Administration, 2009).

7. “Offset term”: a “structural” predictor where its coefficient is not estimated by the regression model but is assumed to have value of 1. “Thus, the values of the offset are simply added to the linear predictor of the dependent variable. This is especially useful in Poisson regression models, where each case may have different levels of exposure to the event of interest” (“GENLIN and Poisson and offset,” 2011).
8. “PDI” or “Pedestrian Demand Index”: an estimation of pedestrian activity developed in 2009 for DDOT’s Pedestrian Master Plan (District Department of Transportation (DDOT), 2009).
9. “PVCs” or “Pedestrian-Vehicle Collisions”: Collisions reported to MPDC in the District of Columbia from 2010 to 2014, where pedestrians were hit by moving vehicles (including personal vehicles, trucks, buses, and motorcycles, but excluding bicycles).
10. “Response Variable” or “Dependent Variable”: Variables that measures an outcome of a study, in this case, a measure of pedestrian safety (PVCs over PDI).
11. “Site-Specific Level”: refers to specific level of spatial boundary examined to analyze the response variable. In this specific study, site-specific level refers to examining PVCs ‘at’ or ‘near’ intersections (e.g., 300ft from an intersection).
12. “TCDs” or “Traffic Control Devices”: Federal Highway Administration (FHWA) defines these devices as sign, signal, marking, or other device used to regulate, warn, or guide traffic, placed on, over, or adjacent to a street, highway, pedestrian facility, or shared-use path. In this research, however, this term is used to mention just several, not all, of the traffic control devices listed by FHWA (The Federal Highway Administration, 2009).

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CHAPTER 1:

INTRODUCTION

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

"About three times every day in the District [of Columbia], someone walking on a city street gets hit by a vehicle and an ambulance races to the scene. This year, four of those people have died"— The Washington Post (Klein, March 2011).

Pedestrian injuries and deaths pose significant health challenges around the world as more than 270,000 pedestrians lose their lives on the world's roads each year (World Health Organization, 2013). In the United States, motor vehicle collisions (MVCs) have been a major source of pedestrian deaths in recent years, especially from 2010 to 2013 (NHTSA, 2015); in Washington D.C., more than half of those killed in the District's road accidents were pedestrians, according to a 2010 study conducted by the National Highway Traffic Safety Administration (NHTSA).

Recognizing the need to improve pedestrian safety, the Mayor of the District of Columbia, Muriel Bowser, unveiled the Vision Zero Action Plan in 2015 (King, 2015), to make D.C. streets safer by attempting to reach zero fatalities and serious injuries to vulnerable travelers—especially pedestrians and bicyclists using the D.C. transportation system—by the year 2024. Such a bold plan, however, may only be accomplished with an improved understanding of contributing environmental factors that cause pedestrian-vehicle collisions (PVCs) in the District. Yet, relatively few researchers have examined environmental factors that cause PVCs, especially at signalized intersections (Moreno, Morency, El-Geneidy, 2011). To better understand contributing factors to PVCs, this study examined the influences of various roadway characteristics on PVCs 'at' and 'near' intersections, where majority of the District's PVCs occurred from 2010 to 2014.

1.2 OBJECTIVE & HYPOTHESES

The objective of this research is to identify contributing environmental factors that influence PVCs. More specifically, this research attempts to measure the influences of intersection roadway characteristics—such as the surrounding built environment, the presence or absence of traffic control devices, and sociodemographic factors of neighborhoods surrounding intersection sites—on PVCs that occurred 'at' or 'near' intersections in Washington D.C. from 2010 to 2014.

To meet this objective, I propose a set of hypotheses. The first is that the presence of traffic control devices (TCDs)—including stop bars, speed humps, puppy tracks, rumble strips, parking space markings, signalized intersections, traffic poles, camera enforcements, other traffic control signs, school crossing guards[1]—would generally enhance pedestrian safety. This is because TCDs are often installed as intersection treatment measures by city or state transportation agencies to inform drivers to either stop or slow down while approaching an intersection.

Second, I hypothesize that sites with high-density residential and commercial land uses, greater area of sidewalks, and more streetlights would experience more PVCs because intersection sites with high population density are likely to observe higher volume of pedestrians walking on the sidewalks.

Third, I hypothesize that sites having greater presence of transit stops, such as bus and Metro stops will show more PVCs because these stops are often located very close to the intersections, inclining some pedestrians to walk against the signals at treated intersections or cross in mid-blocks to save time and catch the next bus or the Metro.

[1] See Appendix 3 for definitions of some TCD terms mentioned.

Fourth, I presume that more risks would be imposed on pedestrians crossing one-way streets than two-way streets because the speeds of vehicles traversing one-way streets are likely to be higher than those of vehicles traveling on two-way streets, assuming that fewer lanes (per direction) would be available on two-way streets than one-way streets.

Fifth, I predict that arterials and collector would show more PVCs, whereas opposite relationships are expected (weak, negative relationship) for local streets. This is because vehicles generally travel at a higher speed in the arterials and collector roads than local streets (Federal Highway Administration, 2013).

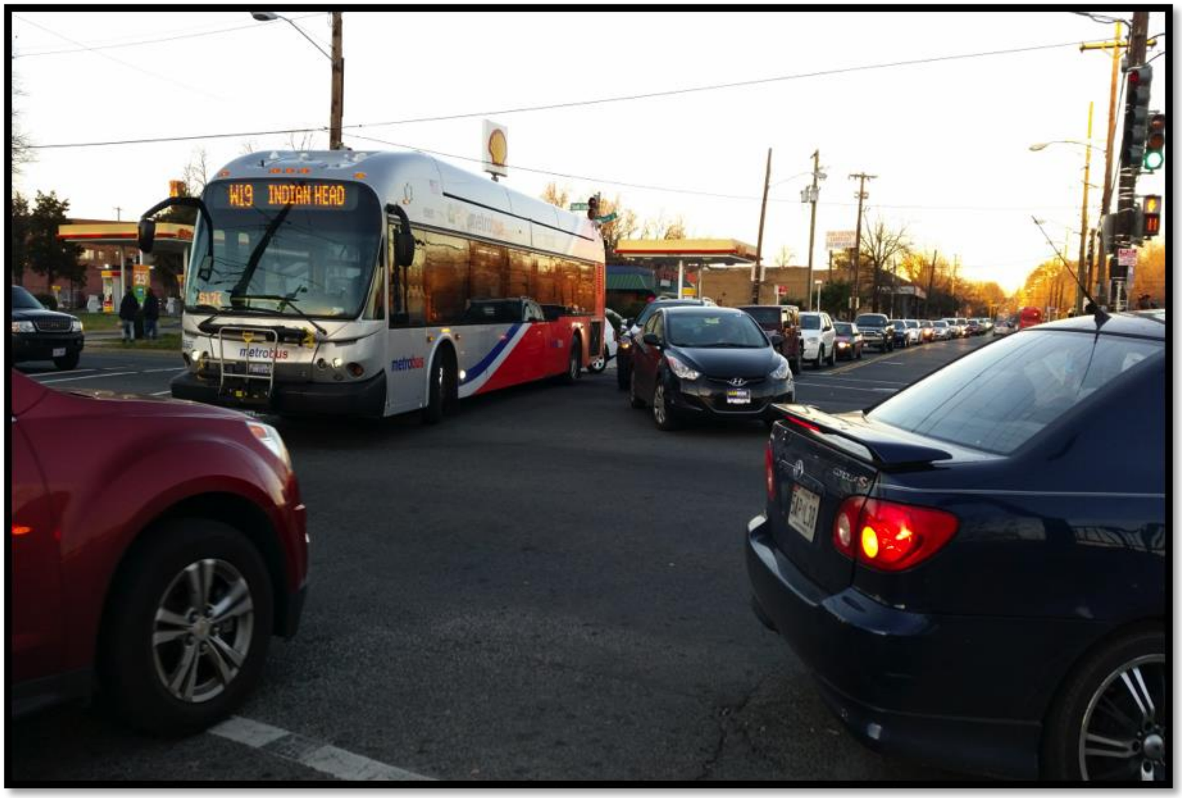
Sixth, I hypothesize that there is a relationship between the race, income, and age of the populations in the census tracts that include the observed intersections and the frequency of PVCs. More specifically, I expect that the intersection sites located in areas with higher percentages of minority (non-Whites) and low-income population would be characterized by more PVCs because many low-income and minority populations are more dependent on public transportation than higher income whites, and thus are more likely to be pedestrians.

Lastly, among the different age groups tested in this research, I predict that children (ages 15 or below) and the elderly (ages 65 plus) would be the most vulnerable pedestrian age groups, because they are likely to have limited access to motor vehicles. Hence, at intersection sites located in census tracts with high percentages of children or the elderly, I hypothesize that the frequency of PVCs would be high.

To thoroughly examine these hypotheses, four stages of analysis are conducted using collision and roadway attribute data sets obtained from the District Department of Transportation (DDOT) and the U.S. Census. Chapter 2 presents a review of previous research that has addressed contributing factors that relate to PVCs. Chapter 3 draws from the literature review to discuss several methodologies for identifying the relationship between PVCs and intersection roadway characteristics. Chapter 4 provides the results from each stage of analysis, while Chapter 5 presents a summary of all the findings along with some countermeasures, which are recommended to enhance pedestrian safety at roadway intersections. Chapter 5 also discusses the limitations of this study and suggestions for future research.

CHAPTER 2

LITERATURE REVIEW



CHAPTER 2

LITERATURE REVIEW

2.1 PREVIOUS RESEARCH

Identifying effective measures to improve pedestrian safety requires a comprehensive understanding and analysis of contributing factors that influence the probability of pedestrian-vehicle collisions (PVCs). Previous studies have examined numerous factors associated with PVCs. Roadway and built environment (BE) characteristics (such as land uses and transit stops), sociodemographic characteristics (such as race, income, and age), and presence of streetlights, transit stops, sidewalks, medians, and crosswalks—are some of many factors that have been already probed by other researchers. However, only a few studies have focused on the association between PVCs and roadway and BE characteristics at signalized intersections (Aziz, Ukkusuri, & Hasan, 2013; Lee & Abdel-Aty, 2005; Lyon & Persaud, 2002; Miranda-Moreno, Morency, & El-Geneidy, 2011). Studies have more often examined such associations at a regional or area-wide (e.g., census tracts) level (Clifton & Kreamer-Fults, 2007; Dai, 2012; Dumbaugh & Li, 2010; D. J. Graham & Glaister, 2003; Joly, Foggin, & Pless, 1991; E. A. LaScala, Johnson, & Gruenewald, 2001; Elizabeth A. LaScala, Gruenewald, & Johnson, 2004; Loukaitou-Sideris, Liggett, & Sung, 2007; Siddiqui, Abdel-Aty, & Choi, 2012; Wier, Weintraub, Humphreys, Seto, & Bhatia, 2009).

Previous studies have varied significantly in their objectives. Some have solely evaluated the effect of BE characteristics (such as land uses, and the presence of transit stops) on PVCs, while others have evaluated the influences of roadway factors (such as traffic control devices, presence of signalized intersections, and other roadway design factors) or sociodemographic factors (race, income, and age) on PVCs. However, only a few studies have comprehensively examined both the effect of BE and roadway factors on PVCs (Loukaitou-Sideris et al., 2007; R. J. Schneider, Arnold, & Ragland, 2009; Ukkusuri, Miranda-Moreno, Ramadurai, & Isa-Tavarez, 2012). Many other studies have focused on modeling pedestrian crash exposure by understanding how pedestrian and traffic volume affect the frequency or severity of PVCs (Greene-Roesel, Diogenes, & Ragland, 2007; Jonah & Engel, 1983; Lassarre, Papadimitriou, Yannis, & Golias, 2007; Lyon & Persaud, 2002; Miaou, Shaw-Pin & Lord, Dominique, 2003; Pulugurtha & Repaka, 2008; R. J. Schneider et al., 2009).

For the purpose of this study, I examine two categories of past studies in detail: (1) research identifying which built environment (BE) characteristics influence the frequency of PVCs and (2) research identifying roadway factors that influence the frequency of PVCs. Subsequently, I explore statistical and pedestrian crash exposure models developed by other researchers.

2.2 REVIEW OF FACTORS THAT INFLUENCE PVCS

2.2.1 The Built Environment (BE) Characteristics

Prior research has identified that surrounding built environment (BE) characteristics can influence personal travel mode choices (Crane, 2000; Ewing & Cervero, 2001). Some have found that higher population densities generally increase walking trips (Frank & Pivo, 1994; Rajamani, Bhat, Handy, Knaap, & Song, 2003) while others have found that high to medium density residential and commercial land uses increase walking trips (Cervero, 1994; Dunphy & Fisher, 1996). Assuming that an increase in the number of walking trips can lead to higher frequency of PVCs, recent researchers have tried to understand the effect of surrounding BE characteristics on PVCs both spatially and statistically.

2.2.1.1 Sociodemographic Factors

Several studies that have examined sociodemographic factors have identified that the neighborhoods with high percentages of low-income, minority, unemployment, and youth population are more likely to exhibit greater number of PVCs. At an area-wide (e.g., census tract or wards) level, Beck, Paulozzi, & Davidson (2007) conducted a Poisson regression analysis, concluding that pedestrian fatality rates for Hispanics, 15-34, and 35-54 year olds were higher in Atlanta than the overall fatality rates for the United States. In California, LaScala et al.(2004) observed four communities and concluded that areas with higher youth population densities, more unemployment, and fewer high-income households revealed more pedestrian injuries compared to other areas observed. Similarly, Loukaitou-Sideris et al. (2007) conducted Ordinary Least Squares (OLS) regression analysis and suggested that "pedestrian accidents are more likely to occur in low-income, minority neighborhoods of Los Angeles once other aspects of risk are controlled for." In Montreal, Canada, children living in neighborhoods with income levels in the lowest quintile were four times or more likely to be involved in pedestrian collisions than the children living in the least disadvantaged neighborhoods (Dougherty, Pless, & Wilkins, 1990). Additionally, Campos-Outcalt, Bay, Dellapena, & Cota (2003) determined that in Arizona, African American females had greater risk of dying in pedestrian collisions than non-Hispanic white females.

Some researchers have written about why pedestrians may be at greater risk of colliding with moving vehicles in low-income neighborhoods. For instance, a study that examined the social and behavioral characteristics of 11,966 preschool children found that social class, age, and mother's psychological distress scores (from Maternal Malaise Inventory[2]) all affected accidental injuries (Bijur, Stewart-Brown, & Butler, 1986). Another study has identified that stressful life changes (which was acquired through a form of Social Readjustment Rating Questionnaire (SRRQ)[3] for survey respondents), predisposed accidents among observed junior high school boys (Padilla, Rohsenow, & Bergman, 1976). Rivara and Barber (1985) also found that neighborhoods in United States with a higher than average proportion of single parents, disadvantaged ethnic minorities, household crowding, and low income have significantly higher rates of injury involving young pedestrians (aged 0 to 14 years). In their research, they argue that the 'crowding of individual housing units' are likely to be the underlying cause for the high rates of pedestrian injuries in the low-income neighborhoods. To be more specific, they argue:

"Poor children, black children, and children from large families headed by women, are more likely to be injured. Why? Individual household and neighborhood crowding appear to be underlying factors through which these other characteristics operate, at least in part. Crowding of individual housing units will result in more time spent outside. Crowding of large numbers of these housing units in a neighborhood increases the number of such children, at the same time providing less room for them to play. Areas with low-income populations are infrequently equipped with playgrounds and parks; the streets become the most accessible substitute. Thus, exposure to motor vehicles and the risk of a collision are consequently increased."

Dougherty et al. (1990) adds that a complex interaction of factors, such as a "lack of secure play space; dwellings adjacent to busy traffic flows; hazardous journeys to school and other

[2] According to the literature, Maternal Malaise Inventory provided psychological distress scores of mothers of the injured children.
[3] Developed by Holmes and Rahe in 1967, SRRQ is "a scaling instrument for the life changes empirically determined to precede major health problems"(Padilla, Rohsenow, & Bergman, 1976).

facilities…and greater stress" puts child pedestrians in low-income neighborhoods at a greater risk of PVCs. While many of these studies have focused on young pedestrians, this summary provides an idea of why pedestrians in low-income and minority neighborhoods are at more risk of pedestrian-vehicle collisions than pedestrians in other neighborhoods.

2.2.1.2 Land Use Factors

Many prior studies have examined the relationships between certain land use types and their effects on the number of PVCs. However, findings are often contradictory and researchers have not yet come to a clear conclusion on how these two types of land use influence PVCs. For instance, LaScala et al. (2004) found that areas with dense commercial land use, especially those with high density of retail and entertainment spaces like bars and restaurants, are associated with high frequency of pedestrian crashes. In fact, Loukaitou-Sideris et al. (2007) stated that "land uses generating pedestrian traffic (such as schools, commercial facilities, multifamily housing) are frequently found to be linked to high [pedestrian-vehicle] collision rates." Moreover, using a negative binomial (NB) regression model, Ukkusuri, Hasan, & Aziz (2011) revealed that pedestrians are more prone to crashes in areas with higher density of commercial and industrial land use.

Similarly, after observing land use effects on traffic accidents, Noland & Quddus (2004) concluded that higher employment densities are associated with more road casualties. In another study, both children and adults were likely to experience traffic accidents where residential populations were high, whereas adults were most likely to have traffic accidents where there are large employment centers (D. Graham, Glaister, & Anderson, 2005). While most of the aforementioned results have indicated that areas with higher commercial land use and employment densities are likely to observe increased frequency of PVCs, some researchers argue that areas with high-density pedestrian activities can also congest traffic flow and reduce traffic speeds, sometimes reducing the severity of PVCs (D. J. Graham & Glaister, 2003). Kim & Yamashita (2002) pointed out the difficult nature of understanding the relationships between land use and PVCs in the following three ways: 1) accidents occur on roadways, not on the adjacent properties 2) the classification of land use may not be the most appropriate categories for analyzing accidents 3) since land use maps do not often portray all uses of land, collisions accounted for in the residential uses may occur also within commercial or other land uses.

2.2.1.3 Transit Stops

Another set of BE factors that researchers have often linked with PVCs is transit stops. But similar to land use characteristics, debates persist over whether or not transit stops truly influence pedestrian safety. Transit stops may expose transit patrons to greater risks of PVCs by tempting the patrons to make rushed, unsafe crossings. Using this logic, some researchers have argued that transit stops are positively associated with the number of PVCs. One researcher, for instance, examined the number of transit stops within 100ft of the intersections (to capture only those transit stops that are within the vicinity of selected signalized intersections) and concluded that an increase in population (residential and employment growth) and transit stops will typically result in an exponential increase in the number of pedestrian crashes (Pulugurtha & Sambhara, 2011). Similarly, some researchers have found the number of bus stops to be a significant variable when predicting pedestrian-automobile collisions (Kim et al., 2010; Miranda-Moreno, Luis et al., 2011). In fact, one study discovered that 89 percent of the high-collision locations were all within 150ft. of bus stops. However, despite its influence on injuries, transit access did not appear to affect pedestrian deaths resulting from MVCs (Clifton, Burnier, & Akar, 2009).

2.2.2 Roadway Factors

2.2.2.1 Roadway Types

In addition to the built environment (BE) factors, some researchers have also associated roadway types with PVCs. Abdel-Aty, Chundi, & Lee (2007) observed five-years of records of crashes involving school-aged children in Orange County, Florida, and found that middle and high school children were more likely to be involved in pedestrian crashes than other age groups, especially on high-speed multi-lane roadways. Similarly, several studies have also indicated that minor roads are associated with fewer pedestrian casualties than major roads(D. J. Graham & Glaister, 2003; Levine, Kim, & Nitz, 1995; Noland & Quddus, 2004). Noland & Quddus (2004)’s study suggested that if minor roads tend to have lower speeds, limiting speeds might be effective at reducing casualties. However, another study of PVCs in Seattle, Washington, found little correlation between the severity of pedestrian injuries and types of roadways (Harruff, Avery, & Alter-Pandya, 1998).

2.2.2.2 Traffic Control Devices (TCDs)

Traffic Control Devices (TCDs) are possible contributing factors to PVCs and have been explored in several studies. Some argue that traffic signals, crosswalks, and stop signs are ineffective (Kim et al., 2010) in enhancing pedestrian safety, while others argue that signal-related interventions have the greatest effect on reducing pedestrian-automobile crashes (Li Chen et al., 2013).

For practitioners working at local transit agencies, the uncertainty over which TCD(s) affect pedestrian safety make it difficult to prioritize and implement specific design and engineering treatments of the intersections with high frequency of PVCs. Instead of prioritizing pedestrian safety when installing TCDs, state and local traffic engineers often mechanically rely on guidelines provided by Federal Highway Administration's (FHWA) Manual on Uniform Traffic Control Devices on Streets and Highways (MUTCD) to warrant TCDs. According to the 2009 MUTCD document, the purpose of traffic control devices is to "promote highway safety and efficiency" through notifying "road users of regulations and provid[ing] warning and guidance needed for the uniform and efficient operation of all elements of the traffic stream in a manner intended to minimize the occurrences of crashes" (The Federal Highway Administration, 2009).

To justify the installation of TCDs, the current MUTCD recommends that traffic engineers study the following factors: eight-hour, four-hour, and peak hour vehicular volume; pedestrian volume; school crossing; coordinated signal system; crash experience (severity and frequency in a year); roadway network (to encourage traffic flow); intersection near a grade crossing. While traffic engineers take these factors and other traffic engineering studies as a proxy for estimating pedestrian exposure and collision risks, the final decision to install TCDs is really based upon each individual's engineering judgments. Such flexibility allows traffic engineers to incorporate various sources of information in making their final judgments as to whether TCDs should be installed or not at an intersection. However, this can also lead to many inconsistencies in the TCD selection process since not all engineers "have the same degree of experience in making TCD decisions, and not all engineers that make these decisions have traffic engineering expertise" (McNeal, 2010). For this reason, to assess the impacts of TCDs and other roadway design elements on pedestrian safety (especially on PVCs), traffic engineers are in need of updated resources and studies, coupled with more recently updated MUTCD guidelines.

2.3 PEDESTRIAN RISK EXPOSURE MODELS

One key element in understanding factors that influence PVCs is pedestrian risk exposure. For this reason, many past studies have concentrated on developing a variety of pedestrian risk exposure models. Among many, several possible ways to assess pedestrian risk exposure at urban intersections include: 1) to determine raw pedestrian volume at intersections during one or more periods of time (usually at morning or afternoon peak time) or 2) estimate pedestrian volume using prediction methodologies (such as creating models or indices based on the built environment) or 3) develop predictive built-environment models based on a sample of intersections in an urban area (Miranda-Moreno et al., 2011; Pulugurtha & Repaka, 2008). Identifying pedestrian risk exposure in these ways allows researchers to control for the dissimilar pedestrian exposure levels at different locations within their study parameter when studying multiple risk factors that may contribute to pedestrian-vehicle collisions.

A review of recent literature on pedestrian risk exposure models (which predict collision frequencies per average daily traffic or pedestrian activity) has identified the difficulty obtaining pedestrian and traffic volume data from numerous transportation agencies (Harwood et al., 2008; Miranda-Moreno et al., 2011; R. Schneider et al., 2010). This difficulty is due to the fact that counting pedestrians frequently at intersections in transportation agencies' jurisdictions is very expensive and time consuming (Miranda-Moreno et al., 2011). Given the difficulty obtaining both pedestrian and traffic volume data from 2010 to 2014, this particular study uses the pedestrian demand index (PDI) developed by the District Department of Transportation (DDOT) in 2009 to estimate the pedestrian risk exposure. In the PDI created by DDOT, higher scores were assigned for street segments having major pedestrian trip generators, greater forecasted population and employment density, greater estimated traffic volume, and higher posted speed limit next to the street segments. In other words, the PDI shows that higher pedestrian index scores mark areas that pose higher risk of PVCs for pedestrians in the District of Columbia (DDOT, 2009).[4]

2.4 METHODS USED TO DETERMINE PEDESTRIAN CRASH FACTORS

To estimate the statistical significance and influences of contributing factors (or independent variables) on pedestrian-vehicle collisions (PVCs), many studies have used some sort of regression analysis as their prime methodology. Researchers predicting factors that contribute to vehicle collisions have estimated one or more of the following regression models: ordinary multiple linear regression, Poisson regression or negative binomial (NB) regression.

2.4.1 Multiple Linear Regression Model

While ordinary multiple linear regression analyses have been applied in few studies involving pedestrian-vehicle collisions, researchers have previously noted that multiple linear regression analysis should be used with a careful caution because 1) collision frequency data do not consist of negative integers (with minimum integer being zero rather than negative); 2) are not normally distributed and are rather skewed; 3) have error terms with unequal variance; and 4) after variance-stabilizing transformations are performed, applying the inverse transformations to the predicted values gives an estimate of the median rather than the mean of the distribution (Jovanis & Chang, 1986; Miaou, 1994; Noland & Quddus, 2004). Also, since multiple linear regression analysis requires a normal distribution, using the count data to perform such analysis could in fact produce biased final estimates in negative values, which would be very hard or impossible to interpret, especially when the count data cannot be negative.

[4] See section 3.3.1 and Appendix 1 for more information on Pedestrian Demand Index (PDI).

2.4.2 Poisson Regression Model

To overcome such problems associated with multiple linear regression model, Jovanis & Chang (1986) proposed that Poisson regression model, otherwise known as Generalized Linear Model (GLM) with Poisson error structure, be considered when predicting collision frequencies. Provided that the collision frequency data are often count data that consist of predominantly zeros and small integers, they claimed that the use of multiple linear regression models can result in inconsistent and biased estimates (Jovanis & Chang, 1986). In contrast, they noted that Poisson regression models can provide a better estimate so long as all the assumptions for the Poisson regression are met. Unlike the ordinary linear regression models, the Poisson regression assumes that the data do not follow a normal distribution (and follow a Poisson distribution), consist of a count data, and that equidispersion—which estimates that the conditional mean and conditional variance are equal to one another (Cameron & Trivedi, 1998)—is met in the response variable.

However, in some instances, researchers have found it very difficult to satisfy the last condition (that equidispersion is met) of the Poisson regression model assumptions, especially when the collision frequency data were found to be 'overdispersed' (M. A. Abdel-Aty & Radwan, 2000; Berk & MacDonald, 2008; Poch & Mannering, 1996). Unlike 'equidispersion,' overdispersion occurs when the response variable's conditional variance exceeds its conditional mean expected in a Poisson distribution. Overdispersion is most likely to be exhibited in discrete, count data, like collisions frequency data, because discrete models do not have to fit to a scale parameter while applying a model to continuous data would require to do so. Moreover, while models with continuous data require the variance to be a function of the mean, discrete models do not have any extra parameter to scale the relationship of the variance and mean (Hardin, Hilbe, & Hilbe, 2007). But, because overdispersion is "generally caused by positive correlation between responses or by an excess variation between response probabilities or counts…it may cause underestimation of standard errors of the estimated coefficient vector" (Hardin et al., 2007) and as a result, some independent variables can appear to be significant when in fact they are not.

2.4.3 Negative Binomial (NB) Regression Model

The problem of overdispersion, however, can be solved by applying a different type of regression model that allows response variables to be both overdispersed and skewed. One such model is negative binomial (NB) regression model within the family of Generalized Linear Models (GLM), which is a flexible generalization of ordinary linear regression that allows for the linear model to be related to the (often skewed) response variable via a link function and let the magnitude of the variance of each measurement to be a function of its predicted value ("Generalized linear model," 2016). Both Poisson and NB regression models are examples of GLM, but researchers have previously noted that Poisson regression models should not be used for overdispersed data because when the mean and the variance do not approximately equal to one another, the variances of the estimated Poisson model can be biased (Poch & Mannering, 1996).

Unlike Poisson regression, NB model does not assume equidispersion (equal dispersion) between mean and the variance of the dependent variable. Therefore, in situations where the collision data is overdispersed and does not meet the condition of Poisson regression, NB regression model is an alternative model many researchers found useful (M. A. Abdel-Aty & Radwan, 2000; Chimba et al., 2014; Miaou, 1994; Poch & Mannering, 1996; Shankar et al., 1995)

2.5 SUMMARY OF THE LITERATURE REVIEW

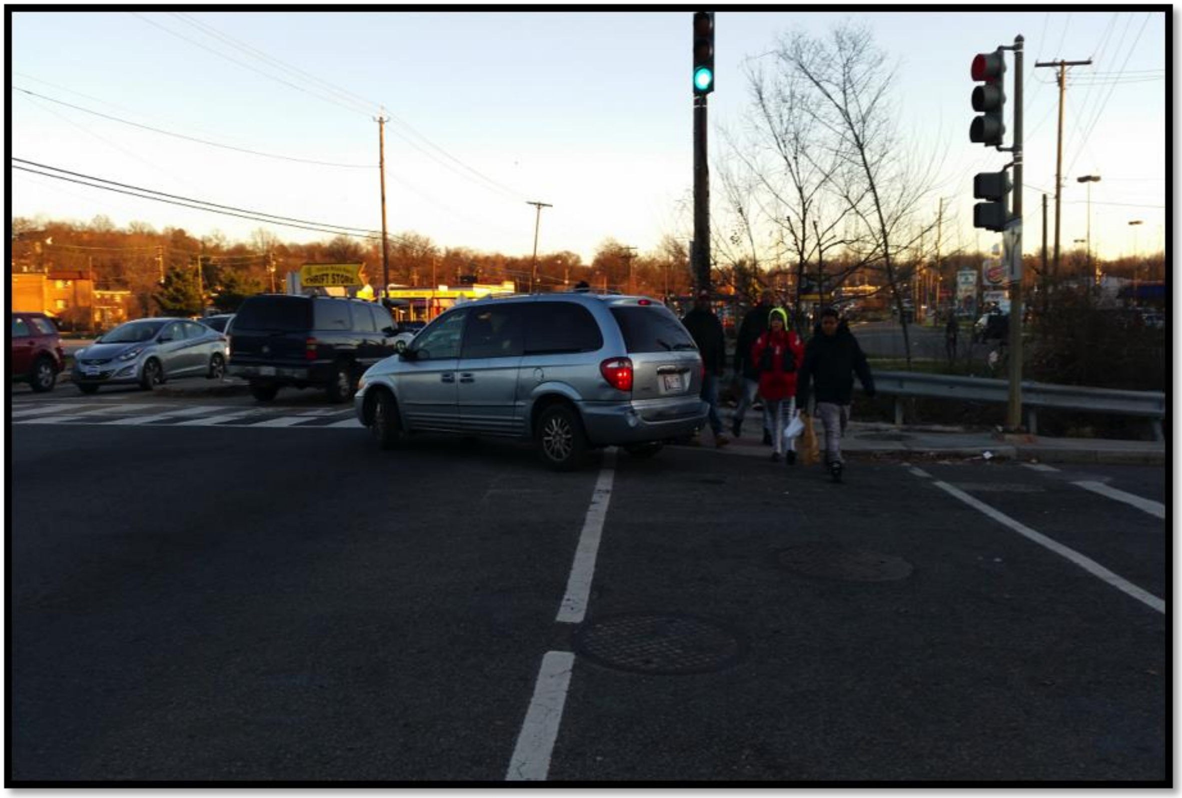
It was shown in previous research that numerous sociodemographic characteristics, types of land use, roadway, the presence of transit stops, and TCDs influence pedestrian-vehicle collisions (PVCs). However, due to limitations on accurately estimating pedestrian crash exposure models and the continuous debate on how some BE and roadway factors, such as land use, transit stops, and traffic control devices (TCDs), influence PVCs, more empirical studies appear to be necessary. Also, as Miranda-Moreno et al., (2011) revealed in their study, very few studies have examined the influences of BE and roadway factors on PVCs at signalized intersections.

To assess the influences of BE characteristics and roadway factors on PVCs, this study adopts four different methods of analysis, which will include archival, spatial, negative binomial (NB) regression, and fieldwork analysis. As opposed to relying on a single method, employing a combination of quantitative and qualitative methods will be used to accurately tell which independent variables (BE and roadway factors) are the most or least influential in enhancing pedestrian safety. While quantitative (archival, spatial, regression) methods allow me to test my hypotheses in a controlled experiment (by using pedestrian demand index), my qualitative methods (fieldwork analysis) test the accuracy of the quantitative results by allowing me to capture field estimates of pedestrian exposure (by counting pedestrian and traffic volume) and environmental risk factors that may potentially contribute to PVCs.

By way of contrast from previous studies that have explored PVCs at an area-wide level (i.e. census tract level), the NB regression analysis will focus on identifying the relationship between intersection roadway characteristics and PVCs 'at' and 'near' (within 100ft. from) signalized intersections in Washington D.C. Additionally, the spatial analysis will show the areas where PVCs are the densest after controlling for pedestrian exposure. Lastly, the fieldwork analysis will help capture detailed pedestrian volume counts and information on existing BE and roadway characteristics that influence pedestrian safety which are often hard to measure through statistical methods. In the end, by identifying BE and roadway factors that relate to PVCs, this study hopes to contribute to the existing scholarly literature that aims to improve pedestrian safety.

CHAPTER 3

METHODOLOGY



CHAPTER 3

METHODOLOGY

3.1 Research Design

The goal of this study is to understand how intersection roadway characteristics play a role in pedestrian safety. To achieve this goal, discerning how pedestrian and traffic volume differ across various intersection is critical. To do so, this study relied upon a pedestrian risk exposure variable to control for the intersection sites that have different traffic and pedestrian volume (Pulugurtha & Repaka, 2008). As shown in the conceptual framework flow chart (Figure 1), the pedestrian risk exposure variable used in this research was derived from DDOT's 2009 Pedestrian Demand Index (PDI), which was "used to select priority corridors in the District for detailed study as part of the Pedestrian Master Plan"(District Department of Transportation, 2009). Using variety of factors that relate to *pedestrian potential* and *pedestrian deficiency*, the PDI allowed this study to control for dissimilar pedestrian and traffic volume at intersections where pedestrian-vehicle collisions (PVCs) occurred over the five-year time period (see Section 3.3.1 for more details).

Instead of using average annual traffic volume and pedestrian volume counts from 2010 to 2014, this research relied on PDI because of the following reasons: 1) difficulty obtaining annual traffic and pedestrian volume counts from 2010 to 2014; and 2) even if traffic and pedestrian volume counts were used, too many roads may be missing the counts. Because the DDOT's 2009 PDI uses forecasted population and employment density, estimated traffic volume, and other built environment factors like the presence of transit stops and the types of land use, this index may be more reliable than the District's average annual traffic and pedestrian volume which appeared to have some missing volume counts. To be more specific, high PDI scores illustrate areas with major pedestrian generators, greater forecasted population and employment density, greater estimated traffic volume, and higher posted speed limit in the street segments. To put it another way, the PDI with high scores pointed out areas that pose higher risk of PVCs for pedestrians in the District of Columbia (DDOT, 2009).

This study also tested multiple factors that may be associated with pedestrian safety. As shown in Figure 1, the independent (or explanatory) variables tested in this study are called “intersection roadway characteristics” and they are composed of built environment characteristics (which include the presence of residential and commercial land use, and transit stops), certain surrounding sociodemographic characteristics, and roadway factors (such as street classification, direction, and traffic control devices) near the collisions sites. With the exception of socio-demographic factors, which were obtained from the U.S. Census at a census tract level, all of the independent variables were tested at the at intersection level in the spatial and regression stages of analysis.[5]

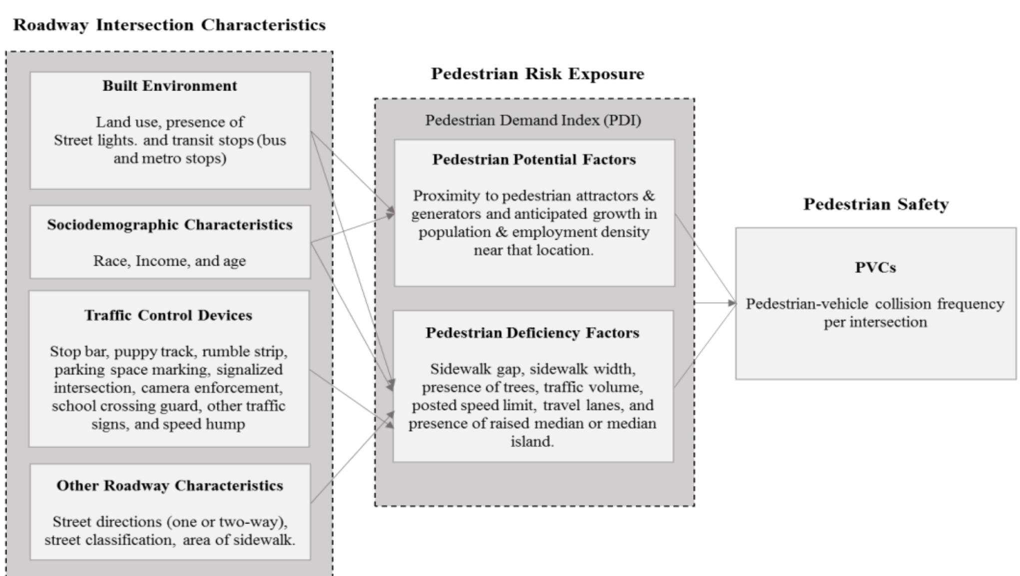


Figure 1. Conceptual Framework for Examining Pedestrian Safety

[5] The terms “site-specific level” and “area-wide level” were used and described more specifically by Miranda-Moreno, Morency, & El-Geneidy (2011). The general definitions of these terms are also found in the glossary.

3.2 Overview of the Methodology

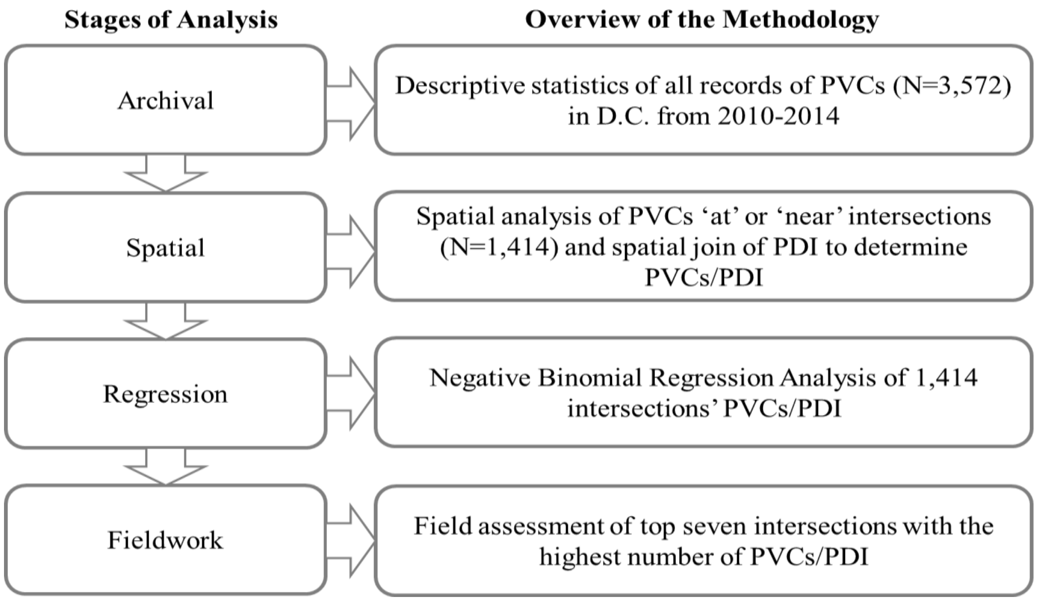


Figure 2. Overview of the Methodology

Four stages of analysis were involved in this study to understand the influences of intersection roadway characteristics on pedestrian-vehicle collisions (PVCs). The first stage was an archival review of 3,572 police records of PVCs from 2010 to 2014. In this stage, various attributes that describe, when, where, near what, and under what conditions the PVCs occurred were explored through generating descriptive statistics. The second stage incorporated various spatial analysis, which involved the use of spatial 'join,' 'clipping,' 'creating buffer' tools in ArcGIS to create and join multiple dependent and independent variables and map density and hotspots of the dependent variables. Here, the dependent variables were composed of 1,444 intersections having 2,664 police records of PVCs. Following this, a general negative binomial (NB) regression analysis was performed using the Statistical Package for the Social Sciences (SPSS). In this stage, only 1,414 intersections having 2,601 PVCs were observed because one census tract that involved 30 of the observed intersections was missing information on all of the independent variables that showed sociodemographic data. Finally, the last stage involved field observations of seven intersection sites that showed the highest number of PVCs from 2010 to 2014 over pedestrian demand index (PDI), which is discussed more in detail following this section.

3.3 DATA DESCRIPTION

3.3.1 Pedestrian Demand Index (PDI)

Multiple sources of data that span five-year period (2010 to 2014) were drawn from different agencies to perform this study (see Table 1). Among them, the pedestrian demand index (PDI) was the most significant variable because it allowed for the results of this study to control for dissimilar pedestrian and traffic volume at observed intersections where pedestrian-vehicle collisions (PVCs) occurred over the five-year time period.

3.3.1.1 What is PDI?

In April of 2009, the District Department of Transportation (DDOT) created a Pedestrian Demand Index (PDI), which was "used to select priority corridors in the District for detailed study as part of the Pedestrian Master Plan"(District Department of Transportation, 2009). To create this PDI, the DDOT used two factors: one, *pedestrian potential*, which accounted for "pedestrian activity on a given roadway segment determined by the pedestrian attractors, generators, the anticipated growth in population and employment density near that location," and two, *pedestrian deficiency*, which measured "how challenging it is for pedestrians to travel along or cross particular roads" (DDOT, 2009).

For pedestrian potential factors, such as the proximity to pedestrian trip attractors and generators such as the Metro stations, the National Mall, convention centers, and stadiums, the DDOT assigned high PDI scores, ranging from 5 to 20, to the street segments depending on whether the attractors were closer (1/8th of a mile) or further (a quarter to half-mile)[6] away. For the remaining daily use pedestrian trip attractors, such as bus stop, schools, major parks, shopping centers, and nursing homes, the PDI scores ranged from 1 to 5. Also, the DDOT used 2025 population and employment density forecasts to create PDI scores. For population density (per square mile), the score of zero (low population) to twenty (high population) were added in calculating PDI scores and for employment density, the scores of 0 (low population) to 12 (high population) were added.[7]

To account for pedestrian deficiency, the DDOT calculated PDI scores which considered the following factors: sidewalk gap,[8] sidewalk width, presence of planting strip (narrow strip of grass or plants near sidewalks), presence of street trees, traffic volume, posted speed limit, and barriers to walking on the city's network of roadways. For instance, since higher traffic volume is associated with greater barriers to walking on roadways, the score of 5 was given for annual average daily traffic of roadway segments with 25,001 or more vehicles passing by. Also, road segments with 2 sides of street with a sidewalk gap were given a PDI score of 20, whereas if only one side of the street had a sidewalk present, a score of 10 was given. Overall, higher PDI scores were assigned to a roadway, if the roadway had a more deficient environment for walking.

The PDI provided a generalized estimate of pedestrian and traffic volumes at the site-specific level, which was critical in estimating the relationships between pedestrian-vehicle collisions and other explanatory factors. For this reason, the average PDI scores for each of the observed intersection buffers (100ft. from each intersection) were used throughout this study to estimate the relationships between PVCs and intersection roadway characteristics.

[6] For details on how each street attributes were given PDI scores. See Appendix 1.
[7] See Appendix 1 for more details of how PDI was calculated.
[8] Sidewalk gap refers more than 10% of block length without sidewalk. See Appendix 1.

Table 1. Data and Data Sources

Category	Variables	Type of GIS Shapefile (Aggregated to)	Originated From	Year
Pedestrian Safety	Pedestrian-Vehicle Collisions	Point*	MPDC	2010-2014
Pedestrian Exposure	Pedestrian Demand Index	Line / Street Segments*	DDOT	2009
Traffic Control Devices (TCD)[9]	Stop bar Crosswalk[10] Puppy track Rumble Strip Lane Divider Lane Reduction Arrow Parking Space Marking Signalized Intersection Traffic poles Camera Enforcement Other Traffic Signs School Crossing Guard Speed Hump	Point*	DDOT	2014
Built Environment Factors	Streetlight	Point*	DDOT	2014
	Area of Sidewalk (within 100ft by sq.ft)	Polygon*		
	Number of Metro Stop (within 1/4 mile)	Point (1/4 mile buffers)		
	Number of Bus Stop (within 100ft)	Point*		
	Number of Bus Stop (within 300ft)	Point (300ft. buffers)		
	Commercial Land Use[11]	Polygon*		
	Residential Land Use	Polygon*		
Other Roadway Characteristics[12]	Street Direction Street Classification	Line / Street Segments*	DDOT	2014
Sociodemographic Factors	Household Median Income White Population (%) Black Population (%) Population (%) of All Other Races Median Age of Nearest Census Tract Population 0 to 14 years old (%) Population 15 to 24 years old (%) Population 25 to 44 years old (%) Population 45 to 64 years old (%) Population 65+ years old (%)	Polygon (Nearest Census Tracts)	U.S. Census (ACS 5-year Estimate)	2010-2014

* Data aggregated to 100ft. buffers from the observed intersections; Line / Street segments: Line shapefile by street segments

9 More descriptions on each TCD variable are shown in Appendix 3.
10 More descriptions on the type of crosswalks examined in this study are shown in Appendix 3.
11 Commercial and Residential Land Use Coverage Maps are shown in Appendix 4.
12 More descriptions on the different types of street direction and classification are shown in Appendix 3.

3.3.1.2 Calculating Average PDI per Intersection

Using ArcGIS, the average PDI per intersection was calculated. Since PDI scores[13] were provided as line shapefile where road segments are tied with certain PDI scores, this shapefile was spatially clipped to 100 ft. buffers that radiated from each of the observed intersections. After that, all PDI scores in each intersection buffer were combined into a single number, which was divided by the number of total road segments in the buffer. As shown in the example below (Figure 3), if A Street has PDI score of 30 and B Street has PDI score of 20 in a 100 ft. buffer (shown as a circle), the sum of PDI score in that buffer is 20+30= 50; and since there are two street segments, 50 would be divided by 2, which would yield 25. In this example, the average PDI is calculated as 25.

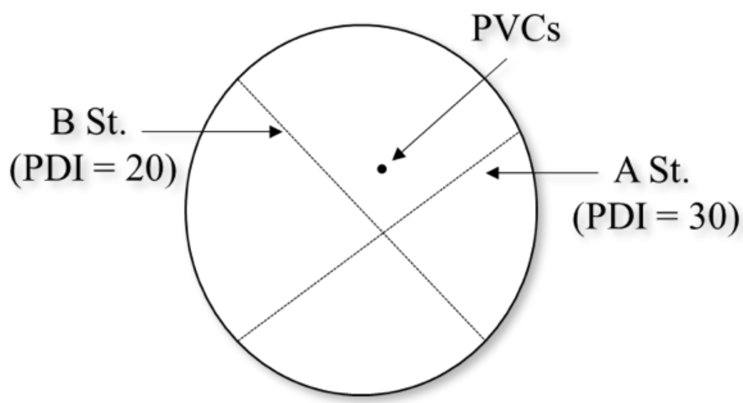


Figure 3. Example of Average PDI Calculation

Average PDI was calculated, as follows:

$$\text{AvgPDI} = \text{SumPDI} / \text{\# of street segments} \quad (1)$$

where

[13] The scoring guide for DDOT's 2009 PDI Index is shown in Appendix 1.

SumPDI = Aggregated PDI scores in 100 ft. intersection buffers where ‘at’ or ‘near’ intersection PVCs occurred from 2010 to 2014.

3.3.2 The Dependent Variables

To create a set of dependent (or response) variables, the data on all pedestrian-vehicle collisions (PVC) from 2010 to 2014 were extracted from the Metropolitan Police Department of the District of Columbia (MPDC)’s accident reports. This data set consisted of individual collision records with time, weather, location, and surrounding characteristics associated with each record. For the purpose of observing how intersection roadway characteristics (and not driver or pedestrian behavior changes) affect pedestrian safety, all PVCs that have been marked as “impaired”[14] or “PDO (Property Damage Only)” were discarded. After that, three separate dependent variables (equations 2 to 4) were created using the frequencies of PVCs per intersection over the five-year period (2010-2014) in the following ways:

$$y = AllPVCs \qquad (2)$$

$$yint = IntPVCs \qquad (3)$$

$$ymid = MidPVCs \qquad (4)$$

where

AllPVCs = sum of pedestrian-vehicle collisions (PVCs) observed over five-year period (2010-2014) both ‘near’ and ‘at’ intersection

IntPVCs = sum of pedestrian-vehicle collisions (PVCs) observed over five-year period (2010-2014) ‘at’ intersection only

MidPVCs = sum of pedestrian-vehicle collisions (PVCs) observed over five-year period (2010-2014) ‘near’ intersection but not ‘at’ intersection crossings

[14] PVCs that were marked as ‘impaired’ meant that either drunk driving or drunk-pedestrian were involved.

3.3.2.1 The Dependent Variables Used in Regression Analysis

The three aforementioned dependent variables were used in the negative binomial (NB) regression models along with the control variable, pedestrian demand index (PDI), to estimate the effects of various intersection roadway characteristics on pedestrian safety. Instead of using the sum of PVC counts per intersection over Average PDI (AVGPDI) as I did for the spatial analysis, in the negative binomial regression, I used the original counts of PVCs per intersection as the dependent variables. This was done because the log of PDI was applied as a control variable (or an offset term[15]) to control for the different pedestrian and vehicle volume at each of the observed intersections studied; and at the same time, calculate predictions for the dependent variables.[16]

3.3.2.2 The Dependent Variables Used in Spatial Analysis

For spatial analysis, the previously mentioned three dependent variables, (Y), (Y_{int}), and (Y_{mid}) were transformed in this manner:

$$Y = AllPVCs \,/\, AvgPDI \qquad (5)$$

$$Y_{int} = IntPVCs \,/\, AvgPDI \qquad (6)$$

$$Y_{mid} = MidPVCs \,/\, AvgPDI \qquad (7)$$

where

AvgPDI = an average PDI of all PDI values assigned per road segment within 100 ft. buffer from an intersection the PVC(s) occurred from 2010-2014.

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[15] "The offset term is coefficient that is not estimated by the model but is assumed to have the value 1; thus, the values of the offset are simply added to the linear predictor of the dependent variable. This is especially useful in Poisson regression models, where each case may have different levels of exposure to the event of interest." ("GENLIN and Poisson and offset," 2011)

[16] For more details, please see the subsequent part named "Negative Binomial Regression Analysis" in Section 3.4.2.2.

As mentioned previously, the 2009 Pedestrian Demand Index (PDI) data (which was obtained as a GIS shapefile from DDOT) can distinguish the street segments that attract high versus low number of pedestrians and vehicles in the District of Columbia. To control for dissimilar street segments with varying pedestrian and traffic volume, the average PDI scores were calculated for each of the observed intersections. The total number of PVCs per intersection was then normalized by the average PDI scores of that same intersection. As described in the equations 6 to 7 above, similar normalization was applied to create the dependent variables of PVCs observed 'at' versus 'near' intersections.

Provided that some intersections have greater pedestrian exposure than others, examining the frequency of PVCs per intersection did not provide a clear idea of which intersections have the highest pedestrian-vehicle collisions per extent of pedestrian exposure. Therefore, the frequency of PVCs per intersection was normalized, or simply put, divided by its corresponding average pedestrian demand index (AvgPDI) score (pedestrian exposure variable) of the intersection. Normalizing the pedestrian exposure at disparate locations provided a means for higher level of accuracy in predicting factors that contribute to PVCs.

3.3.2.3 Re-geocoding PVC Count Data

Reorganizing PVC count data proved to be difficult, especially when the PVC count data that I received were geocoded at incorrect locations.[17] It was observed that many PVCs that were reported to occur "at intersection" or "within 100ft. from intersection" were not always geocoded 'at' or 'near' intersections. To address this, I manually re-geocoded 2,664 pedestrian-vehicle collisions (that occurred from 2010 to 2014) at 1,444 intersections. To attain better accuracy

[17] It was determined that the PVC count data was geocoded at incorrect locations when the PVC data specified that the observed PVCs occurred 'at an intersection' but the x, y coordinates were found to be far away from any intersection.

from the previously geocoded PVC count data, I relied on the addresses and major cross streets (instead of solely relying on x, y coordinates) described in the police reports when re-geocoding the original data. But, because not all of the addresses and major cross streets were readable by a geocoder, which is an application that helps to geocode using addresses, some PVCs were aggregated to the intersections by identifying all PVCs with the same intersection identification codes.[18] The duplicated intersection identification codes were verified using "Find Identical (Database Management)" tool in ArcGIS[19] and afterwards, all of the PVCs that contained the same intersection codes were merged into a unique intersection identification code. This way, 2,664 PVCs and their attributes were aggregated into 1,444 different intersections. Following this, 100ft. buffers for all 1,444 intersections were created to calculate both the average PDI of each intersection and the frequencies of other independent variables tested in this study.

3.3.3 Independent Variables

32 independent variables used in this study were created from GIS shapefile data provided by the District Department of Transportation (DDOT) and the U.S. Census. As listed in Table 1, these independent variables were formed using the data on traffic control devices, built environment, sociodemographic factors, and other roadway characteristics of Washington, D.C. In the following sections, I refer to these independent variables as "intersection roadway characteristics" as described in my conceptual framework of this study (see Figure 1). Most of the data used in creating independent variables were updated in 2014 by DDOT and analyzed at the site-specific level,[20] or near the observed intersections. However, the set of data I obtained

[18] The intersection identification codes indicate unique intersections in D.C. and are used internally by the District Department of Transportation (DDOT).
[19] The "Find Identical (Database Management)" tool in ArcGIS was used to discover duplicates of intersection IDs within the pedestrian-vehicle collision data set.
[20] Refer glossary for the term "site-specific level."

from the U.S. Census Bureau's American Community Survey (ACS) 5-year estimate provided estimates of sociodemographic data from 2010 to 2014 at the census tract level. Therefore, all of the sociodemographic data (race, age, and median income) were aggregated at the census tract level than at the intersection level. However, one census tract (Census Tract 62.02)[21] was missing information on all sociodemographic data I wanted to review. For this reason, 30 out of 1,444 observed intersections were excluded in the negative binomial regression analysis.

3.4 STAGES OF ANALYSIS

3.4.1 Archival Analysis

As Figure 2 describes, in the first stage of analysis, all records of pedestrian-vehicle collisions (PVCs) were reviewed from 2010 to 2014, except for the ones that were identified in the Metropolitan Police Department of the District of Columbia (MPDC) police report as 'PDO (Property Damage Only)' or 'impaired.' Since 'PDO' rarely involves any pedestrian injuries, I decided to exclude these cases. PVCs involving 'impaired' driver(s) or pedestrian(s) were omitted from this study because impaired driving or walking could lead to a different set of behavioral patterns that cannot be explained by the built environment or roadway characteristics of intersections. After discarding the PVCs that were marked as 'PDO' or 'impaired,' various descriptive statistics were calculated for some attributes found in the remaining 3,572 police records of PVCs.

Using these records, the descriptive statistics were calculated to reveal *when* and *where* PVCs happened, under *what* specific traffic, weather, roadway type, and lightning conditions the collisions happened, and *how* pedestrians were hit (whether the motor-vehicle made a right turn, left turn, or went straight) in the collisions. Some of the many attributes analyzed here are the

[21] See Appendix 5 for a map of all the census tracts in D.C.

frequency of PVCs by the year, month, day of week, wards, quadrants, weather conditions, light conditions, traffic volume, roadway type, type of collisions, and traffic control measures near the collision sites. Generating these statistics uncovered general patterns of where, when and why PVCs occurred in D.C. from 2010 to 2014.

3.4.2 Spatial & Regression Analysis

The second and third stages involved spatial analysis and negative binomial (NB) regression analysis. After discarding PVCs that were reported as 'PDO' or 'impaired,' in these stages, only the pedestrian-vehicle collisions (PVCs) that have been reported to occur 'at' or 'near' (within 100 ft. from) intersections were examined. As discussed in the literature review, only few researchers have previously examined the relationships between PVCs and various intersection roadway characteristics at site-specific levels. Hence, discovering how intersection roadway characteristics are related to PVCs that occurred 'at' or 'near' intersections may be important in addressing the gap in the existing literature.

3.4.2.1 Creating Dependent and Independent Variables

In the second and third stages of analysis, about 2,664 pedestrian-vehicle collisions (PVCs) were examined at 1,444 'observed' intersections. To increase the accuracy of the collision data for spatial analysis, all of the 2,664 PVCs were re-geocoded to the observed intersections. Then, 100ft. buffers radiating from each of the observed intersections were created. Following this, I mapped the pedestrian demand index (PDI) and joined it with the observed intersection buffers. Next, the average PDI (AvgPDI[22]) was calculated for each of the observed intersections. Then, the numbers of PVCs per intersection were divided by the calculated AvgPDI to create three dependent variables (Y, Y_{int}, and Y_{mid}).

[22] See section 3.3.1 for more details on how (Y), (Y_{int},) and (Y_{mid}) were calculated.

To create independent variables, the observed intersection buffers were spatially joined in ArcGIS with the data on traffic control devices, built environment and sociodemographic factors, and other roadway characteristics in Washington, D.C.[23] By performing such spatial joins, ArcGIS automatically generated the counts of each data (e.g. data on number of crosswalks, signals, etc.) within the joined buffer, resulting in a set of independent variables. For example, the independent variable indicating the number of crosswalks within 100ft. from the observed intersections was created in this manner.

Not all independent variables were created exactly like this and at site-specific levels. The Metro stop variable, for instance, was created using ¼ mile buffers from the observed intersections and one bus stop variable was created using 300ft. buffers from the observed intersections. As opposed to using half-mile buffers others have often been used by researchers when creating transit sheds (Canepa, 2007), the ¼ buffers were used to count the nearest Metro stops because these buffers resulted in less overlaps among stops. Likewise, instead of applying ¼ mile walkable shed for bus stops, both 100ft. and 300ft. buffers were created to count the number of bus stops near the observed intersections. Also, as mentioned previously, all of the sociodemographic data retrieved from the U.S. Census were aggregated at the census tract level. For this reason, to create independent variables that demonstrate the sociodemographic information of census tracts that contain one or more of the observed PVCs, the observed intersections (instead of buffers) were spatially joined to the D.C. census tracts.

3.4.2.2 Spatial Analysis

ArcGIS was used to perform additional spatial analysis of both the observed 'PVCs (per intersection)' and 'PVCs (per intersection) over pedestrian demand index (PDI).' Two separate

[23] See table 1 for the more details on which data was used to create the independent variables in this study.

maps were created showing the density of PVCs (Map 1) and the density of PVCs over PDI (Map 2).[24] In creating the density maps, Jenks *natural breaks* Optimization method was used to identify clusters of the data based on a method that minimizes the in-class variance while maximizing the variance between class breaks ("Jenks natural breaks optimization," 2015). Jens Optimization method was selected because using other type of classification breaks, such as the standard deviation breaks, on a skewed data may lead to misleading maps. The density maps were created to compare and contrast the densities of PVCs per intersection before and after controlling for the observed intersections using PDI (see Maps 1 and 2). In similar ways, several other density maps (Map 5,6,8, and 9) were created as well to demonstrate the wards with highest 'at intersection' and 'near intersection' PVCs over PDI. These density maps demonstrate the densities of PVCs 'at' or 'near' the observed intersections so that policymakers and transportation agencies can easily determine which road segments or intersections need improvements. Lastly, four separate maps (Maps 3,4,7, and 10) were created using 'hotspot analysis' tool in ArcGIS to identify statistically significant hotspots of where PVCs are likely to occur the most and the least at the 90 to 95% confidence level, before and after controlling for the observed intersections using PDI.

3.4.2.2 Negative Binomial Regression Analysis

After creating both dependent and the independent variables in ArcGIS, the Statistical Package for the Social Sciences (SPSS) was used to run the negative binomial (NB) regression analysis. In order to check for normality of the dependent variables, several histograms were created showing the frequency for each of the dependent variables in the 1,414 observed intersections (See Figure 4 to 6). The 30 intersections that were missing data on the explanatory variables

[24] Maps 1 and 2 are found in the findings section (Section 4.2.1).

were removed from the originally observed intersections when conducting NB regression analysis. Removing the 30 intersections also removed all of the lane reduction narrows examined in this study, hence, this explanatory variable (involving the number of lane reduction arrows) was removed from the analysis.

Descriptive statistics were created to identify the most appropriate regression analysis for this study. As mentioned in the literature review, the two most common regression models used when analyzing pedestrian-vehicle collisions are Poisson and negative binomial (NB) regression analyses. This is because the traffic collision data is often count data, resulting in a distribution that is not normal (Miaou, 1994; Noland & Quddus, 2004). Also, since the distribution of counts is discrete and is limited to non-negative values, there are several problems with applying ordinary linear regression models to count data. One is that the count data is often skewed in one-direction with many zero values in the observed data set. Another is that a regular linear regression model is likely to produce negative predicted values, which appear impossible with the count data.

While a Poisson model assumes that the data does not follow a normal distribution, it also assumes that the variance is equal to the mean. On the other hand, NB regression model is a generalization of the Poisson regression model that assumes that the response variables' variances are greater than the mean, which is a condition known as 'overdispersion.'[25] This study found that the dependent variables were indeed overdispersed[26] and skewed to the right as shown below in Figures 4-6. For this reason, the NB regression model was chosen as it appeared

[25] For further details on the definition of 'overdispersion,' see Section 2.4.
[26] See dependent variables' mean and variance on Table X

to be the most suitable and justifiable regression model among the generalized linear models (GLM) family.[27]

After creating descriptive statistics to identify best possible statistical models for this analysis, Pearson's correlation matrices[28] were first created for each of the dependent variables to identify significant multicollinearity.[29] If there was a high correlation between two different explanatory variables with correlation coefficient (r) value that is higher than or equal to 0.5, I eliminated those explanatory variables from the list. To further avoid problems associated with multicollinearity, SPSS was used for each of the response variables to generate 'predictors' (predictive or explanatory variables that are tested in the final regression models) through an automatic procedure called 'stepwise backward elimination' methods. In this method, certain predictors were eliminated from all of the predictors one by one based on the F-tests or F-ratio.[30] Through these two processes of elimination, approximately six—crosswalk, lane reduction arrow, number of bus stops (within 100ft. from an intersection), percentages of total white population per census tract, median age of census tract near PVCs, and percentages of total population of age groups 0 to 14—of the thirty two independent variables were discarded from the all of the regression models because they were found to have weaker relationships (lower correlation) with the dependent variables, and also very associated with other explanatory variables (with moderate to high correlation coefficients).

[27] Both Poisson and NB models are part of the GLM family. For more details, see Section 2.4.
[28] See Appendix 9, Tables A9-2 to Table A9-4 for Pearson's correlation matrices.
[29] In statistics, "multicollinearity (also collinearity) is a phenomenon in which two or more predictor variables in a multiple regression model are highly correlated, meaning that one can be linearly predicted from the others with a substantial degree of accuracy" ("Multicollinearity," 2016).
[30] The steps SPSS took to derive the final model can be viewed in Appendix 9 along with all of the variables that were included in the final regression models.

To run NB regression analysis using SPSS, each of the response (dependent) variables was analyzed against the explanatory (independent) variables as well as the log of the control variable, average pedestrian demand index (AvgPDI). Because SPSS would not allow any non-countable response variable data in its NB regression application, I was not able to control for the effect of pedestrian exposure by simply dividing the PVCs over average PDI per intersection as I have done in the spatial analysis. This was because the ratio of PVCs over average PDI per intersection resulted in integers and NB regression model only accepts countable, whole numbers.

Therefore, to control for the effect of pedestrian exposure, I performed a log-transformation to the average PDI (AvgPDI) scores. Once that was done, to account for AvgPDI scores as a control variable in the negative binomial regression models, I added the log of AvgPDI (or "Exposure" variable) as an offset term,[31] which was then used as a structural predictor, where the values of AvgPDI were added as a control variable rather than an explanatory variable. The following model was used to create the NB regression equations:

$$\log(y_i) = \alpha + \ln(PDI) + b_1(X_1) + b_2(X_2) + b_3(X_3)\ldots + \varepsilon \qquad (8)$$

where

α = alpha or a constant coefficient of the intercept

b_i = beta or coefficient of the explanatory variables tested in this study

ε = error term in predicting the value of Y, given the value of X

[31] "The offset term is coefficient that is not estimated by the model but is assumed to have the value 1; thus, the values of the offset are simply added to the linear predictor of the dependent variable. This is especially useful in Poisson regression models, where each case may have different levels of exposure to the event of interest." ("GENLIN and Poisson and offset," 2011)

X_i = explanatory variables

ln (PDI) = log-link of average pedestrian demand index (AvgPDI) scores, which is used as an exposure variable in this study; this was done by performing log-transformation on AvgPDI scores and setting this variable as an 'offset' variable in the negative binomial regression analysis.

As noted previously, AvgPDI controlled for the disparate pedestrian and traffic volume in the studied intersections.[32] In addition, as shown in Maps 1 and 2,[33] the frequencies of PVCs per intersection were observed at different locations from the frequencies of the PVCs over AvgPDI (one of the dependent variables), showing that the outcomes between using just PVCs as the dependent variable versus using PVCs with AvgPDI as a control variable could result in completely different regression outputs. The differences in the spatial geography of both PVCs and PVCs per AvgPDI are important because the location of the response variables determine the frequencies of each of the explanatory variables tested in this study. To reveal the effects of AvgPDI as a control variable, I also generated two types of negative binomial (NB) outputs: one, showing six NB models with AvgPDI as a control variable and two, showing another set of six NB models without any control variable. In such ways, the more precise relationships between pedestrian-vehicle collisions and roadway intersections characteristics were shown as opposed to the relationships the archival analysis revealed.

3.4.3 Fieldwork Analysis (Case Study Intersections)

For the final stage of this analysis, field observations to case study intersections were conducted to examine the built environment (BE) and roadway characteristics at the intersections that pose

[32] Refer to Section3.2.1.
[33] See Maps 1 and 2 on the findings section (Section 4.2.1).

highest risk of PVCs on pedestrians in Washington, D.C. Because of time constraints, only the top seven intersections with the highest rate of PVCs over AvgPDI were observed as case study intersections. Some research questions this study explored in this stage were: 1) Are there any distinct patterns in the intersection roadway characteristics of the top seven intersections with the highest PVCs over AvgPDI? What are the patterns? 2) Are there more cars or pedestrians in these top seven intersections? To answer these questions, this stage of analysis involved collecting photos, videos, and documenting any variables associated with the built environment, street design, and traffic control devices at the site-specific level. Only seven intersections were observed, however, due to limited time

Site visits to the case study intersections were made on multiple weekdays (Mondays and Fridays) during rush hours (in between morning peak time: 8-11am or afternoon peak time: 4-7pm). At each site, the total pedestrian and vehicle volumes were counted for two to three 5-minute cycles. Using the 5-minute volumes, an average 1-hour traffic and pedestrian volumes[34] in each of the case study intersections were calculated through multiplying the 5-minute volumes by 12. Along with this, the number of bus stops, bus lines associated with each stop, nearest Metro stops, types of land use, types of signals, posted speed limit, street legs (to evaluate the intersection geometry), streetlights, average length of sidewalks, and any other notable intersection roadway characteristics—were all recorded. After this, the average distance from the nearest bus stops and Metro stops were counted using Google Earth maps (using the distance calculator). The findings were then documented in a form of graphs, pictures, and tables, which are presented in the following chapter.

[34] One-hour traffic and pedestrian volume were calculated by multiplying the average 5-minute volume by 12.

3.4.3.1 Histogram of the Dependent Variables

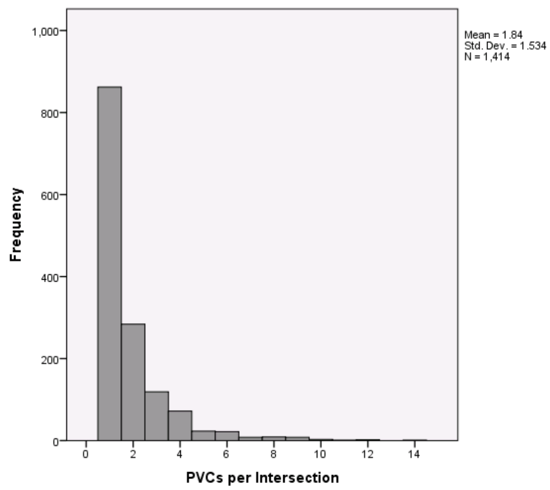


Figure 4. Histogram of the Dependent Variable (*Y*)

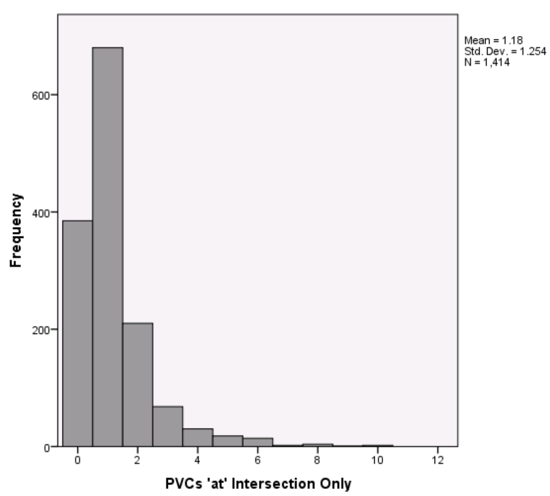


Figure 5. Histogram of the Dependent Variable (*Yint*)

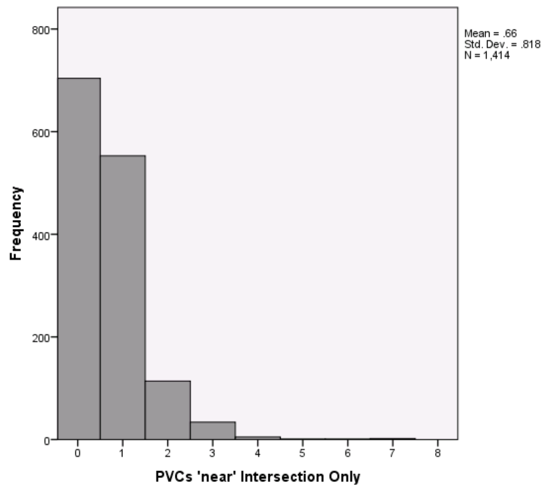


Figure 6. Histogram of the Dependent Variable (*Ymid*)

3.5 DATA LIMITATIONS

There were several limitations to the data I used to conduct this study. First, the pedestrian-vehicle collisions (PVCs) data I obtained from MPDC may have excluded some unrecorded PVCs that have led to injuries in parking lots, driveways, garages, and other places. Only the injuries and deaths reported to the MPDC were in the database. Second, although I excluded six independent variables that were found to have weaker relationships (lower correlation) with the dependent variables, and also very associated with other explanatory variables (with moderate to high correlation coefficients, the regression analysis might still contain some degree of multicollinearity among the explanatory variables,[35] making it difficult to predict the true relationships between the explanatory and response variables. Third, given that the data on pedestrian exposure variable (AvgPDI) and other explanatory variables were created and updated at different periods of time, the inconsistency of dates in the data I was able to obtain from the U.S. Census and DDOT may reduce the reliability of my results.

[35] ("Multicollinearity," 2015)

Additionally, there were some limitations to the data I collected in the field. All of the field observations were made during the winter of 2016, when it was very cold to be walking outside in D.C. For this reason, there is a high chance that I may have over-counted vehicles and undercounted pedestrians, since fewer pedestrians would walk around out in the cold, winter season. In addition, the two to three cycles of 5-minute manual counts (10 to 15 minutes) in my field observations are generally considered shorter than the longer observation traffic engineers often use to count traffic and pedestrian volume (for approximately 20 to 30 minutes) at intersection sites. Thus, the one-hour average traffic and pedestrian volume from my shorter observations may be slightly different from that longer observation.

While I cannot address the first limitation explained above, I hope to address the second and third limitations through the last stage of analysis in this study, fieldwork analysis. For this stage, I physically visited, identified, and assessed the influences of various intersection roadway characteristics near the top seven intersections with highest numbers of PVCs over pedestrian exposure (AvgPDI). The field observational study provided the most reliable and important findings (when compared with other stages of analysis) and it has allowed me to test the accuracy of my quantitative results (from regression analysis and descriptive statistics) while documenting detailed pedestrian and vehicle volume and information on existing built environment and roadway characteristics that may influence pedestrian safety. Also, this stage of analysis was the most reliable of all stages because the observation time period (January, 2016) was fixed and was therefore, consistent in the analysis.

CHAPTER 4

FINDINGS

CHAPTER 4

FINDINGS

4.1 ARCHIVAL ANALYSIS

The initial stage of my analysis involved analyzing various attributes of the data I obtained from MPDC's police reports in regards to 3,572 pedestrian-vehicle collision (PVC) records that have been reported from 2010 to 2014. As mentioned in Chapter 3, these records do not include any "impaired" drivers or pedestrians and exclude any pedestrian-vehicle collisions (PVCs) that involved "Property Damage Only" (PDOs). In this section, the descriptive statistics of 3.572 PVC records are presented to better assess *when*, *where*, and *what* type of built environment and roadway characteristics were present at the collision sites. Following this, the different types of accidents (right-turn, left-turn, straight hit, and etc.) and the types of injuries that were involved in the observed PVCs are explored.

4.1.1 When, Where, and How Many Injuries?

The total number of pedestrian-vehicle collisions (PVCs) has been rapidly rising in Washington, D.C. from 2010 to 2014 (see Figure 7). About 602 PVCs resulted in pedestrian injuries or fatalities in 2010; whereas in 2014, those pedestrian injuries increased by 38.2%, to 832 PVCs. In fact, each year, since 2010, the annual number of PVCs has never shown any declining trend. This clearly indicates that the District's efforts are needed to reduce future PVCs.

4.1.1.1 Temporal Variation

To examine if the District of Columbia's pedestrian-vehicle collisions exhibit any distinct trends by month and day of the week from 2010 to 2014, the frequencies of the observed PVCs were graphed by month and day of week. In the monthly variation (Figure 8), the results show that, in general, fewer PVCs occurred in the first two quarters of the year (January to June) when compared to the second two quarters of the year (July through December). In the day of week variation (Figure 9), the frequencies of the observed PVCs were much higher during weekdays than on weekends. In fact, similar to Dai's observation (Dai, 2012), Wednesdays and Fridays appeared to have the highest percentage of injuries. These trends indicate that higher caution should be given to drivers and pedestrians during the weekdays and during the second semester of the year.

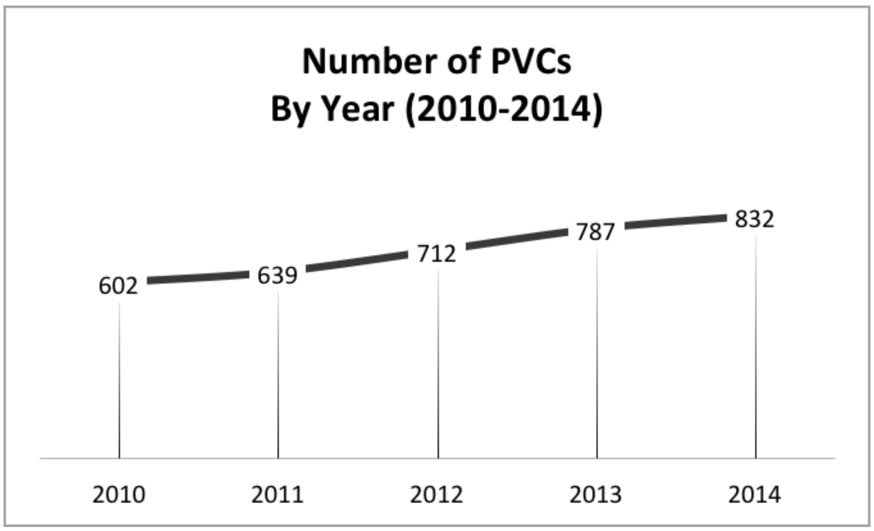


Figure 7. Number of PVCs by Year (2010 to 2014)

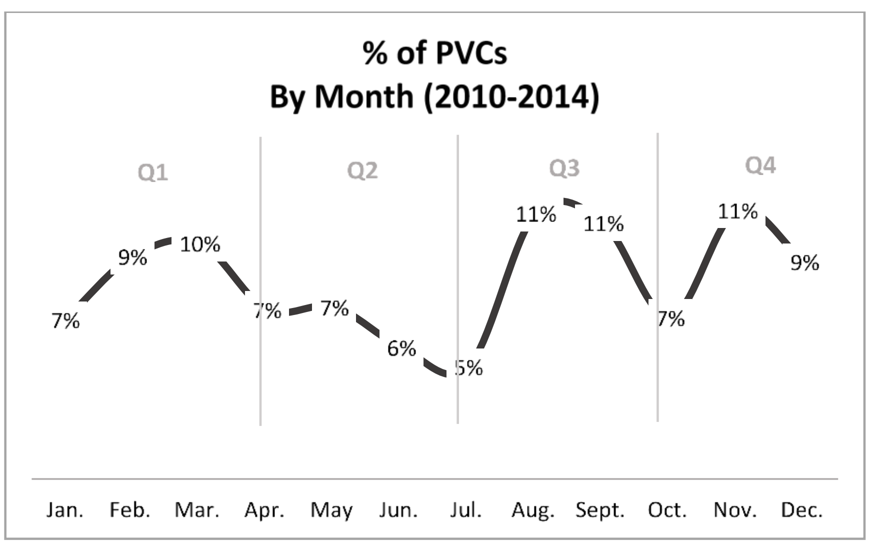


Figure 8. Percentage of PVCs by Month (2010 to 2014)

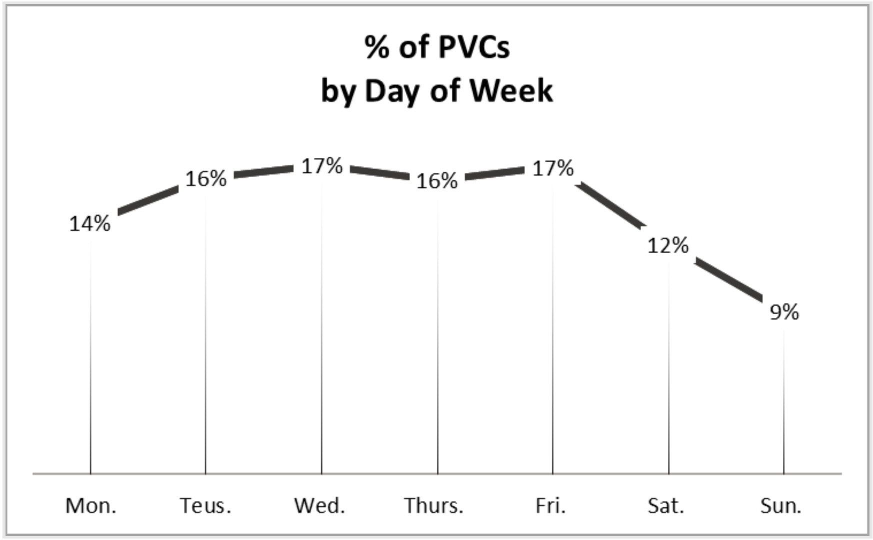


Figure 9. Percentage of PVCs by Day of Week (2010 to 2014)

4.1.1.2 Spatial Variation

Upon investigating *where* PVCs occurred most in the District of Columbia, the descriptive statistics (Table A7-1, Appendix 7) revealed that Northwest (NW) quadrant (54.5%), Police District 1 (20.4%), and Police District 2 (21.7%) had the greatest number of PVCs over the five-year period. However, these statistics do not reveal PVCs per square meters of the quadrant or police districts despite their dissimilar land areas. To address this issue, I divided the number of PVCs by the land area (in square meters) of each quadrant and police districts to generate better statistics that calculate PVCs per square meters. As shown in Figure 10, when the land areas of each of the quadrants were taken into account in estimating the frequencies of PVCs, both Northeast (NE) and Southeast (SE) quadrants seemed to have high percentages of PVCs per square meters (NE: 27% and SE: 29%).

Similarly, when the frequencies of PVCs were estimated by the land area coverage (in square meters) of Police Districts, the results were different from simply examining the frequencies of PVCs. For instance, the descriptive statistics showed that Police Districts 1 and 2 had the most number of PVCs, but, when PVCs per square meters were examined, Police District 3 had the most number of PVCs (39% of all PVCs) among all the districts (Figure 11). These statistics reveal that more focus and attention for pedestrian safety are needed in Police District 3 and NE, NW, and SE quadrants[36]

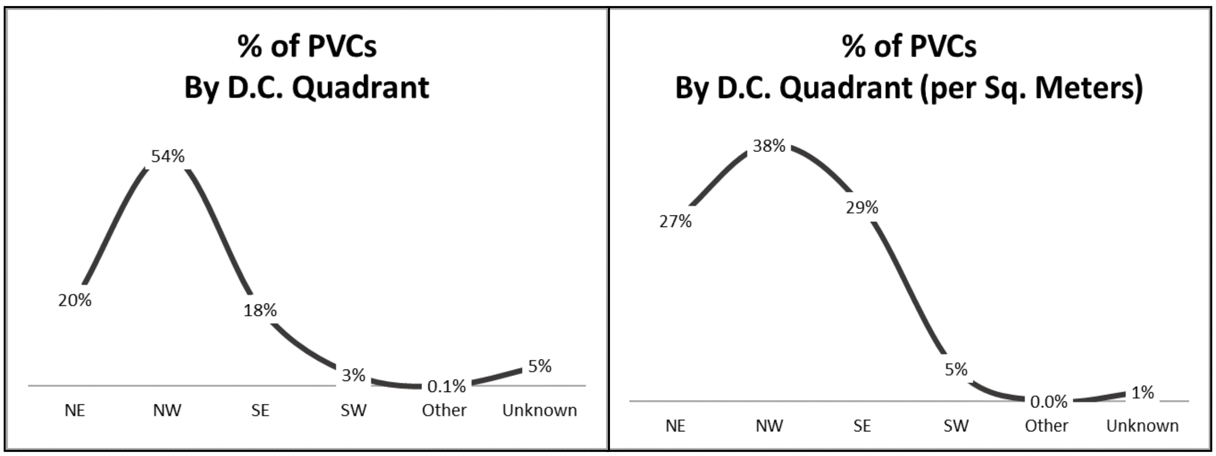


Figure 10. Percentage of PVCs by D.C. Quadrant (Original vs. per Square Meters)

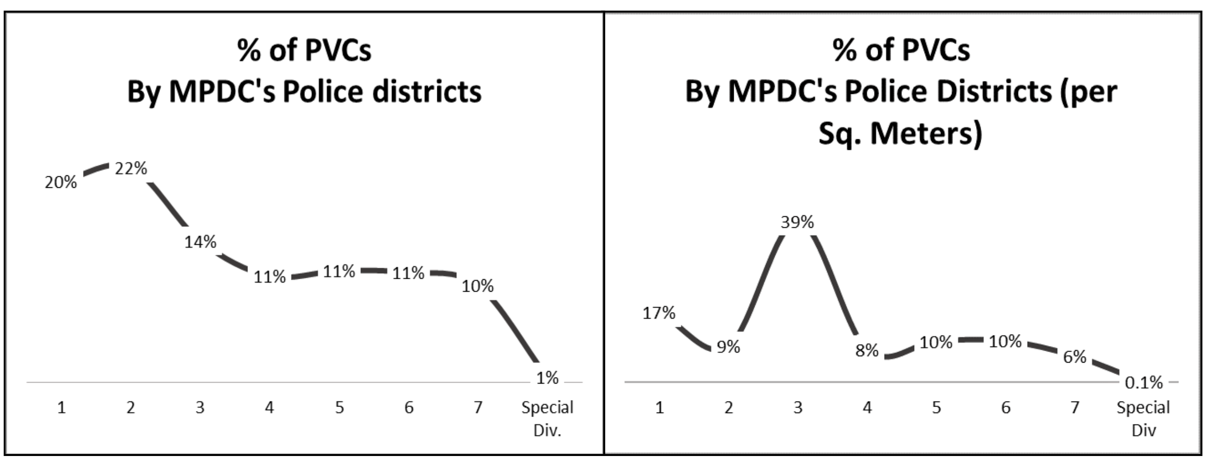


Figure 11. Percentage of PVCs by Police Districts (2010 to 2014)

[36] Refer to Appendix 6 for maps to see the land area boundaries of the Police Districts and quadrants of the District of Columbia

4.1.1.3 Number of Pedestrian Injuries

Pedestrian injuries and fatalities from PVCs mostly occurred near or at the crosswalk at an intersection (48.1%), whereas about 20% of all PVCs did not happen near any crosswalk. Also, a small but significant percentage of the observed PVCs occurred while crossing the street between parked cars (6.7%). In terms of the types of collisions that were involved, the majority were straight-hit pedestrian collisions (43.8%), followed by left turn (25.6%) and right turn (9.7%) collisions, and finally cars backing (7.0%) (see Table A7-1 for more details in Appendix 7).

Over the five-year period, only 1.1% (or 41) of all 3,572 observed PVC cases led to deaths (see Table A2). However, 10.2% (or 367) of the cases led to permanently disabling injuries. The remaining 3,134 cases involved non-severe, yet, evident injuries to pedestrians. Non-severe injuries should not be undermined, because on average, 626 cases of non-severe injuries occurred per year. As a matter of fact, about 52 out of 59 PVC cases per month were associated with non-severe pedestrian injuries.

4.1.2 Under What Road Conditions Have PVCs Occurred?

An archival review of the 3,572 cases involving pedestrian-vehicle collisions (PVCs) also summarized where PVCs from 2010 to 2014 have generally occurred, depending on the presence of light, weather, and some roadway characteristics (such as type of roadway, roadway geometry and grading, surface, and the presence of traffic controls). First, a higher percentage of PVCs (55.7%) occurred when the streetlights were off than when the lights were on (33.6%). In a like manner, a higher percentage of PVCs occurred during the daytime (63.2%) as opposed to nighttime, or when it was dark outside (31.7%). Also, most of the PVCs occurred when the weather was clear (79.4%) or raining (13.2%) and the road conditions were dry (80%) or wet

(15.6%). PVCs were less likely to occur on other types of road and weather conditions. In fact, only about 1.2% (or roughly 42 cases) of all PVCs happened in snowy weather or icy road conditions (see Table A7-1 for more details in Appendix 7).

The different types of roadway characteristics also mattered in determining the frequency of the observed PVCs. As shown in Table A7-1, most of the PVCs occurred on a straight (69.1%), two-way road (77%) paved with asphalt (87.9%), as opposed to uphill or leveled (3.8%), one-way road (13.3%) paved with concrete (8.8%). Lastly, most of the PVCs occurred at signalized intersections (43.4%) as opposed to an intersection or roadways with a stop sign (10.6%).

4.2 Spatial Analysis: *Where Should the Focus Be?*

Following the archival review of 3,572 pedestrian-vehicle collisions (PVCs), in this stage of analysis, 1,444 roadway intersections having 2,664 PVCs that occurred 'at' and 'near'[37] intersections were observed. Using ArcGIS, various maps were produced mainly to understand the spatial patterns and clustering of the dependent variables (Y, Yint, Ymid).[38] Even though this stage did not involve assessing any correlations between the dependent and independent variables, it identifies *where PVCs occurred previously* and *where PVCs are likely to occur in the future* based on the previous samples of PVCs. This is especially important for policymakers because it provides area(s) of focus where factors that contribute to PVCs can be examined in detail. Furthermore, it can assist policymakers to determine which clusters and Wards in the District of Columbia need prioritization for pedestrian safety interventions, such as re-evaluating the built environment or placing warning and caution signs for drivers and pedestrians in the targeted sites.

[37] In this study, PVCs 'near' intersection refers to PVCs that occurred "within 100 ft. from the observed intersections.

[38] Refer to Section 3.3.2 for details on how the dependent variables were created.

4.2.1 Evaluating the Spatial Distributions of PVCs

4.2.1.1 AllPVCs vs. the Dependent Variable Y (AllPVCs over AvgPDI)

In order to understand the spatial distribution of where PVCs occurred and would most likely occur in the future, this section generally focuses on identifying the spatial clusters and patterns of *AllPVCs*—or PVCs that happened 'at' and within 100ft from an intersection. From 2010 to 2014, many of the PVCs occurred towards the center of Washington D.C., generally clustered in Wards *1,2, and 6*, as illustrated in Map 1. As a matter of fact, an astronomic number of AllPVCs (766 cases, which is nearly 30% of all PVCs) occurred principally in Ward 2 (29%); followed by Ward *6*, which observed 392 PVCs (15%); and Ward 1, which observed 328 PVCs (12%) (see Table 2).

Yet, when the average pedestrian-demand index (AvgPDI[39]) normalized the effect of pedestrian exposure, a slightly different spatial distribution was found. While Map 1 shows that AllPVCs tend to concentrate in the heart of D.C. (especially near Downtown, Dupont Circle, Chinatown, NoMa and Judiciary Square[40]), Map 2 illustrates that AllPVCs are more scattered and not concentrated in one particular area within D.C. In fact, when the two density maps were compared to one another by the sum of incidents per ward, the differences in the spatial distributions were more clearly pronounced.

As Figure 12 reveals, the map to the left (which shows the sum of AllPVCs per ward) displays Wards 2, 6, and 1 as the wards with the highest sum of PVCs; yet, as seen in the map to the right, when pedestrian exposure was normalized, the map of the dependent variable *Y*—or PVCs 'at' and 'near' intersection over AvgPDI—displays that Wards 2, 5, and 7 appear to be the most

[39] Refer to section 3.3.1.2 for a better understanding of the term 'AvgPDI.'
[40] See Appendix 8 to see where these neighborhoods are located in Washington, D.C.

dangerous. Table 2 corroborates this finding with more detailed statistics that show the sum of incidents per ward. Furthermore, while the same Jenks Optimization algorithm[41] was applied in all maps to break the densities of AllPVCs per intersection into five groups, Map 2 depicts a greater number of points with higher intensity, or higher rate of collisions, than the points shown in Map 1. All in all, these findings indicate that controlling for the effect of pedestrian exposure significantly changes the spatial locations and the intensities of AllPVCs per intersection.

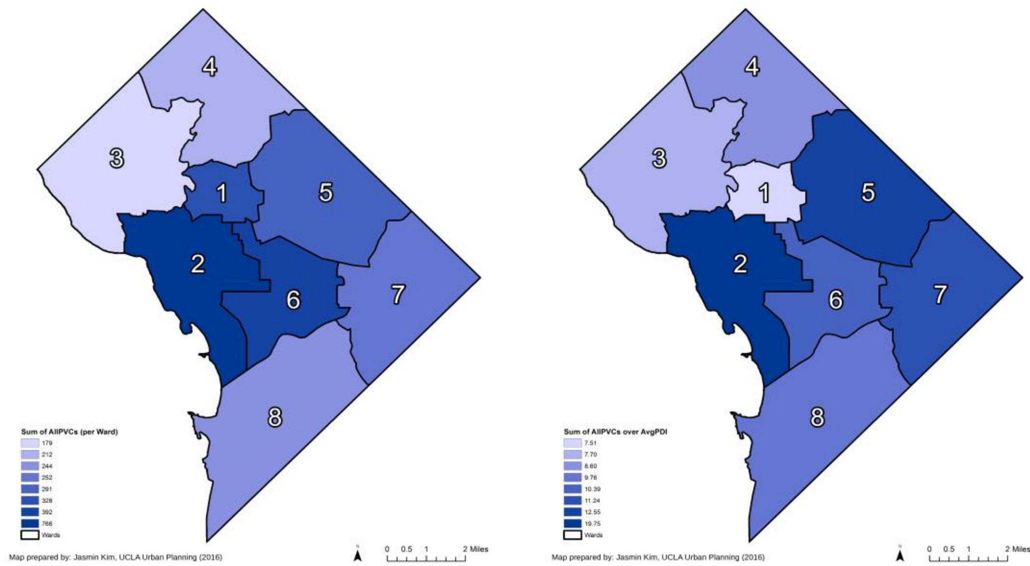


Figure 12. The Sum of AllPVCs vs. the Sum of Y (by Ward)

Similar differences were observed from the hotspot analysis between AllPVCs and the dependent variable (Y).[42] The hotspot analysis identifies ‘hot’ or ‘cold’ spots, which represent statistically significant spatial clustering of area(s) with high or low values of incidents. As Map 3 illustrates, under the 99% confidence level (where p-values is equal to or less than 0.01), 211 intersections

[41] See Section 3.4.2.2 to better understand the Jenks Optimization method used here.
[42] Y is calculated as AllPVCs over AvgPDI. This is described more in detail in section 3.2.2.1.

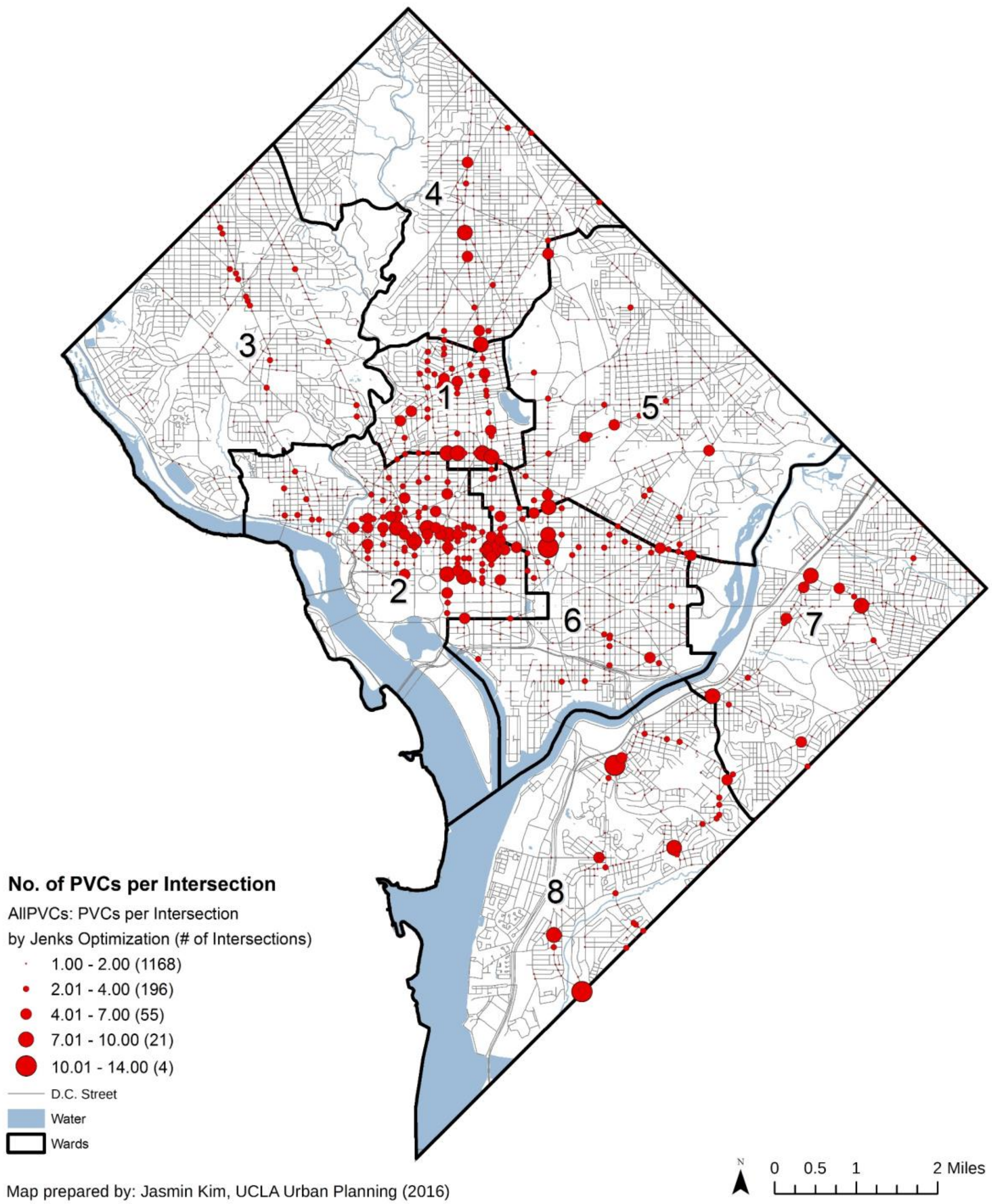
with the highest counts of AllPVCs (hot spots) were mainly found in Wards 2,1, and 6; whereas, 4 intersections with the lowest counts of AllPVCs (cold spots) were clustered in Ward 6. In simpler words, the hot spots of 211 intersections represent the most dangerous areas where pedestrians are prone to AllPVCs and the cold spots represent the safest areas for pedestrians (from vehicle collisions). It is notable, however, that these hot and cold spots change after normalizing the effect of pedestrian exposure using AvgPDI (see Map 8). As shown in Map 4, after the control variable (AvgPDI) was calculated into the equation, large number of hot spots representing the highest rate of AllPVCs (AllPVCs over AvgPDI) were found in Wards 7, 8, and 2 at the 95 to 99% confidence level. In a stark contrast to Map 3, however, Map 4 demonstrates that Wards 6 and 1 mainly consist of cold spots (significantly low rate of AllPVCs at the 90 to 99% confidence level). As matter of fact, Map 4 appeared to have no significant hot spots in Wards 6 and 1 that were previously observed from Map 3. Despite the dense number of AllPVCs that were found in Wards 2,1, and 6, these findings illustrate that when pedestrian exposure is taken into account, the most significant intersections that impose the highest risk of AllPVCs (those with high rates of PVCs) in D.C. are located in Wards 7, 8, and 2.

Table 2. Descriptive Statistics of PVCs (Before and After Normalizing Pedestrian Exposure)

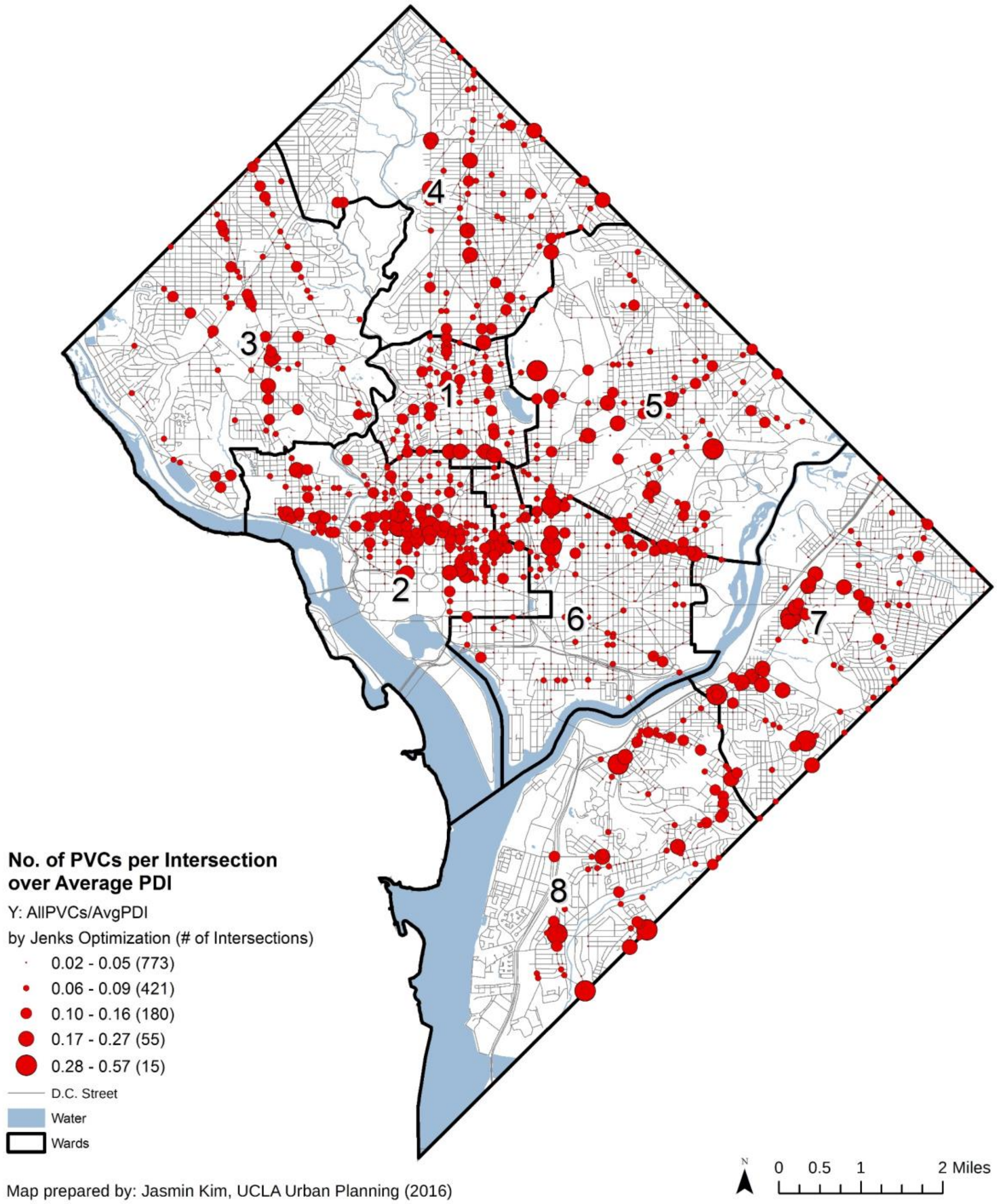
Number of AllPVCs Per Ward (2010-2014)								No of (Y) or AllPVCs/AvgPDI Per Ward (2010-2014)							
Ward	*Sum*	*%*	*Avg.*	*Min.*	*Max.*	*Var.*	*S.D.*	*Ward*	*Sum*	*%*	*Avg.*	*Min.*	*Max.*	*Var.*	*S.D.*
PVCs *(N=2,664)*								Y: AllPVCs/AvgPDI *(N = 87.50)*							
2	766	29%	2	1	14	3.31	1.82	2	19.75	23%	0.06	0.02	0.31	0.00	0.05
6	392	15%	2	1	12	1.89	1.37	5	12.55	14%	0.07	0.02	0.37	0.00	0.05
1	328	12%	2	1	10	3.73	1.93	7	11.24	13%	0.07	0.02	0.56	0.01	0.07
5	291	11%	2	1	7	1.36	1.17	6	10.39	12%	0.04	0.02	0.31	0.00	0.04
7	252	9%	2	1	9	2.02	1.42	8	9.76	11%	0.08	0.02	0.57	0.01	0.08
8	244	9%	2	1	12	3.26	1.81	4	8.60	10%	0.06	0.02	0.25	0.00	0.04
4	212	8%	1	1	8	1.13	1.06	3	7.70	9%	0.06	0.02	0.20	0.00	0.03
3	179	7%	1	1	4	0.54	0.74	1	7.51	9%	0.05	0.02	0.22	0.00	0.04
IntPVCs *(N=1,710)*								Yint: IntPVCs / AvgPDI *(N = 55.59)*							
2	534	31%	2	0	9	2.23	1.49	2	13.79	25%	0.04	0.00	0.31	0.00	0.04
6	253	15%	1	0	10	1.13	1.06	5	7.91	14%	0.04	0.00	0.30	0.00	0.05
1	199	12%	1	0	8	2.01	1.42	6	6.74	12%	0.03	0.00	0.26	0.00	0.03
5	183	11%	1	0	6	1.14	1.07	7	6.02	11%	0.04	0.00	0.32	0.00	0.05
8	143	8%	1	0	10	2.11	1.45	3	5.66	10%	0.05	0.00	0.20	0.00	0.04
7	135	8%	1	0	6	1.18	1.08	8	5.58	10%	0.04	0.00	0.43	0.00	0.06
4	133	8%	1	0	6	0.97	0.98	4	5.34	10%	0.04	0.00	0.24	0.00	0.04
3	130	8%	1	0	4	0.60	0.77	1	4.56	8%	0.03	0.00	0.17	0.00	0.03
MidPVCs *(N = 954)*								Ymid: MidPVCs / AvgPDI *(N = 31.91)*							
2	232	24%	1	0	7	0.83	0.91	2	5.97	19%	0.02	0.00	0.15	0.00	0.02
6	139	15%	1	0	3	0.60	0.77	7	5.22	16%	0.03	0.00	0.24	0.00	0.04
1	129	14%	1	0	7	1.07	1.04	5	4.63	15%	0.03	0.00	0.15	0.00	0.03
7	117	12%	1	0	4	0.61	0.78	8	4.19	13%	0.03	0.00	0.20	0.00	0.04
5	108	11%	1	0	5	0.53	0.73	6	3.65	11%	0.02	0.00	0.10	0.00	0.02
8	101	11%	1	0	6	0.89	0.95	4	3.26	10%	0.02	0.00	0.20	0.00	0.03
4	79	8%	1	0	3	0.42	0.65	1	2.96	9%	0.02	0.00	0.13	0.00	0.02
3	49	5%	0	0	2	0.32	0.57	3	2.04	6%	0.02	0.00	0.14	0.00	0.03

Notes: All of the wards are ranked from the highest value of sum to the lowest value of sum; *N* indicates the total sample size; *Var.* indicates variance; and *S.D.* indicates standard deviation.

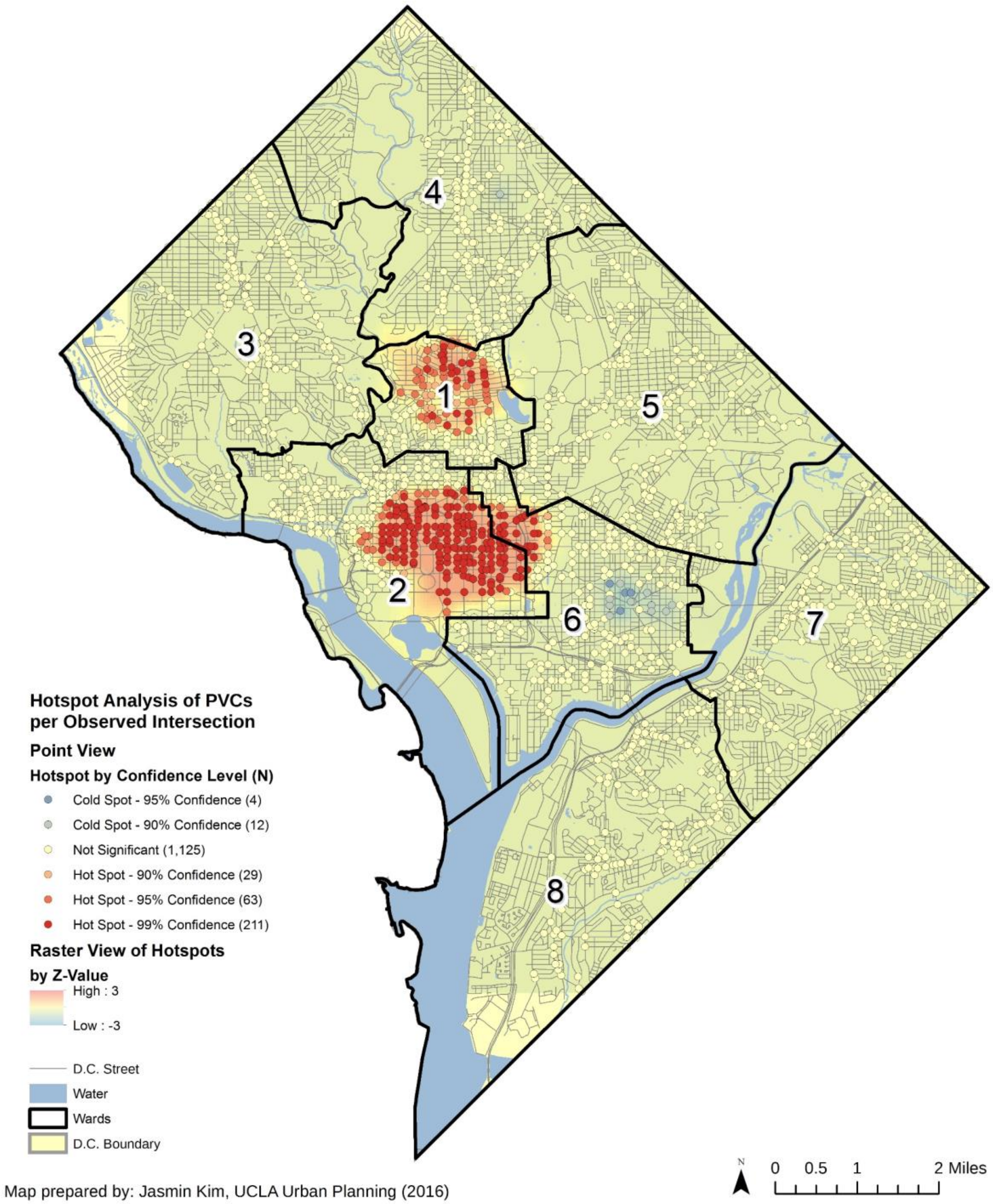
Map 1. Density of AllPVCs per Observed Intersection by D.C. Ward



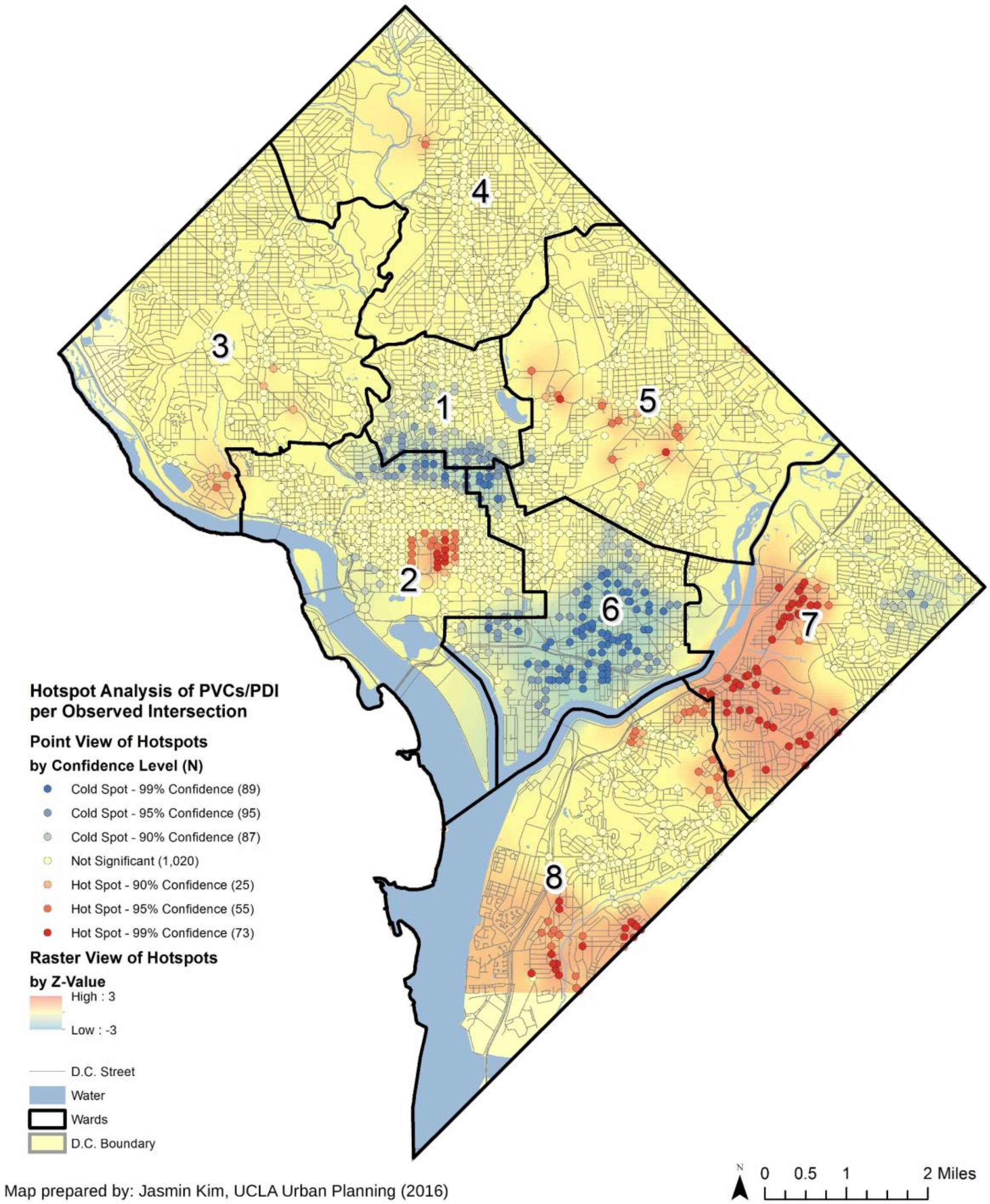
Map 2. Density of AllPVCs over PDI per Observed Intersection by D.C. Ward



Map 3. Hotspot Analysis of AllPVCs per Observed Intersection



Map 4. Hotspot Analysis of AllPVCs/PDI per Observed Intersection



4.2.1.2 IntPVCs vs. the Dependent Variable (Yint)

The previous section informs where spatial clusters and patterns are found among all of the PVCs that were observed 'at' and 'near' intersections in D.C. However, the sites that experienced high number of PVCs 'at' intersections (*IntPVCs*) often require different types of pedestrian safety interventions from those that show high number of PVCs in mid-blocks (*MidPVCs*), the two different groups of PVCs were isolated and observed individually. In this section, the spatial clusters and patterns of IntPVCs that occurred in the District of Columbia are discussed in more detail.

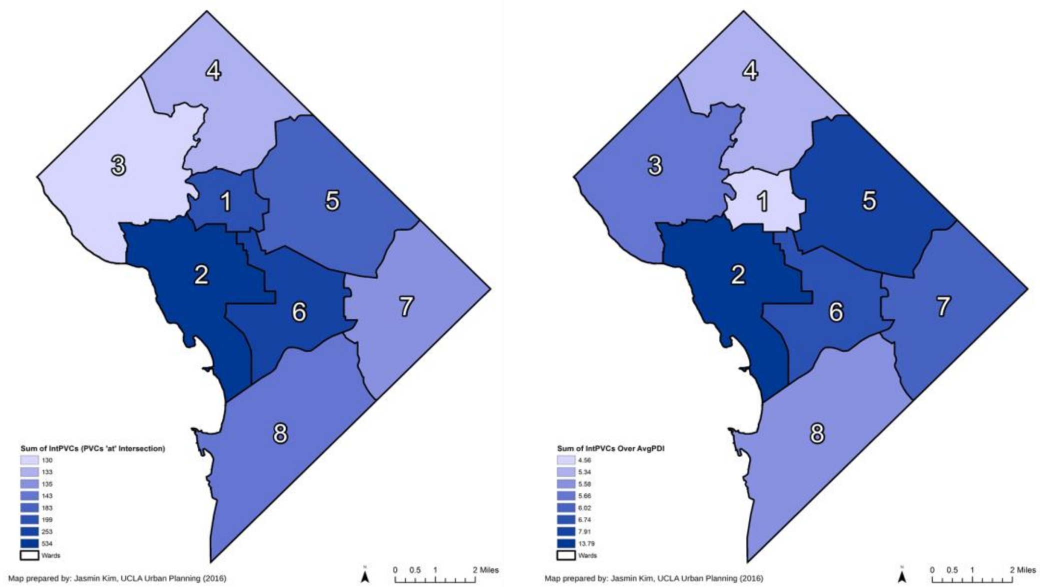


Figure 13. The Sum of IntPVCs vs. the Sum of Yint (by Ward)

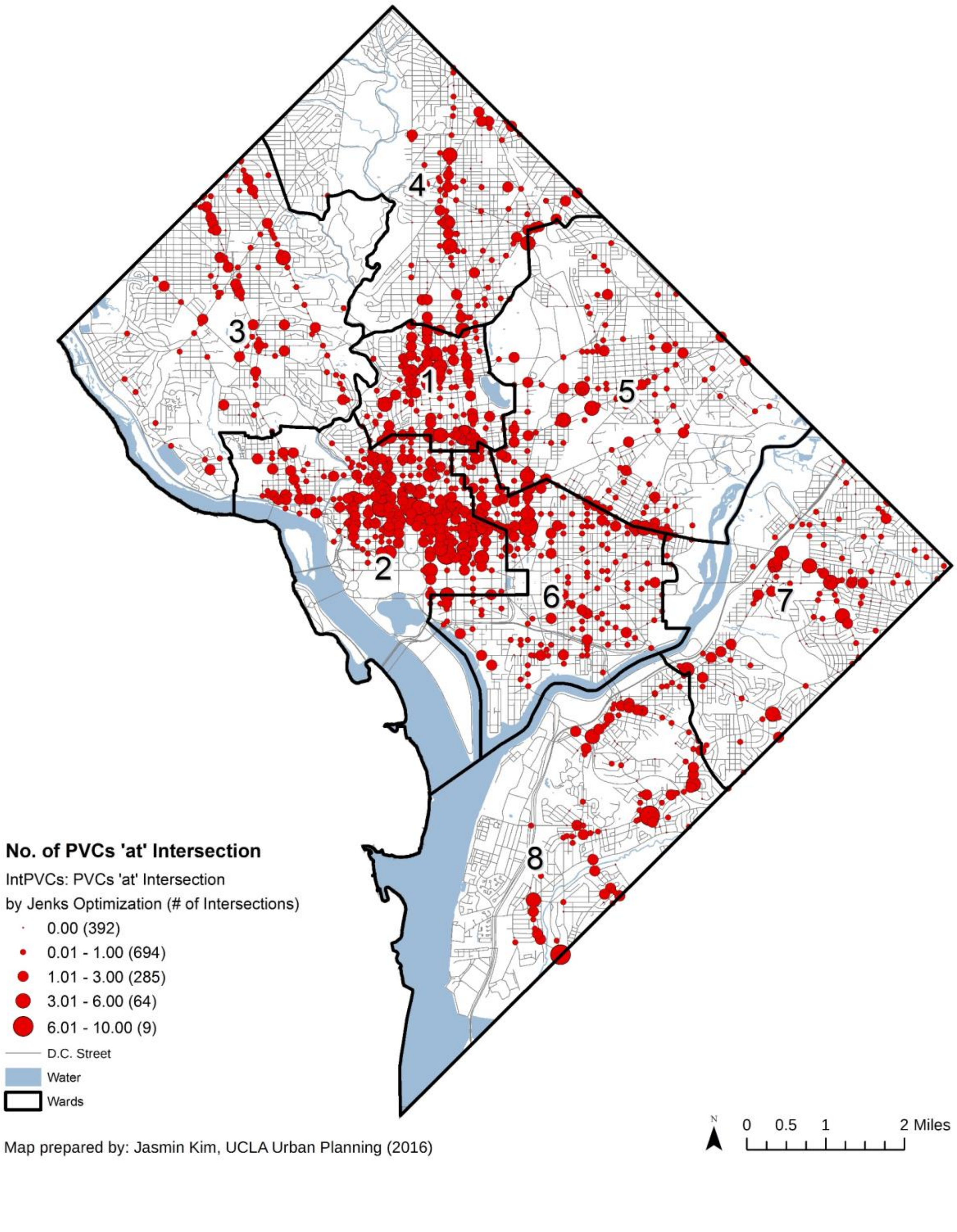
From 2010 to 2014, the PVCs that occurred 'at' intersections—otherwise referred to as IntPVCs in this study—were primarily found at the center of Washington, D.C., particularly within Wards 1, 2, and 6 (see Map 5). To be more specific, of the total number of IntPVCs, which was estimated to be about 1,710 cases, 31% occurred at Ward 2, followed by 15% at Ward 6 and

12% at Ward 1 (see Table 2). But, as Map 6 reveals, when pedestrian exposure at each intersection was normalized through the use of average pedestrian-demand index (AvgPDI), which is referred to as the dependent variable Yint in the maps, the number of intersections with high collision rates (which is marked by large red circles) suddenly increase from what was revealed in Map 5, especially in Wards 3, 4, 5, 7 and 8. As Figure 13 illustrates, however, Ward 2 still remained as the top ward with the highest percentage of collision frequency even after normalizing pedestrian exposure. As Table 2 shows, the percentage of IntPVCs only decreased from 31% to 25%. On the other hand, Ward 1 was the only ward that showed a significant decrease in the collision frequency after being normalized by AvgPDI near observed intersections (Figure 13). This calls for special attention and interventions for pedestrian safety at Ward 2, where both the number and the rate of PVCs were found to be the highest.

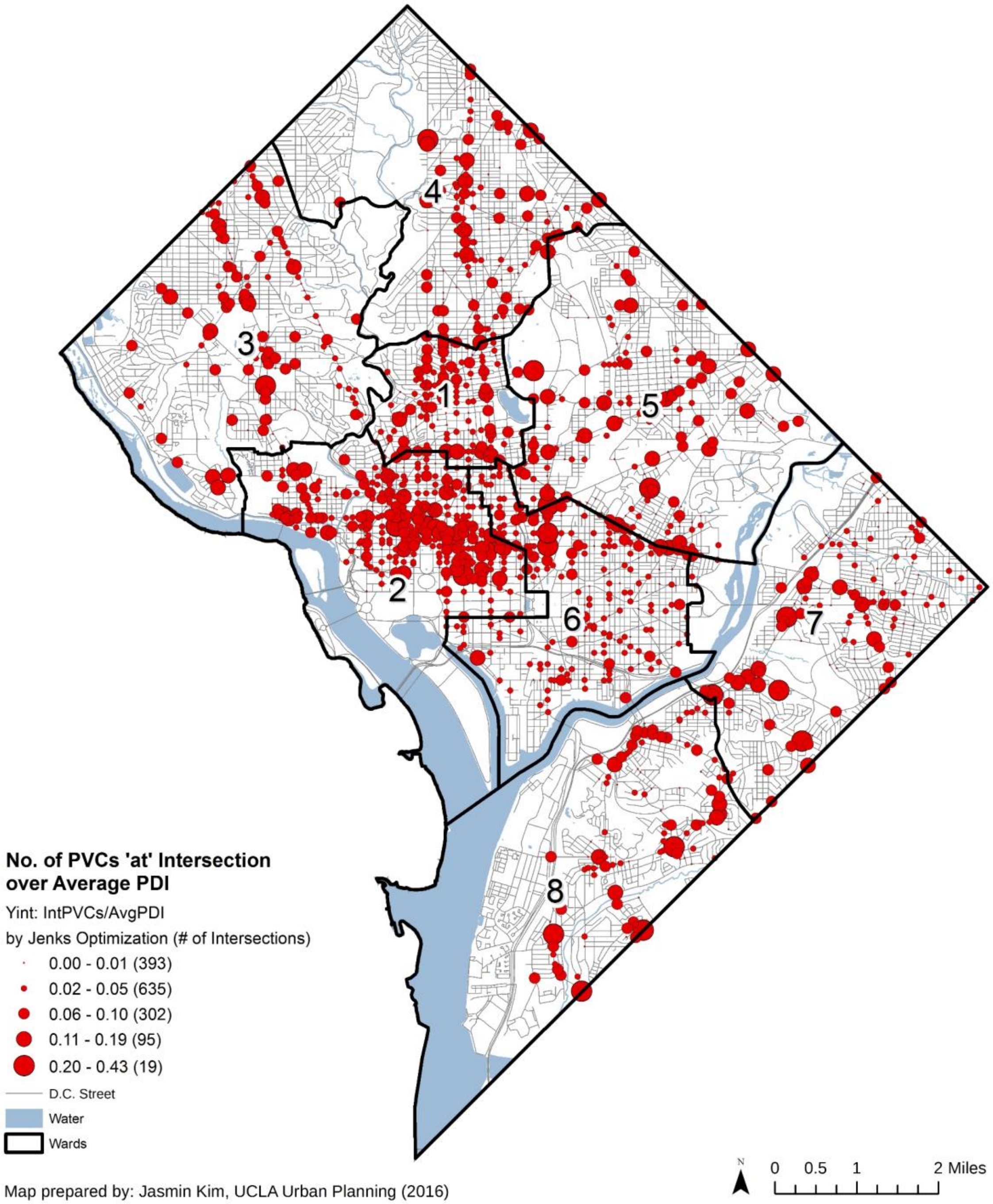
Contrary to the density maps, however, only a few hot spots—which present clusters of intersections with significantly high rate of ‘at’ intersection PVCs (*IntPVCs*)—were shown (see Map 7). In fact, out of 1,444 intersections that were observed in this stage, only ten intersections were identified as hot spots at the 99% confidence level. Significant hot spots were also most commonly found in just two of the eight wards, Wards 7 (near Fairfax Village and in between Fort Dupont Park and Twining[43]) and Ward 2 (near Penn Quarter and Downtown area).[44] This reflects that a few intersections, particularly those in Wards 2 and 7, pose greater risks for pedestrian-vehicle collision injuries than do other intersections in D.C. Also, these findings suggest the need for various pedestrian safety interventions and intersection improvements at the ‘hot spots’ that have seen unusually high number of PVCs ‘at’ intersection crossings.

[43] See Appendix 8 for neighborhood maps.
[44] See Map 7.

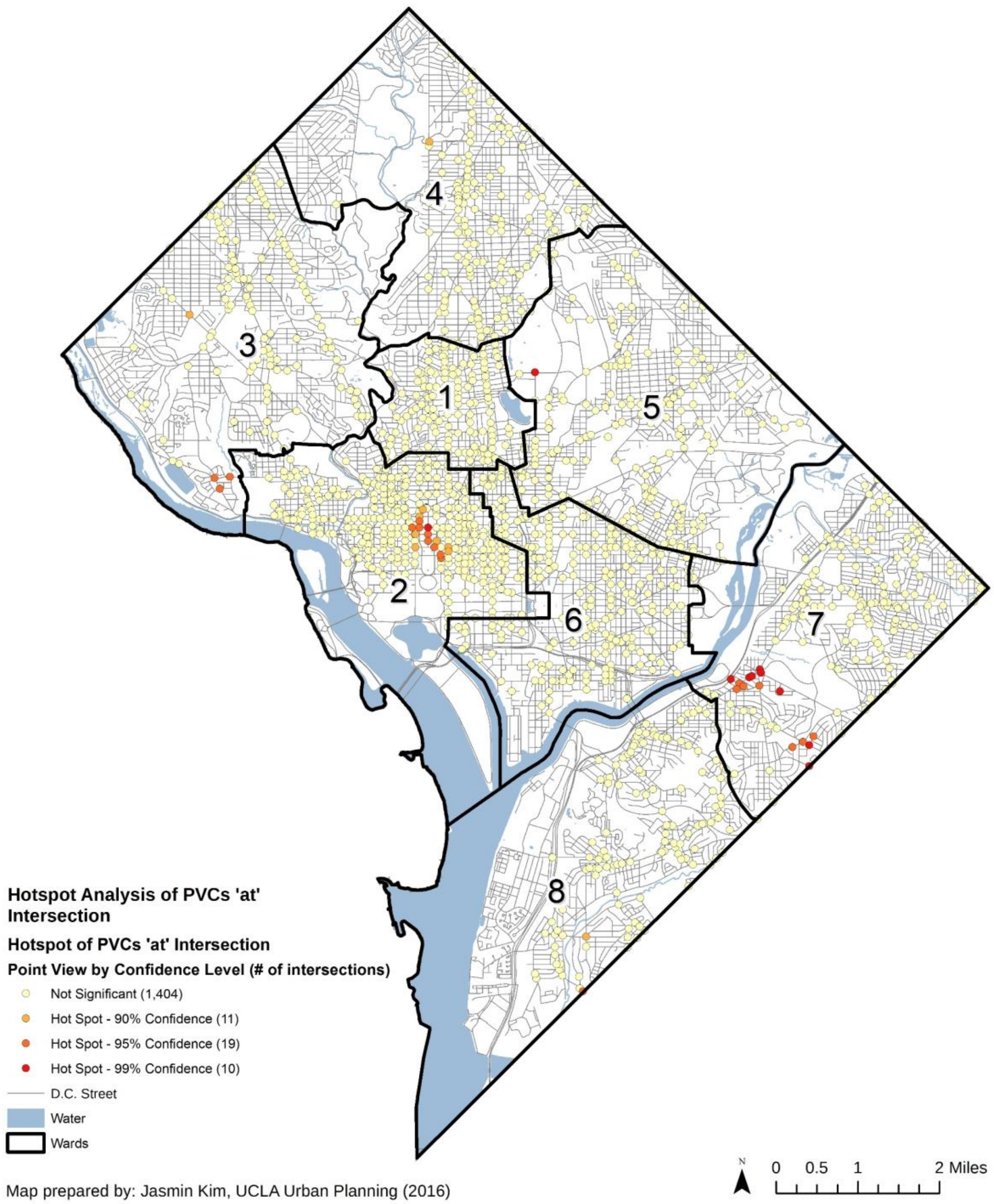
Map 5. Density of IntPVCs per Observed Intersection by D.C. Ward



Map 6. Density of IntPVCs over AvgPDI per Observed Intersection by D.C. Ward



Map 7. Hotspot Analysis of IntPVCs over AvgPDI per Observed Intersection



4.2.1.3 MidPVCs vs. the Dependent Variable Ymid (MidPVCs over AvgPDI)

Unlike IntPVCs, *MidPVCs* indicate all PVCs that occurred at mid-block locations 'near' or 100ft away from intersections, but *not* 'at' intersections. Identifying the spatial distribution of MidPVCs from 2010 to 2014 is important because not only are mid-block crossing treatments different from intersection crossing treatments, the spatial patterns and clusters could be completely different from those that only involve PVCs 'at' intersections. To test this, I assessed the spatial distribution of MidPVCs in the District of Columbia.

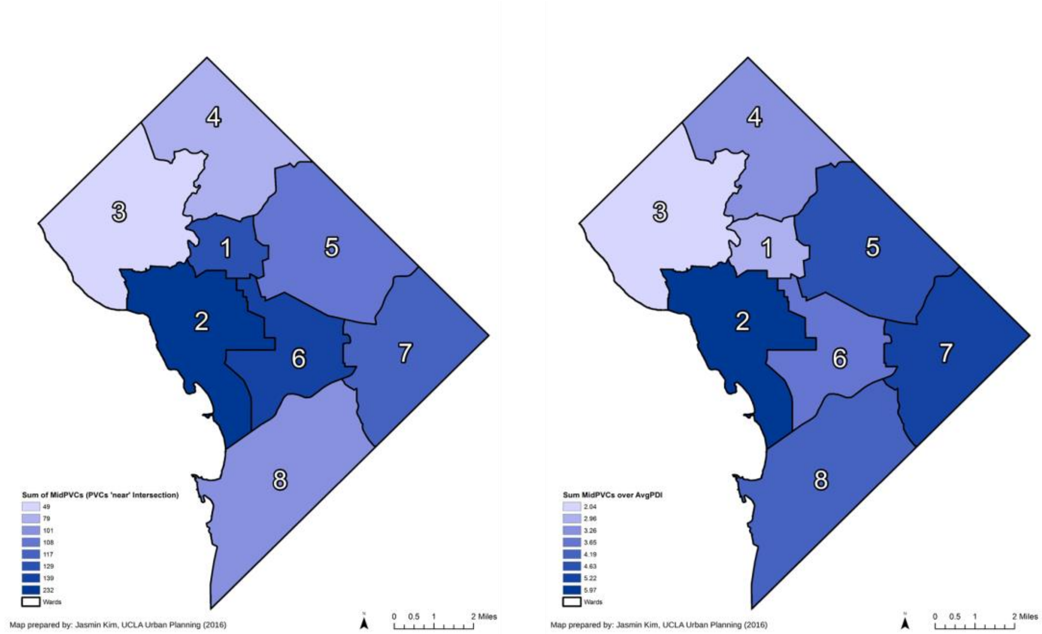


Figure 14. The Sum of MidPVCs vs. the Sum of Ymid (by Ward)

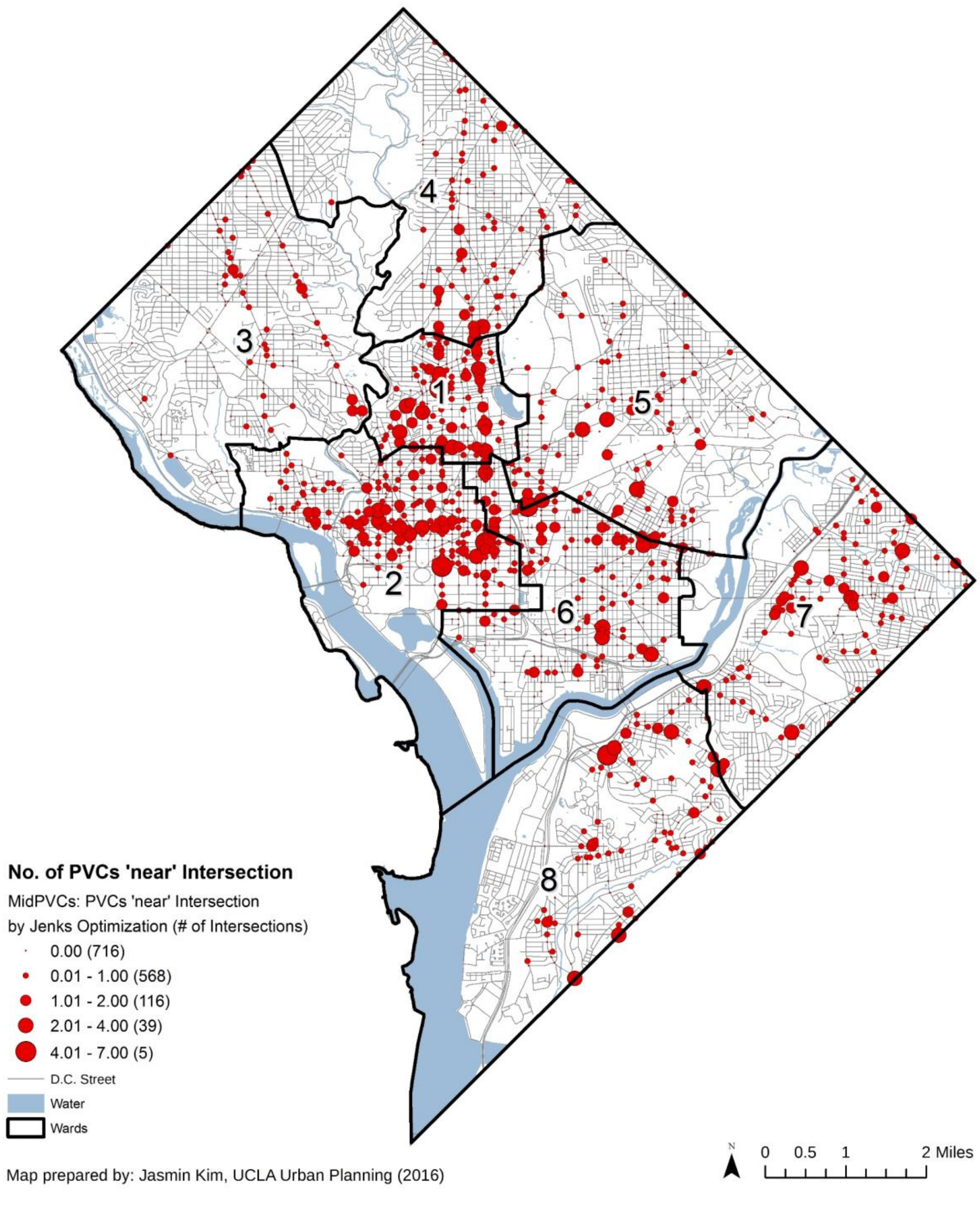
Analogous to the maps of AllPVCs and IntPVCs (Maps 1 and 5), the general distribution of MidPVCs was also concentrated in Wards 1, 2, and 6 (see Map 8). As a matter of fact, four of the top 5 intersections with the highest number of MidPVCs were all located in those wards. When the dependent variable, Ymid (MidPVCs over AvgPDI), was mapped, however, different spatial distribution and intensity were observed (see Map 9). For instance, compare Maps 8 and

9's Wards 3,4,5,7, and 8. It is easily seen in these two maps that the rates of MidPVCs per intersection (represented by the red dots) all of a sudden increase in those wards from Map 8 to Map 9. These maps demonstrate that after pedestrian exposure was normalized using AvgPDI, the intersections with the highest rate of collisions per average PDI were actually located in Wards 3,5, 7, and 8 (see Map 9).

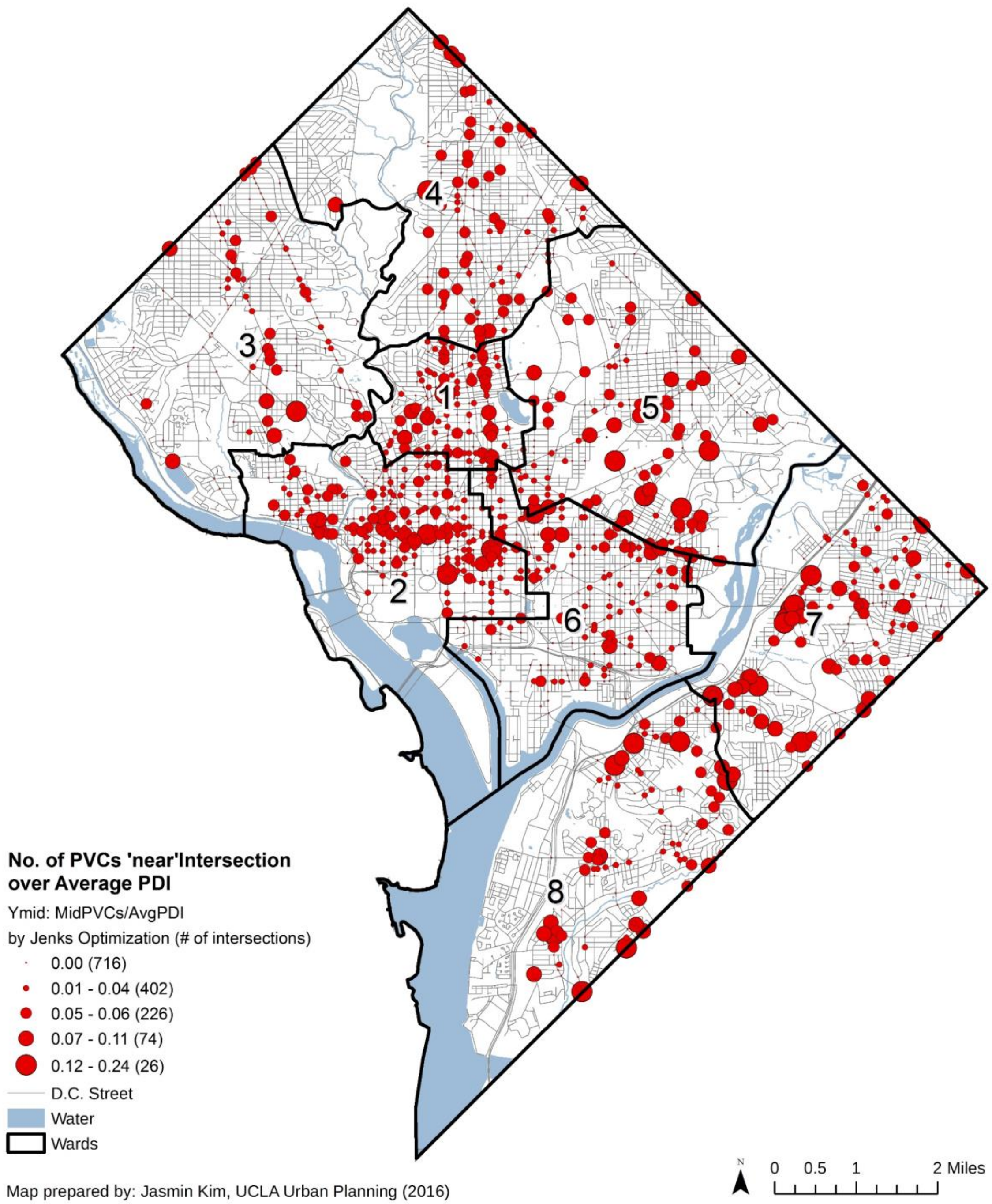
Compared to the sum of all MidPVCs per ward, which were found to be higher in Wards 2, 1, and 6 (shown in the left map), the sum of the dependent variable, Ymid (MidPVCs over AvgPDI), per ward was higher in Wards 2, 7, and 5. The statistics shown in Table 4 also corroborate these findings. Table 4 describes that approximately 19% of all Ymid occurred at Ward 2, followed by Ward 7 (16%) and Ward 5 (15%). These findings are analogous to the previous findings of AllPVCs vs. the dependent variable, Y, in that for both, the top wards with the highest rate of PVCs were Wards 2, 5, and 7.

Interestingly, the hot spots of Ymid were not analogous to the hot spots of other dependent variables. The significant clustering of intersections with the highest MidPVCs (or "hot spots") were in fact, very concentrated in two wards: Ward 7 and 8. Apart from this, no other wards with the exception of Ward 3 (which appeared to have one intersection hot spot), showed any significant hot spots. This implies that Ward 7 and 8 need special attention for mid-block treatments and interventions to prevent pedestrian-vehicle collisions in the future.

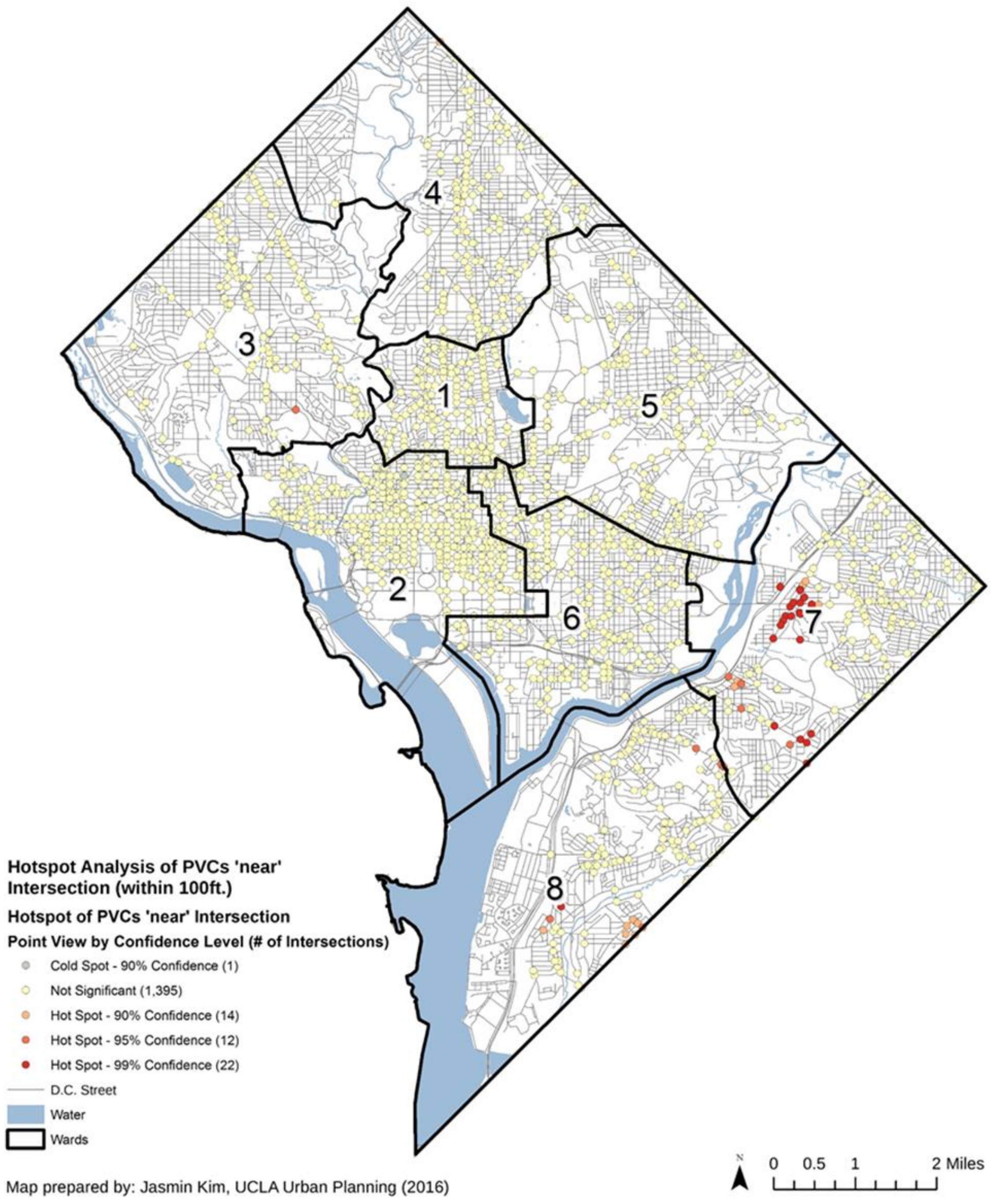
Map 8. Density of 'Near Intersection' PVCs (MidPVCs) by D.C. Ward



Map 9. Density of MidPVCs over AvgPDI by D.C. Ward



Map 10. Hotspot Analysis of MidPVCs over PDI per Observed Intersection



4.3 Negative Binomial (NB) Regression Analysis

This stage of analysis involves multiple negative binomial (NB) models to predict and identify the relationships between pedestrian-vehicle collisions (PVCs) and the surrounding intersection roadway characteristics. Specifically, twelve NB models with three different types of response variables were tested in this stage (*y*, *yint,* and *ymid*) to see if the relationships between the explanatory variables examined in this study and *AllPVCs* ('at' and 'near' intersections) differ from those relationships with *IntPVCs* (PVCs that happened 'at' intersections); or *MidPVCs* (PVCs that happened at mid-block locations 'near' intersections). Also, to test the variability and the strengths of relationships before and after the pedestrian exposure was normalized with average pedestrian-demand index (AvgPDI), six models before and after normalizing were compared side by side. Moreover, to minimize issues of multicollinearity, both manual[45] and automatic stepwise backward elimination methods were adopted to remove highly correlated explanatory variables (or 'predictors') and identify the best regression models.[46] The following sections discuss how the most appropriate regression distribution model was chosen for this stage of analysis and summarize which factors enhance or impede pedestrian safety after evaluating all the models tested in this stage.

4.3.1 Identifying the Most Appropriate Regression Model

Per the literature review, there are multiple ways of analyzing statistical correlations between road traffic casualties and the surrounding environmental factors that could possibly contribute to such casualties. Some ways of identifying those correlations are through the use of either Poisson

[45] In the manual elimination process, variables with correlation coefficient higher than $r \geq 0.5$ were eliminated. See Pearson's correlation matrices in Appendix 9 to see how variables were eliminated. Similarly, the stepwise backwards regression models tested through SPSS are listed in detail in Appendix 9.

[46] See Appendix 9 for which variables were included in the manual or automatic stepwise backward elimination process.

or negative binomial (NB) regression, which can predict the response variables' relationships to the explanatory variables even when the data is skewed, discrete, and consist of non-integer values. As seen in Table 4, the summary statistics show that all of the response variables tested in this study were in line with most of the assumptions the negative binomial regression necessitates—that the response variables' conditional means are smaller than their conditional variances, and thus, overdispersed; that the response variables are not normally distributed; and lastly, that the response variables are discrete (count) variables.

Table 3. Summary Statistics: Mean vs. Variance of the Response Variables

Response variables	Variable Description	*N*	Mean	vs.	Variance	VMR (Variance/Mean)
y	PVCs	1,414	1.84	<	2.35	1.28
yint	PVCs 'at' Intersection Only	1,414	1.18	<	1.57	1.33
ymid	PVCs 'near' Intersection Only	1,414	0.66	<	0.67	1.02

* *See Table 5 for other descriptive statistics of the response variables.*

Table 3 also shows the variance-to-mean ratio (VMR) for each of the response variables. VMR is the dispersion index for count data, or a "normalized measure of the dispersion of a probability distribution" that indicates whether a response variable is over- or under-dispersed. When VMR exceeds one, this indicates that the response variable is over-dispersed and suggest that a negative binomial distribution is followed for such variable ("Index of dispersion," 2016). As described in Table 3, the VMR for all of the response variables were higher than one, and for this reason, the negative binomial regression model appeared to be the best statistical model to use in this study.

Moreover, Table 4 demonstrates that using the general NB model may provide better results than the zero-inflated negative binomial (ZINB) model, which accounts for excessive zeros when running the regressions. As seen in the table, the number of intersections with and without PVCs differed from one response variable to another. For the response variable *y*, all of the sample intersections (*N* = 1,414) had at least one AllPVCs. As for *yint*, approximately 27.2% of the sample intersections did not observe any IntPVCs and for *ymid*, about 49.8% of the samples consisted of zeros, indicating that a high percentage of intersections did not have any MidPVCs. Because all three response variables had more intersections with PVCs than without, or simply more counts than zeros, applying the general NB model seemed more appropriate than the ZINB model.

Table 4. Identifying Excessive Zeros in the Response Variables

Response Variable	*N*	No. of Intersections with PVCs	No. of Intersections without PVCs
y	1,414	1,414 (100%)	0 (0%)
yint	1,414	1,029 (72.8%)	385 (27.2%)
ymid	1,414	710 (50.2%)	704 (49.8%)

4.3.2 Summary Statistics of Data and Models Used

As listed in Table 6, three response variables and 32 explanatory variables were used to conduct this study. The explanatory variables mainly consisted of traffic control devices (TCDs), built environment factors, such as streetlights, area of sidewalk, transit stops, roadway design factors, and sociodemographic characteristics surrounding the studied intersections. To normalize the dissimilar traffic and pedestrian volume at each intersection, a ‘control’ variable—the log of average pedestrian-demand index (AvgPDI)—was applied to six of the twelve negative binomial regression models created. The remaining six NB models were tested without any control variable to determine the effects of the control variable before and after adding it. Tables 7 illustrates these effects. Compared with the first six models, where no control variable (or offset term[47]) was applied, the last six models with an offset term (log of AvgPDI) generally showed *higher* deviance per degree of freedom and Pearson's chi-square per degree of freedom. As described in Table 5, if the deviance and Pearson's chi-square value per degree of freedom approaches one, this means that the model best fits the data. While obtaining the value of one would be very unlikely as that would mean that these NB models perfectly fit the data, obtaining a value closer to one indicates that the models have improved. In fact, it can be assumed from the table that among all of the models tested, models 7 to 12 have significantly improved from the models without any offset term. In the following sections, the results of these models are further discussed and later compared to the models without offset terms to determine the importance of controlling for pedestrian exposure.

Table 5. Goodness-of-Fit Statistics (of all 12 NB models)

Type	Model No.	Response Variable	Deviance/df	Pearson's X^2/df	Significance
Before Normalizing Ped. Exposure *(No Offset Term)*					
Manual	*1*	*y*	0.183	0.229	0.000
	2	*yint*	0.552	0.479	0.000
	3	*ymid*	0.654	0.535	0.000
Stepwise Backward	*4*	*y*	0.18	0.226	0.000
	5	*yint*	0.518	0.399	0.000
	6	*ymid*	0.647	0.521	0.000
After Normalizing Ped. Exposure *(Offset Term: Log of AvgPDI)*					
Manual	*7*	*y*	0.231	0.302	0.000
	8	*yint*	0.52	0.397	0.000
	9	*ymid*	0.689	0.605	0.000
Stepwise Backward	*10*	*y*	0.239	0.318	0.000
	11	*yint*	0.555	0.49	0.000
	12	*ymid*	0.685	0.596	0.000

*'df' refers to degrees of freedom; if the deviance and Pearson's chi-square value per df approaches one, the negative binomial model best fits the data;

[47] The offset term is coefficient that is not estimated by the model but is assumed to have the value 1; thus, the values of the offset are simply added to the linear predictor of the dependent variable. This is especially useful in Poisson regression models, where each case may have different levels of exposure to the event of interest." ("GENLIN and Poisson and offset," 2011)

Table 6. Summary Statistics of All Variables in NB Regression

Data Descriptions (N = 1414 Intersections; no missing data)	Type	Mean	Std. Dev.	Min.	Max	Variance
Control (Exposure) Variables						
(PDI) Average Pedestrian Demand Index Scores per Intersection	count	33.50	11.97	5.00	66.67	143.30
(Exposure) Log of PDI	count	3.44	0.40	1.61	4.20	0.16
Response (Dependent) Variables						
y: PVCs per Intersection	count	1.84	1.53	1	14	2.35
yint: PVCs 'at' Intersection Only	count	1.18	1.25	0	10	1.57
ymid: PVCs 'near' Intersection Only	count	0.66	0.82	0	7	0.67
Explanatory (Independent) Variables						
Traffic Control Devices (TCDs)						
Stop bar	count	3	1.48	0	7	2.2
Crosswalk	count	3	1.56	0	8	2.4
Puppy track	count	0	0.58	0	6	0.3
Rumble Strip	count	0	0.13	0	4	0.0
Lane Divider	count	3	3.46	0	17	11.9
Lane Reduction Arrow	count	0	0.00	0	0	0.0
Parking Space Marking	count	0	0.78	0	5	0.6
Signalized Intersection	count	0	0.50	0	2	0.3
Traffic poles	count	6	2.96	0	19	8.8
Camera Enforcement	count	0	0.24	0	5	0.1
Other Traffic Signs	count	1	1.99	0	20	4.0
School Crossing Guard	count	0	0.24	0	2	0.1
Speed Hump	count	0	0.09	0	1	0.0
Built Environment Factors						
Streetlight	count	4	1.90	0	20	3.6
Area of Sidewalk (within 100ft in sq. ft)	scale*	5,489	3,108	399	29,248	9,656,772
Number of Metro Stop (within 1/4 mile)	count	0	0.54	0	3	0.3
Number of Bus Stop (within 100ft)	count	1	0.79	0	4	0.6
Number of Bus Stop (within 300ft)	count	2	1.37	0	7	1.9
Commercial Land Use	ordinal	1	1.37	0	4	1.9
Residential Land Use	ordinal	1	1.22	0	4	1.5
Roadway Design Factors						
Street Direction	ordinal	2	0.40	1	2	0.2
Street Classification	ordinal	2	1.14	1	6	1.3
Sociodemographic Characteristics						
(Median) Household Income	scale*	$78,962	$39,983	$14,813	$231,042	1,598,665,585
White Population (%)	scale*	42%	31%	0%	92%	0.1
Black Population (%)	scale*	47%	35%	1%	100%	0.1
Other' Minority Population (%)	scale*	11%	7%	0%	34%	0.0
Median Age of the Nearest Census Tract	scale*	35	7	20	55	43.3
Population 0 to 14 years old (%)	scale*	13%	8%	0%	34%	0.0
Population 15 to 24 years old (%)	scale*	16%	13%	1%	98%	0.0
Population 25 to 44 years old (%)	scale*	37%	13%	1%	70%	0.0
Population 45 to 64 years old (%)	scale*	23%	6%	1%	39%	0.0
Population 65+ years old (%)	scale*	12%	6%	0%	34%	0.0

Notes: All variables shown above have N=1,414.
*average number was calculated for each of the intersections observed.
**average number for each intersection was calculated for the census tracts the intersection belongs.

4.3.3 Selected Variables

This study tested numerous iterations of models with different combinations of explanatory variables before calibrating the 12 best fitting models presented in the previous section. Using both manual and automated stepwise backward elimination methods, six out of 32 explanatory variables were excluded from these twelve models. Respectively, 26 explanatory variables were included in the models. The details on how each of these models combined explanatory variables are shown in Table A9-1, Appendix 9. Since Models 7 through 12[48] appeared to best fit the data observed, these models were further examined in the subsequent sections to illustrate the positive or negative influences of significant predictors (at the 90% confidence level) on pedestrian safety. Nevertheless, to show all of the possible combinations of factors that can reduce or increase the number of pedestrian-vehicle collisions (PVCs), this study lists significant variables that appear in Models 1 through 6 in sections 4.3.4 and 4.3.5.

4.3.4 Factors that Positively Influence Pedestrian Safety

Of the 26 intersection roadway characteristics evaluated, only a handful of explanatory variables seemed to positively influence pedestrian safety at the 90% or higher confidence level with p-values less than or equal to 0.10. As seen in NB Model 10 (Table B4), an increase in the parking space markings (β= -.07), household median income (β= -.2E-5), area of sidewalk (β= -.3E-4), number of Metro stops within a quarter mile (β= -.11), and medium density residential land use (β= -.25) appeared to decrease the values of dependent variable, *y* (or AllPVCs: PVCs that happened 'at' and 'near' intersections). Notice that the coefficient (β)[49] determines either an increase or decrease in the expected log count of PVCs, or the likelihood of PVCs. In other

[48] The statistical parameters of these models are found in Table B3 and B4, Appendix 10.
[49] Beta coefficients (β) indicate that for every unit increase in the explanatory variable, the intercept increases or decreases by the value of coefficient.

words, positive, high coefficient (β) indicates that the variable is likely to increase the expected log counts of PVCs or increase the chance of being involved in PVCs; whereas, the negative coefficient (β) indicates the opposite.

4.3.4.1 Medium Density Residential Land Use

As Model 10 shows, medium density residential land use had a strong influence on the dependent variable (*y)* with a p-value of 0.002 and beta coefficient (β) of -0.25. This means that for each one-unit increase in the count of medium density residential land use (within the 100-ft intersection buffer), the expected log count of *y* decreases by 0.25. As a matter of fact, of all explanatory variables tested in Model 10, the medium residential land use variable reflected *the greatest positive effect* on pedestrian safety by reducing the risk of PVCs at intersection surroundings. Moreover, medium density residential land use appeared to show positive influence in reducing IntPVCs (PVCs that occurred 'at' intersections)—at least in Model 8, with a coefficient (β) of -0.33 and a p-value of 0.043 (see Table A10-3, Appendix 10). These results suggest that intersection surroundings with a significant amount of medium density residential land use (such as locations with a combination of single family homes and apartment complexes) are likely to see far fewer pedestrian-vehicle collisions than those without.

4.3.4.2 Young to Middle-Aged Population

The percentages of young (aged 15 to 24) and young to middle-aged (25 to 44) population per census tract also seemed to decrease IntPVCs considerably. As Model 11 shows (Table A10-4, Appendix 10), for each unit increase in the percentage of population aged 15 to 24, the expected log count of IntPVCs decreased by a coefficient (β) of 0.37. It is notable, however, that this variable barely qualified at the 90% confidence level with a p-value of 0.101.

Young to middle-aged population (aged 25 to 44) were also significant (p-value=0.000) in reducing the risk of PVCs that happened ‘at’ intersections (IntPVCs). Among all variables tested in Model 11, this variable had the highest influence in reducing IntPVCs with a large coefficient value (β) of -1.10. Similar to its effect on IntPVCs, the percent aged 25 to 44 also significantly influenced PVCs that happened in mid-blocks (MidPVCs). In Model 9, this variable had a coefficient (β) value of -1.11, meaning that for each one-unit increase in the young to middle-aged population, the intercept coefficient (β=-3.82) decreases by 1.11. This is, by far, one of the largest coefficient values among all other variables tested in this model, with the exception of one variable, percent aged 45 to 64, which was shown to have a coefficient (β) of 1.38. This indicates that the percentages of young to middle-aged (ages 25 to 44) and very young (aged 15 to 24) population near intersections are *likely to be involved in fewer PVCs* than older pedestrians (45 to 64) as young people are probably more vigilant of their surroundings while crossing and tend to be more ‘physically healthy,’ often walking at different (faster) speeds than older pedestrians (Lee & Abdel-Aty, 2005).

4.3.4.3 Metro Stops

As shown in Model 10, Metro stops (within a quarter-mile from an intersection) surfaced as another factor that can significantly reduce the response variable *y* (or the number of AllPVCs per intersection). Here, the variable (representing count of Metro stops per intersection) appeared to negatively influence the log likelihood of PVCs by a coefficient (β) of -0.11 and p-value as low as 0.004 (see Table B4). This finding suggests a lower risk of PVCs ‘at’ or ‘near’ intersections in the vicinity of Metro stops.

4.3.4.4 Parking Space Markings

The presence of parking space markings is also a factor that can reduce the risk of PVCs ‘at’ or ‘near’ intersections (see Table B4). While models 6 through 9 did not identify parking space markings as a significant variable under the critical p-value ($p \leq 0.10$), Model 10 found this variable as a very significant predictor for the dependent variable *y*, with a very low p-value of 0.015. This means that the relationship between AllPVCs and parking space markings can be validated at the 98.5% confidence level. Parking space markings, however, exhibited a moderately low coefficient (β) value of -0.07, indicating that the variable has only a slight effect in reducing PVCs, when compared to other factors such as young to middle-aged population and medium density residential land use.

4.3.4.5 Traffic poles

In Model 9, the number of nearest traffic poles (poles for traffic signals and any other traffic control devices) *slightly reduced* the likelihood of MidPVCs by a coefficient (β) value of 0.03. Compared to other coefficient values, however, the coefficient value for this variable was very small along with a low significance level ($p = 0.069$). Therefore, the effect of traffic poles on MidPVCs is debatable and may need further assessment.

4.3.4.6 Household Median Income (per Census Tract)

Also, from Model 10, the variable that represents median household income (per census tract) reduced the log count of AllPVCs by a diminutive coefficient value of -.2E-5, and yet, this variable was one of the most significant (p-value = 0.000) variables in reducing the likelihood of PVCs. Accordingly, while this study indicates that household median income matters, more exploration with better income data may be needed to fully understand the effect of incomes on PVCs.

4.3.4.7 Area of Sidewalk

Lastly, as Model 9 shows, the area of sidewalk reduced the log count of MidPVCs by a diminutive coefficient value of -.3E-4 and a p-value of 0.069. This indicates that increasing the area of sidewalk most likely reduces the number of PVCs (by slightly), especially in mid-blocks. However, assuming that larger area of sidewalk attracts more pedestrians and thereby expose them to higher level of risks of PVCs, even though the prediction indicates that PVCs are likely to be reduced by a slight amount, the positive effect of increasing the area of sidewalk should not be underestimated.

4.3.4.8 Significant Factors that Positively Influence Pedestrian Safety

This section lists all of the significant factors (at the 90% confidence level) that were found in models 1 through 12.

Before Controlling for Pedestrian Exposure

- Parking Space Markings (*y*)*
- Traffic poles (*ymid*)*
- Household Median Income (*y*)*

After Controlling for Pedestrian Exposure

- Area of Sidewalk within 100ft. (*ymid*)
- Stop Bar (*ymid*)*
- Metro Stop within a quarter mile (*y*)
- Residential Land Use – Medium Density (*y, yint*)
- Percent of Census Tract Population – Ages 15 to 24 (*yint*)
- Percent of Census Tract Population – Ages 25 to 44 (*y, yint, and ymid*)

Note: All of the variables shown here are count data except for household median income and % of population; an asterisk (*) indicates that these factors were also found to be significant at the same locations both before and after controlling for pedestrian exposure; for definitions of *y, yint,* and *ymid,* please see Section 3.3.2.

4.3.5 Factors that Negatively Influence Pedestrian Safety

Contrary to the factors that were found to positively influence pedestrian safety, the six models (Models 7 through 12)[50] that controlled for pedestrian exposure illustrate many factors that could negatively influence pedestrian safety. Of many, twelve explanatory variables—stop bar, lane divider, signalized intersection, camera enforcement, other traffic signs, bus stop within 300ft., commercial land use (all levels of density), presence of principal and minor arterials, percentages of Black or African American population per census tract, and percentages of population (per census tract) aged 45 to 64 and 65 or more—emerged from these models as significant contributors (at the 90% confidence level) to pedestrian-vehicle collisions (PVCs). In this section, several of these explanatory variables are explored and all other significant factors that are not discussed in this section are listed in Section 4.3.6.

4.3.5.1 Older & Middle-Aged Population

From models 7 through 12, the percentages of population aged 45 to 64 and 65 and older were found to be two very significant factors contributing to PVCs. Among all variables tested in Model 10, the percentage of senior population (aged 65 or more) had the largest coefficient (β) value of 1.61. This means that the log count of AllPVCs (or the dependent variable *y*) is largely influenced by the senior population variable.[51] Comparably, as displayed in Table B3, Models 7, 8, 9 also found that the percentages of older middle-aged population (ages 45 to 64) significantly influenced all types of response variables (*y*, *yint*, and *ymid*) with large coefficient (β) values of 1.31 (for *y*), *1*.24 (for *yint)* and 1.38 (for *ymid)*. These findings suggest that intersections and mid-blocks with higher percentages of older middle-aged and senior population (aged 45 or

[50] see Tables B3 and B4, Appendix 10

[51] Note that Model 10 has an intercept (β) of -3.28, which is found in Table B4, Appendix 10.

more) are most likely to experience high rates of PVCs. This may be because older pedestrians, who tend to take more time to cross at intersections or mid-blocks (Lee & Abdel-Aty, 2005), are often poor at assessing the speed of an approaching vehicle and "less likely to be able to avoid the sudden onset of a fast car" (Jennie Oxley & Fildes, 1999). On the other hand, as Lee & Abdel-Aty (2005) noted, it may also be that the middle-aged population, especially male drivers, who "are more involved in crashes as causers" are involved in predicting the high number of PVCs. But regardless of the reason, this study shows that these age groups may prove to be significant contributors to PVCs in the District of Columbia.

4.3.5.2 Percentage of Black Population

Of the six models discussed in this section (Models 7 to 12), only one, Model 12, showed the relationship between *ymid* (MidPVCs) and the variable that represents percentage of Black or African American population[52]. In Model 12, this variable seemed to influence the log count of MidPVCs by a coefficient (β) value of 0.75, which appeared to be the greatest (β) among all of the explanatory variables' coefficients tested in the model. Also, this variable had a p-value of 0.000, which indicates that the variable is very significant at the 99% confidence level. This implies that race matters considerably and could be a significant determining factor for MidPVCs in Washington, D.C.

4.3.5.3 Density of Commercial Land Use

Different types of commercial land use—low to high density—negatively influenced pedestrian safety in models 7 to 12 (see Tables B3 and 4 for details). Of particular concern were moderate, medium, and high density commercial land use (CLU), which increased the risk of PVCs at

[52] The U.S. Census term 'Black or African American population' is also called 'Black Population' in this study.

intersection surroundings (with β values that ranged from 0.19 to 0.44). Model 11 exemplifies how medium to high density CLUs have greater effect on reducing PVCs than do low to moderate density CLUs. In this model, the Exp(β) for medium to high density ranged from 1.25 to 1.36, whereas the Exp(β) for low to moderate density ranged from 1.16 to 0.96. Provided that Exp(β) for having no CLU is equal to 1.0, the results revealed the rate of IntPVCs for high density CLU is 0.36 times higher than the rate of IntPVCs for no CLU. Likewise, the rate of IntPVCs for medium density CLU appeared to be 0.25 times higher than the rate of IntPVCs for no CLU. In Models 7 and 10, similar results were found for the response variable *y* (AllPVCs), which showed that the rate of IntPVCs for medium to high density CLU are likely to be higher than the rate for low to moderate density CLU.

Additionally, Moderate density CLU significantly increased MidPVCs. Model 9 exemplifies this by indicating that moderate density CLU had the highest Exp(β) value (1.62) among all CLU variables. In fact, moderate density CLU had higher rate of MidPVCs than that of high density CLU (by 0.07 times) and medium density CLU (by 0.30 times). These findings suggest that MidPVCs are most likely to happen near significant amount of moderate density CLU than any other types of CLU. In sum, these results indicate that intersection surroundings with a significant amount of moderate to high density commercial land use are likely to experience far more pedestrian-vehicle collisions than those without.

4.3.5.4 Principal and Minor Arterial Roads

A few types of roadways—principal and minor arterials—also increased the risk of PVCs, especially at intersections. In model 11, for instance, variables indicating principal and minor arterial were found to increase risk of PVCs at the 99% confidence level ($p \leq 0.01$). Moreover, the Exp(β) of this model revealed that the rate of IntPVCs for principal and minor arterials were higher than that of the collector or local street. Compared to the rate of IntPVCs for a local street, the rate for principal arterial was 0.36 times higher while the rate for minor arterial was 0.21 times higher. These comparisons suggest that PVCs ‘at’ intersections are more likely to occur at principal and minor arterials than any other classification of roadways examined in this study.

4.3.5.5 Traffic Control Devices (TCDs)

In Models 7 through 12, intersection surroundings with high number of TCDs—signalized intersection, stop bar, lane divider, camera enforcement, and other traffic signs—increased the risk of PVCs. While these findings seem counterintuitive, it may indicate that unaccounted traffic volume (in the pedestrian-demand index) and geometric design of the roads matter in determining the likelihood of PVCs. Previous studies have indicated that more TCDs are found near high traffic volume roads and that some geometric attributes of the roads—such as having wider road width and more number of lanes—increase collision frequency even after controlling for pedestrian and traffic volumes (Harwood et al., 2008; Ukkusuri et al., 2012).

Two TCD variables that increased this risk by a considerable amount were ‘signalized intersection’ and ‘camera enforcement.’ Among all TCDs, signalized intersection was most strongly associated with the risk of PVCs. For example, when compared to the rate of AllPVCs for ‘area of sidewalk’ or ‘traffic poles’ (see Model 7), the rate for signalized intersection was 0.24 times higher. Notice here, however, that ‘traffic poles,’ which also indicate the presence of traffic signals, was ironically found to reduce PVCs rather than increase, which contradicts the findings here—that having more than one signalized intersection next to one another (within a 100ft buffer),[53] increases the risk of PVCs on pedestrians. This may suggest that complicated geometric design of the roads matter more so than traffic signals in determining the likelihood of

[53] See Appendix 3, A3-3 for picture of a sample intersection buffer with more than one intersections.

PVCs. In fact, the results of 'signalized intersection' was found to be very significant under the 96.5% confidence level (p-value ≤ 035) in all six models. This reveals that having more than one signalized intersection within 100ft buffer (which often complicates the geometric design of the roads) can significantly increase the rate of PVCs.

Similarly, camera enforcement (p-value ≤ .077) in the intersection surroundings increased the risk of PVCs as well (β = 0.19 to 22). In Model 10, the rate of AllPVCs for the variable 'camera enforcement' was 0.20 times higher than the rate for 'lane divider,' and 0.21 for 'streetlight.' Comparatively, in Model 12, the rate of MidPVCs for camera enforcement was 0.21 times higher than the rate for streetlight, and .17 times higher than the rate for 'number of bus stops.' Cameras, however, are more likely to be installed in more dangerous intersections that either have experienced high number of collisions due to high amount of traffic or pedestrian volumes or a very complicated geometric design of the roads. Also, since the DDOT's 2009 pedestrian-demand index (PDI) relied on the predicted traffic volume, these findings may suggest that the traffic volume calculation for some intersections are not accurate. For this reason, more studies are needed to explore the true relationship between TCDs and the likelihood of PVCs.

4.3.5.6 Bus Stops

Contrary to the Metro stops, in Models 7 to 12, 'bus stops (within 300 ft.)' increased all of the response variables, *y, yint, and ymid.* In all six models, the bus stop variable positively influenced the log likelihood of PVCs by coefficients (β) that ranged from 0.05 to 0.07. Likewise, the p-values for this variable ranged from 0.000 (Model 10) to 0.109 (Model 8). These findings suggest that an intersection with a high number of bus stops in its vicinity is more likely to experience a higher rate of PVCs 'at' and 'near' intersections than intersections with few bus stops.

4.3.5.7 Significant Factors that Negatively Influence Pedestrian Safety

This section lists all of the significant factors that were discussed in the previous section along with significant factors found in Models 1 through 6 that appeared to negatively influence pedestrian safety. Tables 9 and 10 summarize all of the significant variables *before* and *after* controlling for pedestrian exposure in a simplified table format.

Before Controlling for Pedestrian Exposure

- Stop Bar (*yint*)*
- Puppy Track (*y* and *ymid*)
- Lane Divider (*y* and *yint*)*
- Signalized Intersection (*y*, *yint, and ymid*)*
- Camera Enforcement (*y*, *yint, and ymid*)*
- Other Traffic Signs (*yint*)*
- School Crossing Guard (*y*, *yint, and ymid*)
- Streetlight (*y* and *ymid*)
- Metro Stop within a quarter mile (*y* and *yint*)
- Bus Stop within 300ft. (*y*, *yint, and ymid*)*
- CLU (Commercial Land Use) – High Density (*y*, *yint, and ymid*)*
- CLU – Medium Density (*y*, *yint, and ymid*)*
- CLU – Moderate Density (*y* and *ymid*)*
- CLU – Low Density (*y*, *yint, and ymid*)*
- Presence of Principal Arterial (*y* and *yint*)*
- Presence of Minor Arterial (*y* and *yint*)*
- Percent of population – Black or African American (*ymid*)*
- Percent of population – Ages 0 to 14 (*ymid*); (r = 0.065 with % Black variable)
- Percent of population – Ages 15 to 24 (*yint*)
- Percent of population – Ages 25 to 44 (*yint*)
- Percent of population – Ages 65 Plus (*y*)*

After Controlling for Pedestrian Exposure

- Percent of population – Ages 45 to 64 (*y*, *yint*, *and ymid*)

Note: All of the variables shown here are count data except for the % of population; an asterisk (*) indicates that these factors were also found to be significant at the same locations both before and after controlling for pedestrian exposure. Variables that were found to be significant at different locations *after* controlling for pedestrian exposure were underlined.

4.3.6 List of Factors that were Not Significant

In the previous sections, only the factors that were found to be significant at the 90% confidence level were discussed. Of the 26 explanatory variables tested in twelve models, eight variables were not included in the analysis because they were *not* found to be statistically significant at the critical p-value (p = 0.10). However, the parameter estimates for these variables are available to view in Tables A10-1 to A10-4 in Appendix 10.

Eight variables that were not discussed in the previous are shown below:

- Rumble Strip
- Streetlight
- Speed Hump
- Interstate
- Other Freeway
- Collector
- Local Street
- Percent of Population—Other than Black or White

Note: All of the variables shown here are count data except for the % of population

Table 7. NB Regression Results *Before* Controlling for Pedestrian Exposure

Results of NB Regression without any Offset term; Sig. Factors (p ≤ 0.10)	Manual Elimination of factors with (r≥ 0.5)			Stepwise Backward Elimination (SPSS)		
Explanatory (Independent) Variables	*Model 1 (y)*	*Model 2 (yint)*	*Model 3 (ymid)*	*Model 4 (y)*	*Model 5 (yint)*	*Model 6 (ymid)*
Traffic Control Devices (TCDs)						
Stop bar					-	-
Puppy track				-		-
Lane Divider		-		-	-	
Parking Space Marking				+		
Signalized Intersection	-	-	-	-	-	-
Traffic poles			+			
Camera Enforcement				-	-	
Other Traffic Signs		-				
School Crossing Guard			-	-	-	-
Built Environment Factors						
Streetlight				-		-
Number of Metro Stop (within 0.25 mile)				-	-	
Number of Bus Stop (within 300ft)	-		-	-	-	-
Commercial Land Use (CLU)	-	-	-	-	-	-
CLU (High Density)	-		-	-	-	-
CLU (Med. Density)	-	-	-	-	-	
CLU (Moderate Density)	-		-	-		-
CLU (Low Density)			-	-	-	-
Roadway Design Factors						
Street Classification				-	-	
Principal Arterial		-		-	-	
Minor Arterial		-		-	-	
Sociodemographic Characteristics (per Census Tract)						
Household Median Income				+		
Black Population (%)						-
Population 15 to 24 years old (%)					-	
Population 25 to 44 years old (%)					-	
Population 65+ years old (%)				-		

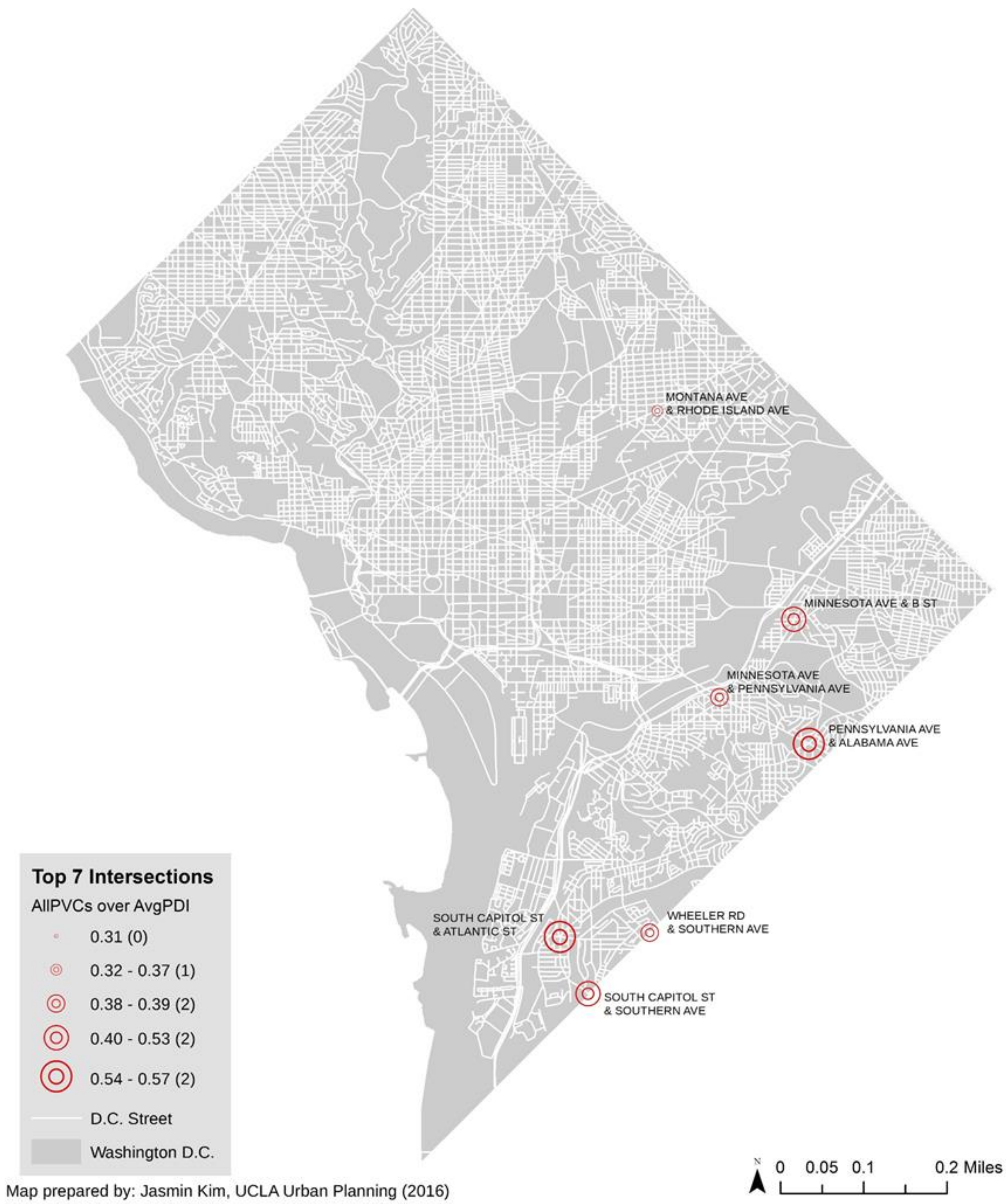
* All of the data on *sociodemographic factors* were gathered at the census tract level; + sign indicates factors that are likely to reduce the risk of PVCs, whereas the – sign implies the opposite, indicating factors that are likely to contribute to more risk of PVCs. This table only indicates factors that were found to be significant with p-values less than 0.10.

Table 8. NB Regression Results *After* Controlling for Pedestrian Exposure

Results of NB Regression with offset term: Log of AvgPDI; Sig. Factors (p ≤ 0.10)	Manual Elimination of factors with ($r \geq 0.5$)			Stepwise Backward Elimination (SPSS)		
Explanatory (Independent) Variables	*Model 7 (y)*	*Model 8 (yint)*	*Model 9 (ymid)*	*Model 10 (y)*	*Model 11 (yint)*	*Model 12 (ymid)*
Traffic Control Devices (TCDs)						
Stop bar					-	-
Lane Divider	-	-		-	-	
Parking Space Marking				+		
Signalized Intersection	-	-	-	-	-	-
Traffic poles			+			
Camera Enforcement				-	-	-
Other Traffic Signs		-			-	
Built Environment Factors						
Area of Sidewalk (within 100ft by sq.ft.)			-			
Number of Metro Stop (within 0.25 mile)				+		
Number of Bus Stop (within 300ft)	-	-	-	-	-	-
Commercial Land Use (CLU)	-		-	-	-	-
CLU (High Density)	-	-	-	-	-	-
CLU (Med. Density)	-	-		-	-	
CLU (Moderate Density)			-	-		-
CLU (Low Density)			-	-	-	-
Residential Land Use (RLU)				+		+
RLU (Med. Density)		+		+		
Roadway Design Factors						
Street Classification		-		-	-	
Principal Arterial	-	-		-	-	
Minor Arterial				-	-	
Sociodemographic Characteristics (per Census Tract)						
Household Median Income				+		
Black Population (%)						-
Population 15 to 24 years old (%)					+	
Population 25 to 44 years old (%)	+	+	+		+	
Population 45 to 64 years old (%)	-	-	-			
Population 65+ years old (%)				-		

* All of the data on *sociodemographic factors* were gathered at the census tract level; + sign indicates factors that are likely to reduce the risk of PVCs, whereas the – sign implies the opposite, indicating factors that are likely to contribute to more risk of PVCs. This table only indicates factors that were found to be significant with p-values less than 0.10.

Map 11. Top Seven Case Study Intersections



4.4 Fieldwork Analysis

To further explore the influences of intersection roadway characteristics on pedestrian-vehicle collisions (PVCs), this study involved a case study of the top seven intersections with highest rate of PVCs at a site-specific level. As mentioned in the methodology,[54] for each case study intersection, this stage of analysis involves counting traffic and pedestrian volume for 15 to 20 minutes to estimate an average hourly pedestrian and traffic volume. Following the volume counts, the study examined comparative characteristics of street design, traffic, land use, and any other apparent intersection roadway characteristics of the case study intersections.

4.4.1 Why Seven Case Studies?

The top seven intersections selected for this study posed the highest predicted risk of PVCs on pedestrians in Washington, D.C. from 2010 to 2014. Predictive risk, in this case, was calculated as PVCs per intersection over average pedestrian-demand index (AvgPDI[55]). Furthermore, the locations of top seven case study intersections spatially paralleled to that of hot spot intersections found in Wards 7 and 8 (see Maps 4,7, and 10). Therefore, to better understand why some intersections in Wards 7 and 8 appear as consistent high-risk intersections over the period of five-years, these top seven intersections were examined more extensively.

4.4.2 Average PDI: Is It Accurate?

While much of this study relies on the DDOT's 2009 average pedestrian-demand index (AvgPDI) to control for the dissimilar pedestrian exposure levels at different intersections, however, whether this AvgPDI is an accurate estimation of pedestrian exposure—which should take into account both pedestrian and traffic volume—was only to be discovered by comparing it

[54] See section 3.4.3 for more details on the methodology used.

[55] Refer to section 3.3.1.2 for a better understanding of the term 'AvgPDI.'

with the actual volume ratio obtained from each of the seven case study intersections. Actual volume ratio, in this case, refers to an estimated average hourly data of pedestrian volume dividec

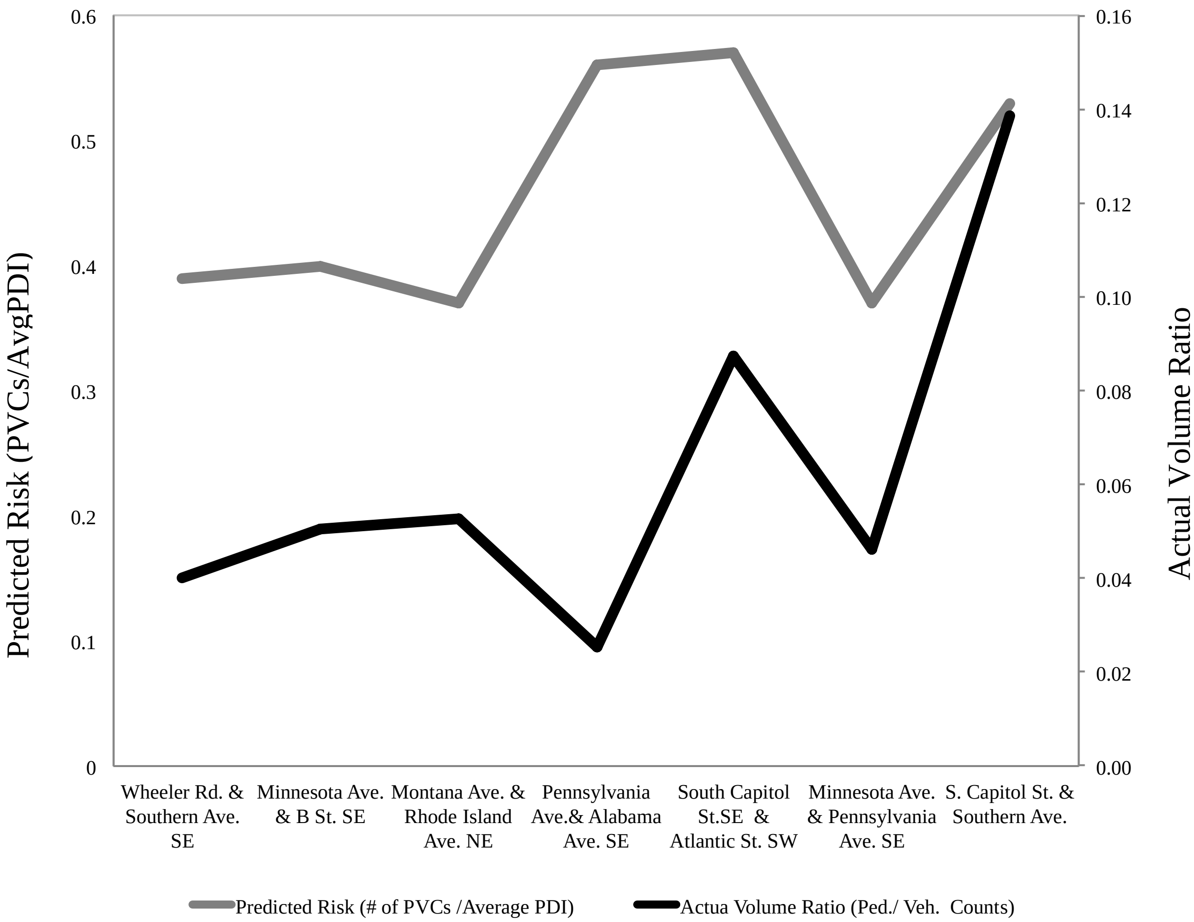


Figure 15. Predicted vs. Actual Risk

To see how the predicted risk compares to the actual risk (actual volume ratio) for each of the seven case study intersections, both were plotted in the same graph as shown in Figure 15. Surprisingly, as seen in the graph, the predicted risk for each intersection follows a very similar trend to that of the actual volume ratio for each intersection, with the exception of Pennsylvania Ave & Alabama Ave. In Pennsylvania & Alabama, the actual volume ratio was much lower than the predicted risk. Broadly speaking, however, this graph suggests that pedestrian-demand index

[56] To see the actual counts of pedestrian and vehicle volume per intersection, refer to Figure 17,

(PDI) may be a good proxy measurement of pedestrian risk exposure to PVCs as it can almost resemble the actual volume ratio observed in the field.

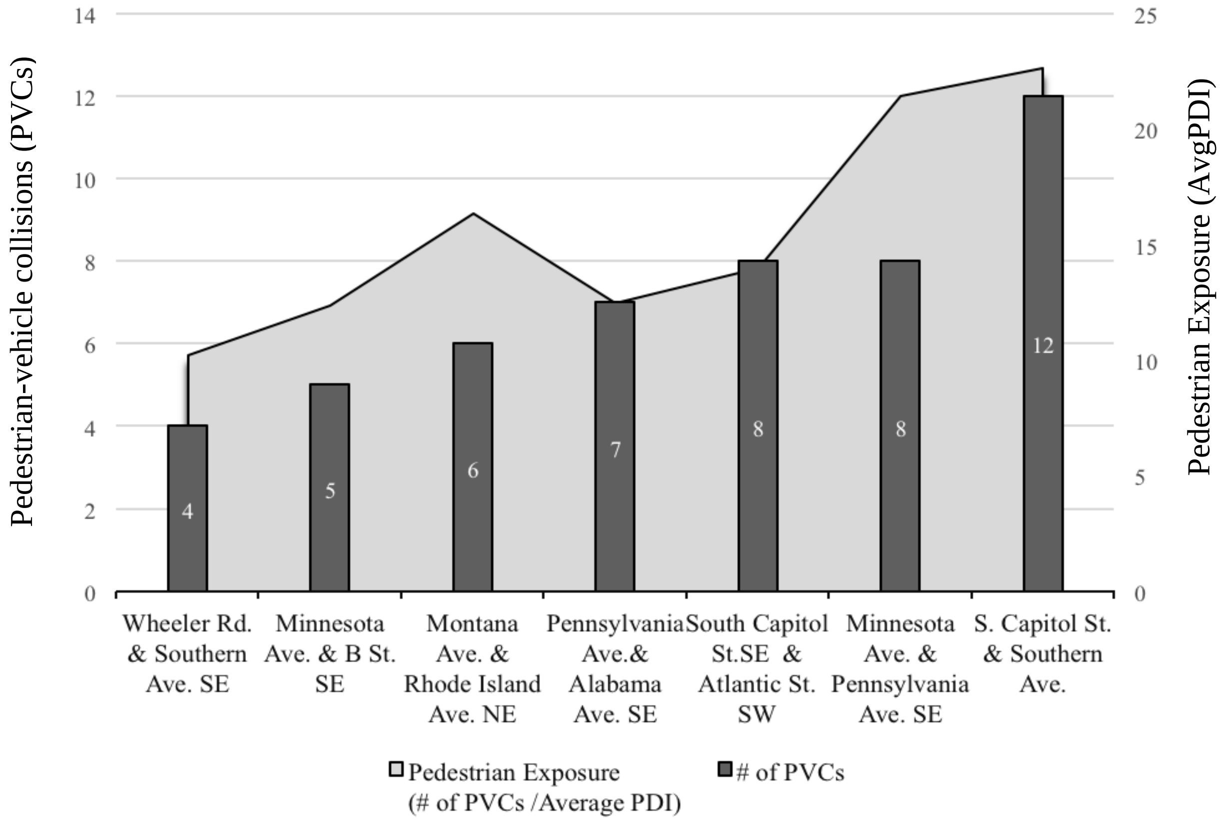


Figure 16. Pedestrian-Vehicle Collisions (PVCs) vs. Average PDI (AvgPDI)

Moreover, as Figure 16 shows, pedestrian exposure (AvgPDI) also follows the pattern of PVCs per intersection. With the exception of Montana Ave. & Rhode Island Ave., the figure illustrates AvgPDI as a good indicator that identifies where the most PVC-prone intersections may be in D.C. For example, S. Capitol St. & Southern Ave. experienced the highest AvgPDI score of about 22. At the same time, the same intersection experienced the highest number of pedestrian-vehicle collisions (12 PVCs) over the course of five years (2010-2014). Similarly, the intersections that had lower AvgPDI scores (e.g. Wheeler Rd & Southern; Minnesota Ave. & B St.) had fewer PVCs. While all of these findings can be coincidental, the seven case studies demonstrate that AvgPDI can be a good indicator of pedestrian risk exposure. As matter of fact, if well-devised and updated annually, the average PDI may be an alternative method of calculating pedestrian risk exposure to PVCs as opposed to having field engineers visit every intersection in the District to count annual traffic and pedestrian volume, which can be very costly and labor-intensive.

4.4.3 Roadway Characteristics of Case Study Intersections

Similar to the results Loukaitou-Sideris et al. (2007) found, most of the seven case study intersections in Washington D.C. were located near commercial land uses with a multitude of various retail stores—such as drug stores, auto repair shops, laundromat, small shopping centers, post office, car wash, restaurants, convenience stores, banks, carry-outs, and gas stations—which almost always had some surface parking lots. One intersection that did not follow this trend was Minnesota & B. This intersection primarily consisted of residential apartments and single-family homes nearby.[57]

One notable trend among all case study intersections with the highest rate of PVCs was the multitude of bus stops near each intersection. All of the seven intersections had at least one bus stop that was very close to the intersection. The buses that stood near the intersection crosswalks appeared to be problematic because they represented visual impairment not just for pedestrians who were about to cross, but also for drivers whose view was substantially obstructed by the buses. To add to this, approximately 2 to 10 bus lines passed by each of these intersections, attracting numerous transit riders, who were often found to be ethnic minorities, Black, or African Americans.

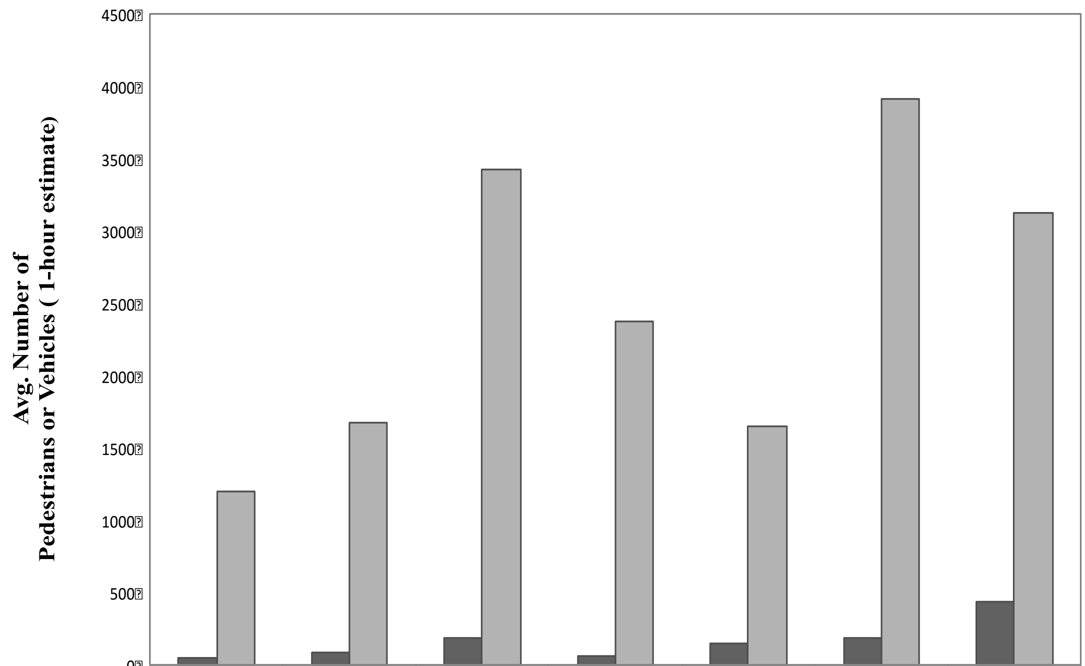
[57] Refer to Table 9 for the list of all findings.

Interestingly, *none* of the case study intersections had Metro stops within a quarter-mile distance from the intersection. Moreover, those intersections that were within a one-mile distance from the Metro stops (Wheeler & Southern; Montana & Rhode Island) had lower rates of PVCs, which corroborates the statistical findings in the previous section—that having a Metro stop near intersection does not increase the rate of PVCs in the intersection surroundings.

Other notable trends in the case study intersections were the absences of speed bumps and signs warning motorists to slow down, cede, and provide right-of-way to pedestrians. Such signs include, but are not limited to ‘no right turn here,’ ‘no turn on red,’ ‘yield to pedestrians ahead,’ and speed limit signs. Speed bumps and signs like these are often used by transit agencies to slow down and help the vehicular traffic interfere less with pedestrians crossing the street. However, absolutely no right turn signs of any kind or yield signs were found in any of these case study intersections. In fact, only one speed bump was found near an intersection that had the least number of MidPVCs over the five-year period (Montana & Rhode Island). Also, only four of the seven intersections had speed limit signs posted near the intersections (although almost always, only one speed limit sign was found per intersection).

Most of the observed intersections had sidewalks, crosswalks, and streetlights. However, no distinct patterns were seen in terms of the number of sidewalks, average width of sidewalks, and average block length. The top three intersections with the highest rate of PVCs—namely South Capitol & Atlantic; Minnesota & Pennsylvania; South Capitol & Southern—had fewer number of crosswalks (three to four) than the other intersections despite the high actual volume ratio. Also, these crosswalks were rarely found with any stripes (otherwise known as zebra or continental crosswalks) while all of the remaining four intersections with lower rate of PVCs had more than 4 crosswalks with many of them being zebra or continental crosswalks. This indicates that the type and number of crosswalk could matter in reducing PVCs.

The number of streetlights also appeared to matter somewhat. At the aforementioned top three intersections, fewer streetlights (2 to 3 light poles) were observed than at the four intersections with lower rates of PVCs (which had 2 to 5 streetlights). Since pedestrians are less visible at nighttime, it is possible that the obscured visibility make pedestrians more vulnerable to traffic accidents at night. Moreover, the top three intersections with the highest rate of PVCs also had higher actual volume ratio, meaning that more streetlights may be necessary at these intersections.



	Wheeler Rd. & Southern Ave. SE	Minnesota Ave. & B St. SE	Montana Ave. & Rhode Island Ave. NE	Pennsylvania Ave.& Alabama Ave. SE	South Capitol St.SE & Atlantic St. SW	Minnesota Ave. & Pennsylvania Ave. SE	S. Capitol St. & Southern Ave.
Ped count avg (1-hr.)	48	84	180	60	144	180	432
Vehicle count avg (1-hr.)	1200	1668	3420	2376	1644	3912	3120

*These averages were calculated after 3 to 4 cycles of 5-minute counts were marked in the field; to account for the variability in time and day of the week, site visits were generally conducted on Mondays and Fridays and during peak hours (from 8-11am or 4-7pm).

Figure 17. Actual Field Estimate of Pedestrian and Traffic Volume (1-hr. avg.)

To see which of the two—pedestrian or traffic—volumes affect the likelihood of PVCs more, Figure 17 illustrates the counts of pedestrians and vehicles that passed by per intersection. As the figure shows, traffic volumes were generally found to be higher than that of pedestrians in most of the observed intersections. But, neither the pedestrian nor the traffic volume followed the pattern depicting the frequencies of PVCs per intersection as shown in Figure 16. This suggests that to predict the risk of PVCs, both pedestrian and traffic volume must be considered at each intersection, provided that accounting for just one or the other volume may lead to bias in the distribution of the response variable (frequency of PVCs per intersection).

Table 9. Top 7 Intersections with highest PACs/PDI

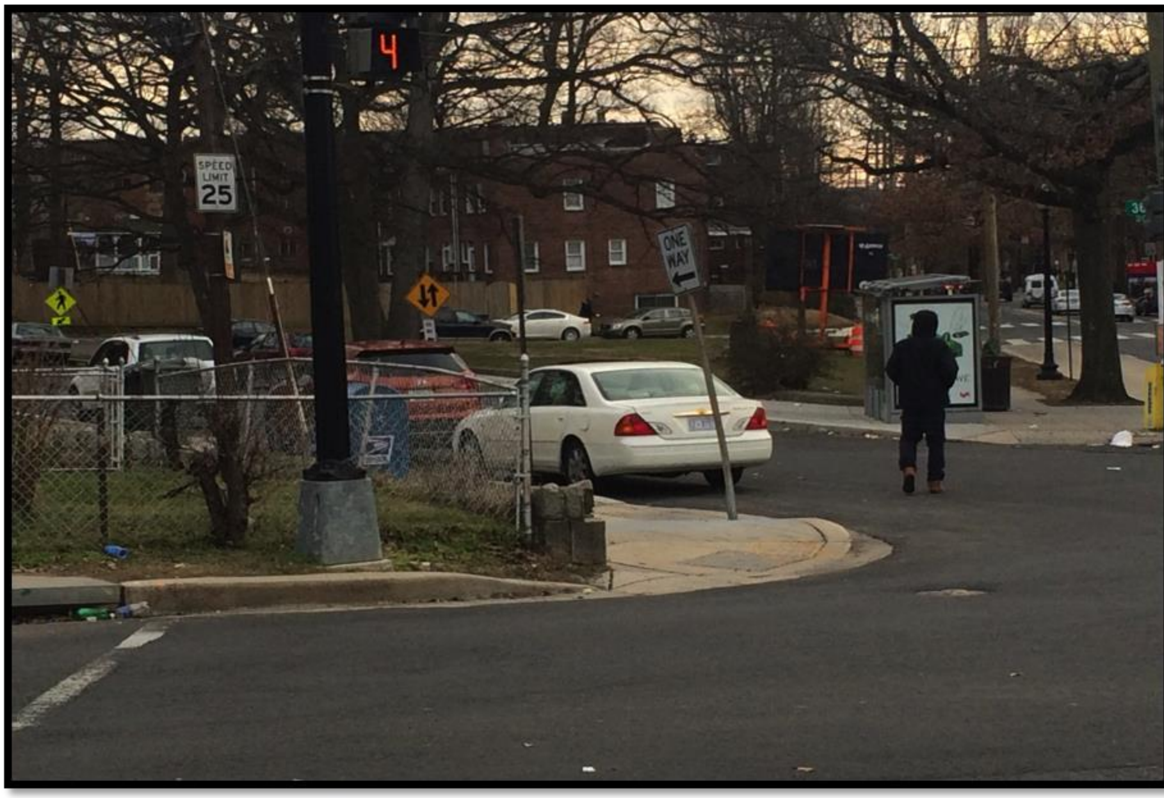
Selected comparative characteristics of case study intersections

Intersection Characteristics	***Wheeler Rd. & Southern Ave. SE***	***Minnesota Ave. & B St. SE***	***Montana Ave. & Rhode Island Ave. NE***	***Pennsylvania Ave.& Alabama Ave. SE***	***South Capitol St.SE & Atlantic St. SW***	***Minnesota Ave. & Pennsylvania Ave. SE***	***S. Capitol St. & Southern Ave.***
# of AllPVCs	***4***	***5***	***6***	***7***	***8***	***8***	***12***
# of IntPVCs	*3*	*3*	*5*	*4*	*6*	*5*	*8*
# of MidPVCs	*1*	*2*	*1*	*3*	*2*	*3*	*4*
AvgPDI	*10.25*	*12.4*	*16.4*	*12.5*	*14*	*21.44*	*22.67*
Predicted Risk	***0.39***	***0.4***	***0.37***	***0.56***	***0.57***	***0.37***	***0.53***
Ped count avg. (1-hr.)	48	84	180	60	144	180	432
Vehicle count avg. (1-hr.)	1,200	1,668	3,420	2,376	1,644	3,912	3,120
Actual Volume Ratio (ped./veh.)	**4.0%**	**5.0%**	**5.3%**	**2.5%**	**8.8%**	**4.6%**	**13.8%**
Average block length Sum of all directions (in feet)	**687**	**385**	**166**	**424**	**357**	**133**	**566**
SB Block	640	321	117	283	433	82	980
EB Block	923	354	62	461	67	140	807
NB Block	856	477	282	670	573	73	290
WB Block	328	387	201	280	355	235	185
No. of sidewalks	4	5	5	4	4	4	4
Average sidewalk width (ft.)	11	7	8	9	11	10	4
# of lanes	15	13	17	17	13	17	15
# of streetlights	2	3	5	4	2	2	3
# of legs (radiating from each intersection)	4	5	5	4	4	4	4
# of no right turn signs	0	0	0	0	0	0	0
no right turn on red	0	0	0	0	0	0	0
# of no left turn signs	0	0	0	1	1	1	0
# of traffic signals	4	5	4	4	4	3	4
# of total crosswalks	4 (all with stripes)	5 (No stripes)	5 (all with stripes)	4 (all with stripes)	3 (1 faded)	3 (1 with stripes)	4 (1 with stripes)
# of standard crosswalks	0	5	0	0	3	2	3
# of zebra/continental crosswalks	4	0	5	4	0	1	1
#of yield to pedestrian signs	0	0	0	0	0	0	0

# of speed limit signs	1	1	0	1	0	0	1
Posted speed limit (avg. mph)	30	25	Not found	30	Not found	Not found	30
# of speed humps / bumps	0	0	1	0	0	0	0
# of median / traffic island	0	1	3	0	2	3	1
# of protected left turn arrows	4	0	0	1	1	2	1
# of unprotected left turn signal	4	4	4	3	3	1	3
# of protected pedestrian signal phasing	4	4	5	4	3	2	0
Type(s) of Land Use	Commercial (gas station) & residential (apartment complexes)	Residential (apartment & single-family homes)	Commercial (restaurants, drug store, auto repair shop, laundromat) & Church	Commercial (gas station and small shopping centers) & Public Space (Park & Library)	Commercial (auto repair shop, liquor store, carry-outs) & Residential	Commercial (gas station, beauty supply shop, post office, car wash & restaurants)	Commercial (gas station & retail stores: 7/11, thrift store, banks, carry out places, & pharmacy)
# of bus stops close to intersection	3	1	2	4	3	5	4
# of bus lines	8	2	8	3	6	10	6
# of rail/Metro stop(s) within 0.25 mile from the intersection	0	0	0	0	0	0	0
Other Notable TCDs / Street Features	Congress Heights Metro (within 1-mile Distance)	Diamond Shaped (5-legged intersection). One leg didn't have protected pedestrian signal phasing and it appeared very dangerous to cross	Diamond Shaped (5-legged intersection)	Other TCDs Present: Puppy tracks &"Photo Enforced" Sign	Crosswalks & road pavement markings were very faded	Video Surveillance Present; Next to Anacostia Fwy	Dead-end street (SB of Southern Ave SE)
Avg. distance to transit stop(s) (miles)	Congress Heights Metro (1 mile); Bus Stops (194 ft)	Bus Stops (85 ft)	Rhode Island Metro Station (0.6 miles) Bus Stops (80 ft)	Bus Stops (205ft)	Bus Stops (223 ft)	Bus Stops (266 ft)	Southern Ave Metro Station (16miles); Bus Stops (248ft)

CHAPTER 5

CONCLUSION



CHAPTER 5

CONCLUSION

5.1 Discussion

This study provides a multi-methodological perspective on risk factors for pedestrian-vehicle collisions (PVCs) in Washington, D.C. from 2010 to 2014. The four approaches used in this study—analysis of archival data, spatial data, negative binomial regression models, and field observation—reveal a number of interesting descriptive statistics, spatial patterns, and relationships between PVCs and intersection roadway characteristics.

Approximately 3,500 police archival records of PVCs were analyzed revealing *when*, *where*, and under *what* types of roadway and weather conditions the observed PVCs occurred. Each year, the total number of PVCs increased in the District of Columbia, and they occurred mostly on weekdays and during the third and fourth quarters of the year. The findings reveal that the NE, NW, and SE quadrants and Police District 3 experienced a high number of pedestrian-vehicle collisions. Also, more PVCs happened on straight, two-way asphalt paved roads. These descriptive statistics show the frequencies of PVCs and do not reveal relationships or correlations between the observed attributes and PVCs. These descriptions complement the findings from and provide the context for spatial, regression, and fieldwork analyses.

Building on the archival work, the spatial analysis of microenvironments having PVCs that occurred 'at' and 'near' intersections identified multiple spatial patterns regarding *where PVCs occurred previously* and *where PVCs are likely to occur in the future*. Many PVCs occurred previously in Wards 2, 6, and 1. However, when the dissimilar pedestrian exposure at different locations was taken into account through normalizing PVCs by AvgPDI,[58] Wards 2, 5, and 7 were found to have the highest rates of PVCs per unit of exposure.[59] Also, a large number of hot spots representing a significant clustering of high rates of PVCs (otherwise interpreted as the 'high-risk' intersections) were found in Wards 7, 8, and 2. When these PVCs were categorized into two types of PVCs—ones that occurred 'at' an intersection (IntPVCs) and others that occurred at mid-blocks 'within 100ft. from' an intersection (MidPVCs)—slightly different results were found. The highest rates of IntPVCs were found in Wards 2, 5, and 6, whereas, the highest rates of MidPVCs were found in Wards 2, 7, and 5. Also, most hot spot intersections of IntPVCs were clustered in Wards 2 and 7, while MidPVCs were clustered in Wards 7 and 8. These findings suggest that interventions focused on improving pedestrian safety at intersections should be given a high priority at the hot spots found in Wards 2 and 7. Likewise, to prevent MidPVCs, mid-block interventions should be given a high priority at the hotspots identified in Wards 7 and 8. The findings call for special attention and interventions for pedestrian safety in Ward 2, where both the number and the rate of PVCs[60] were found to be the highest.

Numerous positive and negative factors were discovered to influence pedestrian safety by estimating multiple non-linear negative binomial (NB) regression models that control for pedestrian exposure. First, several positive factors were found to be associated with lower rates of PVCs were identified as: medium density residential land use, percentages of census tract population aged 15 to 44, the presence of Metro stops, parking space markings, traffic poles, area of sidewalk, and higher household median income. Intersections surrounded by greater medium density residential land use showed *the greatest positive effect* on pedestrian safety. To put it

[58] To see what AvgPDI is and how it was calculated, refer to section 3.3.1.1 to 3.3.1.2.
[59] See Table 2 to see the full list of descriptive statistics per Ward.
[60] The 'rate(s) of PVCs' refers to PVCs over AvgPDI.

another way, low and high medium residential land use showed less positive effect on pedestrian safety. This finding is counterintuitive and contradicts findings of previous studies—that PVCs are most likely to happen near high density residential land use (Miranda-Moreno et al., 2011; Kim et al., 2010). Young to middle-aged (ages 15 to 44) population also reduced the rate of PVCs by a considerable amount. This is because young people tend to be more 'physically healthy' when crossing, often walking at a different (faster) pace than older pedestrians and rapidly scanning traffic coming from various directions at the same time (Lee & Abdel-Aty, 2005). On the other hand, previous studies have found higher crash rates among middle to high school children (aged 12 to 18) because they are more likely to walk on the sidewalks (M. Abdel-Aty et al., 2007; Bernhoft & Carstensen, 2008).

Second, multiple negative factors were associated with a higher rate of PVCs. These factors include the presence of: a stop bar, puppy track, lane divider, having a signalized intersection, camera enforcement, other traffic signs, being a principal or minor arterial, having a bus stop within 300ft. of an intersection, medium to high density of commercial land use, and percent of census tract with higher rates of Black population, and those aged 45 to 65 or more. Among all, the older middle-aged (aged 45 to 64) and senior population (aged 65 or more) were the most influential factors that increased the rate of PVCs by a considerable amount. This may be because older pedestrians, who tend to take more time to cross at intersections or mid-blocks (Lee & Abdel-Aty, 2005), are often poor at assessing the speed of an approaching vehicle and "less likely to be able to avoid the sudden onset of a fast car" (Jennie Oxley & Fildes, 1999). On the other hand, as Lee & Abdel-Aty (2005) noted, it may also be that the middle-aged population, especially male drivers, who "are more involved in crashes as causers" are included in predicting the high number of PVCs. But, regardless of the reason, this study shows that the percentage of older-middle aged and senior populations may be significant predictors of PVCs in the District of Columbia. Neighborhoods housing higher rates of Black population were also found to have significantly higher rates of PVCs by a considerable margin. Greater pedestrian activity and lower automobile ownership rates, which increase the percentage of population walking and using public transit, may be some reasons as to why these neighborhoods experienced more PVCs (Loukaitou-Sideris et. al., 2007; Cottrill & Thakuriah, 2010). Additionally, intersection surroundings having a higher presence of medium to high density commercial land use experienced an increase in the risk of PVCs, similar to findings in previous studies (Kim et al., 2010; Miranda-Moreno et al., 2011).

To corroborate the statistical findings from the regression analysis, field observation was conducted at seven intersections having the highest rates of PVCs. From this analysis, several interesting observations arose. First, six of the seven case study intersections were located near commercial land uses with a multitude of retail stores, which almost always included some surface parking lots. Second, all of the seven intersections had at least one bus stop that was very close to the intersection. Buses when standing near the intersection crosswalks created visual impairment for pedestrians who were about to cross and for drivers whose view of pedestrians was substantially obstructed. Previous studies also have found that the presence of transit stations (including bus stops) near intersections is likely to be associated with higher risks of PVCs (Loukaitou-Sideris et al., 2007; Ukkusuri et al., 2012). Third, many transit patrons and pedestrians were observed to be ethnic minorities, Black. Fourth, *none* of the seven intersections had Metro stops within a quarter-mile distance of the intersection and those that were within one-mile of the intersections experienced lower rates of PVCs. All of these findings were consistent with the results of the NB regression approach.

A few other unexpected findings arose from the fieldwork. One is that most of the case study intersections did not have speed bumps or signage warning motorists to slow down, cede, or yield right-of-way to pedestrians. While D.C. has a law that requires drivers to yield the right-of-way to pedestrians before turning right on a red light, when observing the interactions between pedestrians and drivers, this law seemed almost unenforced. In fact, as one researcher has previously remarked, a "lack of understanding of pedestrian laws and their enforcement may be a major reason for noncompliance by drivers in many areas of the country" (Rivara FP, 1990).

Another significant finding is that fewer crosswalks and streetlights were observed at the top three intersections with the highest rates of PVCs, despite the high volume ratio (pedestrian volume over traffic volume) observed at each of these intersections. The high volume ratio also indicated that the pedestrian-demand index (PDI) may be a good estimation of pedestrian exposure. When collision risk rates were calculated by dividing the frequency of collision over AvgPDI,[61] the risk rates almost resembled the volume ratio observed in the field. This indicates that if well-devised and updated annually, the PDI may be an alternative method of calculating pedestrian risk exposure to PVCs as opposed to having field engineers visit every intersection in the District of Columbia to count pedestrian and vehicle volumes.

In an increasingly complex urban environment, it is probably impossible to select an ideal set of predictor variables that explain pedestrian-vehicle collisions. However, this study offers a new perspective towards deciphering the complex relationship between the intersection roadway characteristics and PVCs through the use of readily available public geospatial database. High-risk intersections may be chosen as locations for future studies to examine potential pedestrian safety interventions. Furthermore, the statistically significant relationships between intersection

[61] AvgPDI is average pedestrian-demand index score per intersection. See Section 3.3.1.2 for more details.

roadway characteristics and PVCs found in this study offer meaningful guidance transportation agencies can use to prioritize particular resources and interventions for specific microenvironments (e.g. at intersections or in mid-blocks).

5.2 Recommendations

Based on the findings, several countermeasures are recommended to reduce the number of PVCs in the District of Columbia. It is recommended that transportation and planning agencies in the District consider updating pedestrian-demand index (PDI) annually, identify high-risk locations of PVCs, provide safer infrastructure (sidewalks, crosswalks, and streetlights) for pedestrians at high-risk locations, restrict parking and bus stops near intersections and crosswalks, design pedestrian safety interventions that accommodate the needs of the residents near the intersection, provide more right-of-way to pedestrians, educate citizens more effectively, and enforce existing traffic laws more strictly. These recommendations are more fully presented in the following paragraphs.

- ***Update pedestrian-demand index (PDI) annually and identify high-risk locations of pedestrian-vehicle collision rates (after controlling for pedestrian exposure).***

Controlling for pedestrian exposure is a critical step in identifying where high-risk locations or hot spots of PVCs exist. As opposed to simply calculating the frequencies of PVCs, normalizing the pedestrian exposure at disparate locations provide a means for higher level of accuracy in predicting multiple factors that contribute to PVCs. To enhance the accuracy of assessing the high-risk locations, the PDI (which was previously used as part of the DDOT’s Pedestrian Master Plan), must be updated annually, reflecting the latest changes in land use, forecasts of traffic volume, population and employment density, and more.

- ***Provide safer infrastructure for pedestrians at high-risk locations.***

Many of the top seven case study intersections observed in the fieldwork analysis were lacking in high-visibility crosswalks (such as zebra or continental crosswalks), multiple streetlights (many had just 2 streetlights per intersection), and wider sidewalks (some sidewalks were as narrow as 4ft.). In the regression analysis, the locations with higher areas of sidewalks were also found to positively influence pedestrian safety, particularly by reducing the occurrences of mid-block PVCs. These results indicate that transportation and planning agencies could provide better infrastructure for pedestrians (such as wider sidewalks, high-visibility crosswalks, better street lighting, and possibly pedestrian overpasses) near the high-risk locations of PVCs. Researchers have previously noted that “safe walking requires sidewalks wide enough and without obstructions so that pedestrians are not forced to walk on the street” (Loukaitou-Sideris et al., 2007).

- ***Restrict curb parking and move bus stops away from an intersection.***

While the statistical results of this study showed that parking space markings are likely to reduce PVCs possibly by slowing down the traffic, the fieldwork observations showed that buses and other vehicles parked near an intersection or adjacent to the crosswalk impairs visibility for both pedestrians and drivers, which also includes buses (see Figure 18). To solve this problem, for the intersections with highest rate of PVCs, the curb parking can be restricted near a crosswalk or an intersection and both parking spaces and bus stops can be moved to about 20 to 30 feet away from the nearest crosswalk or an intersection.

As Figure 19 shows, moving the bus stops or eliminating parking spaces near a crosswalk or an intersection can provide the departing pedestrians and drivers better visibility when travelling. However, moving the bus stops to the mid-block location may encourage patrons to ‘jaywalk’ or cross the street at mid-block, slow down the traffic (hence negatively impacting the transit ridership), require additional distance for no-parking restrictions, and also increase the number of rear-end accidents when drivers behind the buses do not expect the bus to stop in the middle of the block ("Stops, Spacing, Location and Design," 2015). Therefore, another alternative the planning and transit agencies could consider is creating bus bays (see Figure 20). By restricting any curb parking on the side of the roadway for passenger loading and unloading, bus bays not only present better visibility for drivers and pedestrians, they have the potential to reduce rear-end collisions as buses have their own dedicated curb to come to a stop. However, bus bays may generate some conflicts with cyclists when a bicycle lane is provided, especially when buses move back to the travel lane. Also, creating bus bays may only come at a cost of losing more on-street parking spaces.

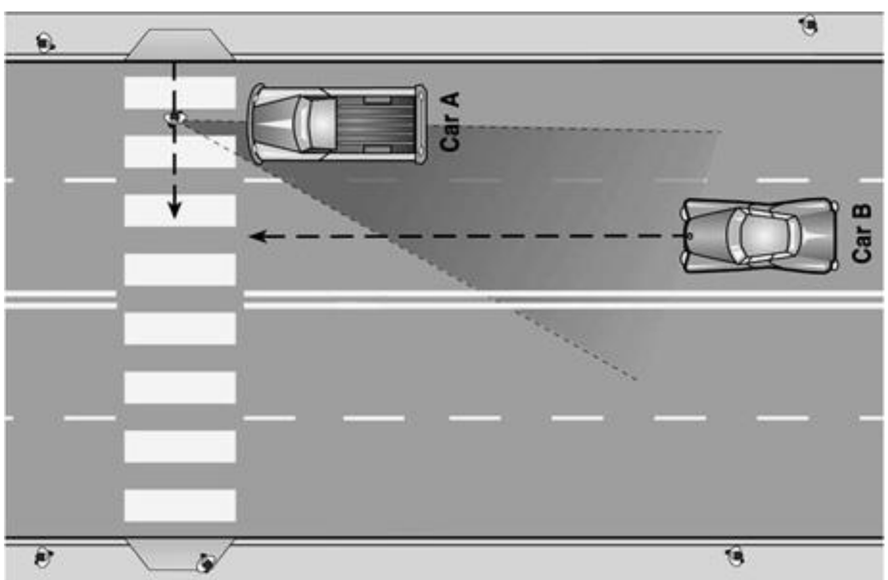


Figure 18. Curb Parking Near the Crosswalk[62]

[62] Source: (Brown et al., 2015)

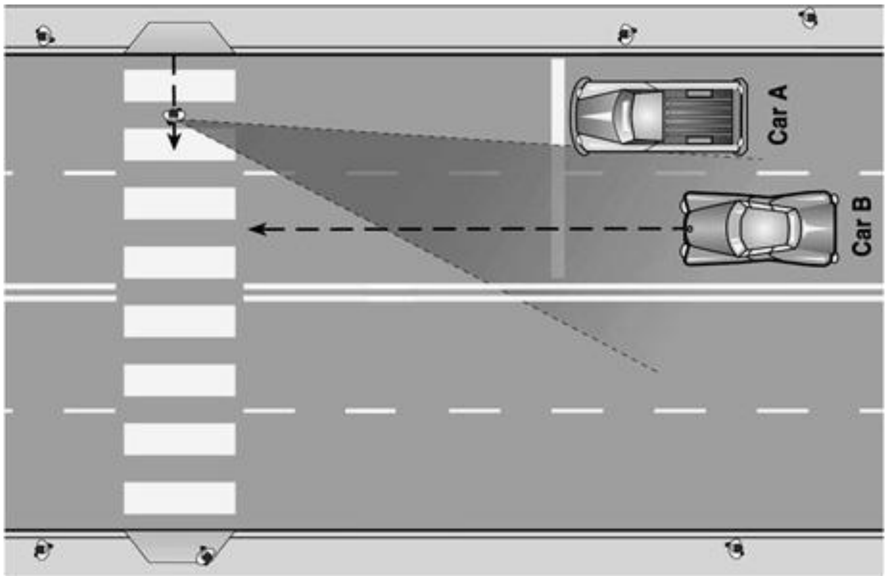


Figure 19. Curb Parking Away from the Crosswalk[63]

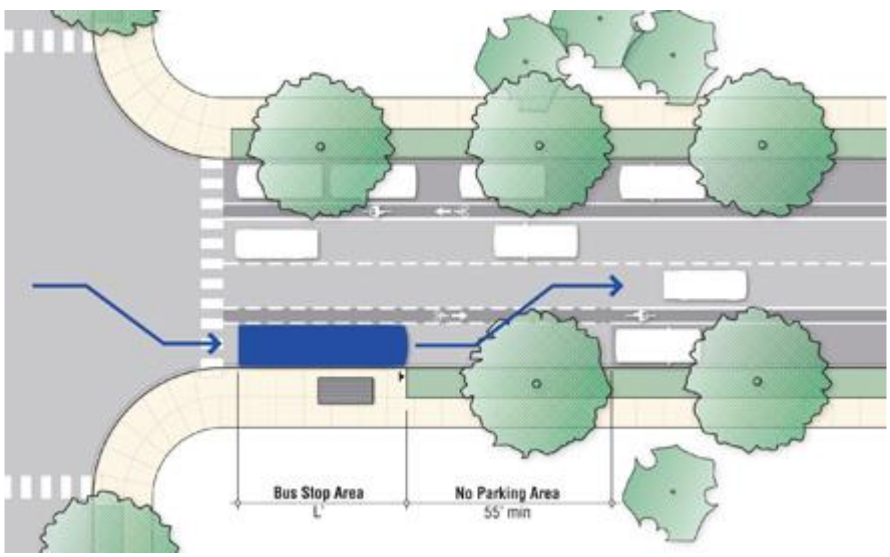


Figure 20. Bus Bays[64]

[63] Ibid.
[64] Image Credit: (Pace Suburban Bus, 2015).

• ***Design pedestrian safety interventions that accommodate the needs of the residents near the intersections.***

Although transportation agencies often rely on engineering principles[65] to install traffic control devices (TCDs), the results of this study show that PVCs are also heavily affected by socio-demographic characteristics (ethnicity and age) of the neighborhoods surrounding an intersection. If possible, transportation agencies should consider customizing TCDs to address the specific needs of certain neighborhoods and populations (Loukaitou-Sideris et al., 2007). For example, the regression results indicate that locations characterized by high rates of use by senior population (aged 65 and more) were more likely to experience PVCs. As mentioned earlier, this may be because older pedestrians, who tend to take more time to cross at intersections or mid-blocks (Lee & Abdel-Aty, 2005), are often poor at assessing the speed of an approaching vehicle and "less likely to be able to avoid the sudden onset of a fast car" (Jennie Oxley & Fildes, 1999). To solve problems like this, at intersections where high percentages of senior population are found, crossing time should be extended to accommodate senior pedestrians (Naveteur, Delzenne, Sockeel, Watelain, & Dupuy, 2013; J. Oxley, Fildes, Ihsen, Charlton, & Day, 1997). Similarly, at mid-block locations where high percentages of senior population may "jaywalk" due to their physical impairments that reduce their ability to get to a pedestrian crossing (Tournier, Dommes, & Cavallo, 2016), two types of interventions are recommended: 1) installing advanced stop or yield lines[66] (see

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[65] Calculating the level of service, traffic flow, and capacity of the locations to determine whether an intersection or a mid-block location needs traffic control devices.

[66] Advance stop or yield lines encourage drivers "to stop further back from the crosswalk, promoting better visibility between pedestrians and motorists, and helping to prevent multiple-threat collisions at mid-block or uncontrolled crossings" (Ibid.)

Figure 21) and 2) installing traffic control devices that flash lights automatically when pedestrians approach the crosswalk.

Figure 21. Advance Stop or Yield Lines[67]

• ***Protect pedestrian right-of-way.***

In the fieldwork analysis, it was found that many case study intersections lacked speed bumps and traffic control signage that warn motorists to slow down, cede, and yield right-of-way to pedestrians. Moreover, despite the local D.C. law that requires drivers to yield the right-of-way to pedestrians before turning right on a red, from observing the interactions between pedestrians and drivers at the case study intersections, the law seemed almost unenforced. Therefore, whether it involves giving more traffic citations to drivers that speed or unsafely interrupt pedestrians at crosswalk, placing more traffic control signage, or speed bumps near the crosswalk—the law that protects the right-of-way to pedestrians should be more strictly enforced

[67] Ibid.

and supported with traffic control devices so that the drivers are easily reminded that they *should yield* the right-of-way to pedestrians.

- ***Retrofit Dangerous Intersections.***

Consistent with findings in other studies, this study found that locations having medium to high density commercial land use and higher number of lanes (i.e. multilane roads with three or more lanes) are more likely to experience PVCs. Some scholars have argued that many PVCs occur near high density commercial land use because at such locations, automobiles often engulf pedestrian spaces and vice versa, especially along the sidewalk, where pedestrian spaces are interrupted or invaded by cars entering or leaving the establishments via driveways or where vehicles are entering or exiting on-street parking spaces (Loukaitou-Sideris et al., 2007). Pedestrian safety can be enhanced in areas of high density commercial land use by separating pedestrian spaces separated from vehicular spaces (Loukaitou-Sideris et al., 2007; Rivara FP, 1990).

For intersections surrounded by medium to high density commercial land use and multilane roads that make pedestrian crossing very difficult, the construction of overpasses or underpasses may be an option. However, this option should be a measure of last resort because it is known as a visually intrusive measure that requires tremendous amount of resources and labor (Federal Highway Administration, 2002). For that reason, this study proposes that planning and transportation agencies in D.C. consider retrofitting such intersections by increasing area of sidewalks, installing some speed humps and possibly raising crosswalks (see Figure 22) so that pedestrians would not have to walk in the roadway (R. Schneider et al., 2010; R. Schneider, Khattak, & Zegeer, 2001).

Figure 22. Example of Great Streets Initiative (Los Angeles)[68]

5.3 Study Limitations & Future Research

As discussed in the data limitation section, this study is not without its limitations and suggests a need for future research. This study only considered pedestrian-vehicle collisions (PVCs) based on data provided by the Metropolitan Police Department of the District of Columbia (MPDC). For this reason, further study is needed to analyze the PVCs that were unrecorded but led to pedestrian injuries (e.g. in parking lots, driveways, garages, and other places).

Second, PVCs that were recorded as ‘impaired’ (involving impaired drivers and pedestrians) or ‘PDOs’ (property damage only) were discarded from the study although including such attributes may have resulted in different outcomes from the regression modeling. Studying these types of PVCs may be valuable in the future as it may help uncover how the behaviors of both pedestrians and drivers affect the likelihood of PVCs.

[68] Image source:(“DIY Great Streets Toolkit — LA Great Streets,” 2016)

Third, this research included mid-block PVCs (MidPVCs) that were only 'within 100ft from an intersection.' Further study is needed to analyze the ways in which roadway surroundings and the built environment affect mid-block PVCs in D.C.

Fourth, since the data on the pedestrian exposure variable (AvgPDI) and other explanatory variables were created and updated at different periods of time, the inconsistency of dates in the data used in this study may reduce the reliability of the results. This calls for more spatial research of PVCs in the future using data that is more temporally consistent.

Fifth, the PVC data that was obtained for the purpose of this research did not include information on demographics (such as sex, age, and race) of pedestrians and drivers. Better explanations can result if future studies incorporate these characteristics to account for pedestrians and drivers' behaviors and develop better countermeasures.

Sixth, while the fieldwork analysis involved visiting the top seven case study intersections on-site, it is likely that some intersection roadway characteristics observed at the time of the fieldwork were not present during the time of the pedestrian-vehicle collisions. To reduce such inaccuracy, future research can conduct similar fieldwork analysis sooner (possibly within a year) after collisions.

Lastly, the pedestrian-demand index (PDI) is only a proxy to pedestrian exposure that relied on several factors (such as forecasted population and employment densities, land use, and traffic volume) that are less than perfect indicators of exposure. For this reason, although PDI was useful in this study, more precise indices are needed for risk exposure in the future. While further research is needed, the findings from this study may help inform intersection planning and design guidelines that enhance pedestrian safety.

APPENDICES

APPENDIX 1. THE 2009 PEDESTRIAN DEMAND INDEX (PDI) METHODOLOGY

Appendix A ~ Pedestrian Demand Methodology

This document describes the methodology used to identify and select priority corridors in the District for detailed study as part of the Pedestrian Master Plan. Eight arterial road segments were selected for this high level of analysis, focusing on corridors with higher levels of pedestrian activity, yet poorer conditions for walking. The pedestrian demand model that was used for this analysis was based on a modified version of Portland, Oregon's Pedestrian Potential and Deficiency Indices.

The selected corridors were analyzed in the field, and detailed recommendations were developed to improve pedestrian conditions (see Priority Corridor Recommendations – a separate document available on the DDOT website). The Pedestrian Plan also incorporates general recommendations to make all streets in the District more walkable, including a neighborhood sidewalk gap analysis to identify needed sidewalk improvements. This pedestrian demand analysis can also be used in the future to prioritize capital projects in other parts of the District.

Road segments in the District have been rated on two factors; pedestrian potential (how much pedestrian activity is expected in particular locations) and pedestrian deficiency (how challenging it is for pedestrians to travel along or cross particular roads). Road segments with high potential for pedestrian activity and high deficiency are considered to be priorities for further evaluation. The criteria used to rate pedestrian potential and deficiency are described below. Because this is a sketch plan method, it is not intended to produce precise estimates of the number of pedestrians along a particular roadway or the relative risk of pedestrian crashes in specific locations. Instead, it is used to select general corridors for additional detailed analysis.

PEDESTRIAN POTENTIAL

The potential for pedestrian activity on a given roadway segment was determined by the pedestrian attractors/generators and the anticipated growth in population and employment density near that location. Corridors that were scheduled for significant transportation and pedestrian improvements were also considered as having potential for greater future pedestrian activity. Pedestrian potential was determined using the following two criteria:

1. Proximity - Roadway segments received more points for being located close to pedestrian attractors and generators*. Buffer zones of one-eighth, one-fourth, and one-half mile (straight line distance, not network distance) were drawn around each attractor and generator. Road segments received points for falling within each of these buffer areas as follows:

Attractor/Generator	1/8 mile	1/4 mile	1/2 mile
Metro Station	15	10	5
Bus stop	5	3	
School (public, charter, and colleges/ universities)	5	3	
Major Park Access Point	3	1	
Shopping	3	1	
Senior Center/Nursing Home	3	1	
The National Mall (proximity to any part of the National Mall)	20	5	
Stadiums/Convention Center (proximity to any part of the building)	20	5	

**point allocations are based on average pedestrian activity.*

For example, the National Mall is a location of significant pedestrian activity for both tourists and residents. Most pedestrian activity is concentrated on the National Mall or within several blocks of it, so roadways that are in or adjacent to the Mall received a large number of points (30), but those locations further away were not assigned any points. In contrast, people are generally willing to walk longer distances to transit (studies have shown that a typical walk to transit is ¼ to ½ mile, and many people walk even further[1]). Therefore, points were given to roadways as far away as ½ mile from each Metro station. In addition, more pedestrians walk to most Metro stations than walk to schools, bus stops, or parks, so the roads near the stations received higher scores.

2. Population and Employment Density - This category incorporates population and employment forecasts for 2025 from the Metropolitan Washington Council of Governments (MWCOG). Roadway segments contained in MWCOG Traffic Analysis Zones (TAZs) with greater future population and employment density were assigned more points. As more pedestrian trips are typically generated from a residential location than an employment location, population forecasts were assigned greater values than employment forecasts. Population and employment projections were divided into quintiles, and points assigned for each class as follows:

Quintile	**2025 Population Forecast** (per sq. mile)	Points	**2025 Employment Forecast** (per sq. mile)	Points
1	0 - 2,527	0	0 – 1,040	0
2	2,528 – 7,929	5	1041 – 2,888	3
3	7,930 – 13,071	10	2,889 – 8,007	6
4	13,072 – 22,626	15	8,008 – 41,258	9
5	22,627 – 134,959	20	41,259 – 464,493	12

PEDESTRIAN DEFICIENCY

Barriers to walking on the city's network of approximately 400 miles of arterial and collector roadways were analyzed to identify roads that are most deficient for pedestrian travel. The pedestrian deficiency factor was determined using the following criteria:

1. Walking Along the Roadway

The deficiency rating for walking along the roadway was developed using sidewalk inventory data. Roadway segments with sidewalk gaps, with narrow sidewalks and without buffers or street trees were given more points to indicate they are highly deficient for pedestrian travel. Points were also given to roadway segments with higher traffic volumes and speed limit to indicate a more deficient environment for walking. Each roadway segment was assigned a deficiency rating for walking along the roadway based on the following factors:

Factor/criteria		Points allocated
Sidewalk Gap: more than 10% of a block length without sidewalk*		
	1 side of street with a sidewalk gap	10
	2 sides of street with a sidewalk gap	20
Sidewalk Width		

[1] Weinstein, A., V. Bekkouche, K. Irvin, and M. Schlossberg. "How Far, by Which Route, and Why? A Spatial Analysis of Pedestrian Preference," Presented at 2007 Transportation Research Board Annual Meeting.

	Under 5' wide	2
	Under 4' wide	3
Presence of Planting Strip		
	No planting strip	3
Presence of Street Trees		
	No street trees	1
Traffic Volume (ADT)		
	5,000 – 10,000	1
	10,001 – 15,000	2
	15,001 – 20,000	3
	20,001 – 25,000	4
	25,001 or more	5
Posted Speed Limit		
	30mph	1
	35mph	2
	40mph	3
	45mph or more	5

**Data from a 2003 inventory of arterial roadways in the District were used to assign points for the walking along the roadway analysis. Where data was missing for a specific road segment, data from the adjacent segment was applied.*

2. Crossing the Roadway

Roads with higher traffic volumes, more travel lanes, higher speed limits and no medians generally present more hazards for pedestrians trying to cross the road. Therefore, the deficiency rating for crossing the roadway at uncontrolled locations was based on roadway characteristics including traffic volume, number of travel lanes, speed limit and the presence of a raised median or median island. The deficiency rating was not based on an actual evaluation of crosswalks in the District, but was derived based on these roadway characteristics. Using categories developed by FHWA[2] (see below), roadway segments are classified into the non-compliant (represented by a "N" in the chart on the next page), possibly compliant ("P"), and compliant ("C") categories based on the following characteristics:

- Traffic Volume (ADT)
  - Less than 9,000
  - 9,000 – 12,000
  - 12,001 – 15,000
  - More than 15,000
- Number of Vehicle Travel Lanes
  - 2 lanes
  - 3 lanes
  - 4 or more lanes with raised median
  - 4 or more lanes without raised median
- Speed Limit
  - Less than or equal to 30mph
  - 35mph
  - 40mph

[2] Zegeer, C., J. Stewart, H. Huang, and P. Lagerwey. "Safety Effects of Marked vs. Unmarked Crosswalks at Uncontrolled Locations- Executive Summary and Recommended Guidelines." Report No. FHWA-RD-01-075, Federal Highway Administration, Washington, D.C., February 2002

APPENDIX 2. THREE COMMON REGRESSION MODELS

A2-1. Multiple Linear Regression Model

One regression model commonly found in various crash statistical analyses is multiple linear regression model, which generally follows this form of equation:

$$\lambda = \beta x + \varepsilon \qquad (1)$$

λ = Expected mean number of accidents.

x = Vectors representing the independent variables.

β = Vectors representing parameters to be estimated.

ε = Error terms assumed to be distributed as normal

The optimized version of multiple linear regression model can be described using F-value, R-square and mean square error. Also, to investigate the null hypothesis (h_0), individual parameters in the β vector are tested to see if a given parameter is zero using t-statistics (Hashimoto, 2005). Researchers, however, have previously noted that this type of regression model should be used with a careful caution since 1) collision frequency data do not consist of negative integers (with minimum integer being zero rather than negative); and 2) are not normally distributed and rather skewed; and 3) have error terms with unequal variance; and 4) after variance-stabilizing transformations are performed, applying the inverse transformations to the predicted values give an estimate of the median rather than mean of the distribution (Jovanis & Chang, 1986). To overcome such problems associated with multiple linear regression model, Jovanis & Chang (1986) proposed that Poisson regression model be used for predicting accident frequencies.

A2-2. Poisson Regression Model

Since collision frequency data are often count data that consist of predominantly zeros and small integers, the use of multiple linear regression model can result in inconsistent and biased estimates as Jovanis & Chang (1986) have previously noted. One way of overcoming such problem is to use different type of regression model that allows response variables to be skewed. A group of such regression models is called generalized linear models (GLM), which is a flexible generalization of ordinary linear regression that allows for the linear model to be related to the (often skewed) response variable via a link function and let the magnitude of the variance of each measurement to be a function of its predicted value ("Generalized linear model," 2016). Both Poisson and NB regression model are examples of GLM. However, unlike NB regression model, Poisson regression model assumes equidispersion—which estimates that the conditional mean and conditional variance are equal to one another (Cameron & Trivedi, 1998).

The Poisson model follow a general form of equation like this:

$$\mathrm{P}(n_i) = \frac{\lambda_i^{\,n_i} \exp(-\lambda_i)}{n_i!} \qquad (2)$$

where

$\mathrm{P}(n_i)$ = probability of an accident occurring on approach *i*, n_i times over the given time period *t* (e.g. per year).

λ_i = Poisson parameter for approach *i*, which is equal to approach *i*'s expected number of accident per given time period *t*.

n_i = Target number of accidents on section *i* over a given time period *t*

The Poisson regression model specifies that Poisson parameter (λ_i) be a function of explanatory (or independent) variables in this manner:

$$\lambda_i = \exp(\beta x_i) \qquad (3)$$

or

$$\ln \lambda_i \quad \beta' x_i \qquad (4)$$

where

x_i = a vector representing explanatory (or independent) variables

β = vector of estimable coefficients (Poch & Mannering, 1996)

Also, the Poisson regression, as defined in equations (2) to (4), can be estimated by a standard maximum likelihood method with the likelihood function shown below (Poch & Mannering, 1996):

$$\mathrm{L}(\beta) = \Pi i \ \frac{\exp[-\exp(\beta x_i)][\exp(\beta x_i)]^{n_i}}{n_i!} \qquad (5)$$

A2-3. Negative Binomial (NB) Regression Model

Negative binomial (NB) regression model is another example of generalized linear models (GLM) researchers can readily estimate for skewed collision data. In contrast to Poisson regression model, the NB regression model does not assume equidispersion (equal dispersion) between mean and the variance of the dependent variable. In fact, when the mean and the variance do not approximately equal to one another, the variances of the estimated Poisson model can be biased (Poch & Mannering, 1996). As such, in situations where the collision data is overdispersed and does not meet the condition of Poisson regression, NB regression model is an alternative model many researchers found useful (M. A. Abdel-Aty & Radwan, 2000; Chimba, Emaasit, Cherry, & Pannell, 2014; Miaou, 1994; Poch & Mannering, 1996; Shankar, Mannering, & Barfield, 1995).

Derived from the Poisson regression model, the NB regression model adds independently distributed error term to equation (4), such that:

$$\mathrm{P}(n_i|\varepsilon_\mathrm{i}) = \frac{\exp[-\lambda_i \exp(\varepsilon_\mathrm{i})][\lambda_i \exp(\varepsilon_\mathrm{i})]^{n_i}}{n_i!} \qquad (6)$$

where

λ_i = Poisson parameter for approach i, which is expected number of accident per given time period.

x_i = a vector representing explanatory (or independent) variables

β = vector of estimable coefficients

$\exp(\varepsilon_i)$ = a gamma-distributed error term with mean equal to one and variance (α) (Poch & Mannering, 1996).

The resulting conditional probability is as follows:

$$\mathrm{P}(n_i|\varepsilon_\mathrm{i}) = \frac{\exp[-\lambda_i \exp(\varepsilon_\mathrm{i})][\lambda_i \exp(\varepsilon_\mathrm{i})]^{n_i}}{n_i!} \qquad (7)$$

And the likelihood function for coefficient estimation is shown in equation (8), which is derived from integrating ε_i out of the expression to produce an unconditional distribution of n_i:

$$\mathrm{P}(n_i) = \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta) \cdot n_i!]} \cdot u_i^{\theta}(1 - u_i)^{\theta} \qquad (8)$$

where

$\theta = {}^{1}/_{\alpha}$

$u_i = {}^{\theta}/_{(\theta + \lambda_i)}$

Unlike the Poisson regression model, the NB model allows the mean to differ from the variance such that:

(9) $\mathrm{var}(n_i) = E(ni)[1 + \alpha E(ni)]$

where α = a measure of dispersion that is estimable by standard maximum likelihood techniques (Poch & Mannering, 1996). Using the estimated coefficient α, the appropriateness of negative binomial (NB) versus Poisson model is determined. If it is found that α is not significantly different from zero, the negative binomial model reduces to a Poisson regression model as shown below:

(10) $\mathrm{var}[ni] = E[n_i]$

However, if α is significantly different from zero, applying negative binomial (NB) instead of Poisson model is the “correct choice” and more appropriate model of estimation (Poch & Mannering, 1996).

APPENDIX 3. DESCRIPTION OF THE EXPLANATORY VARIABLES

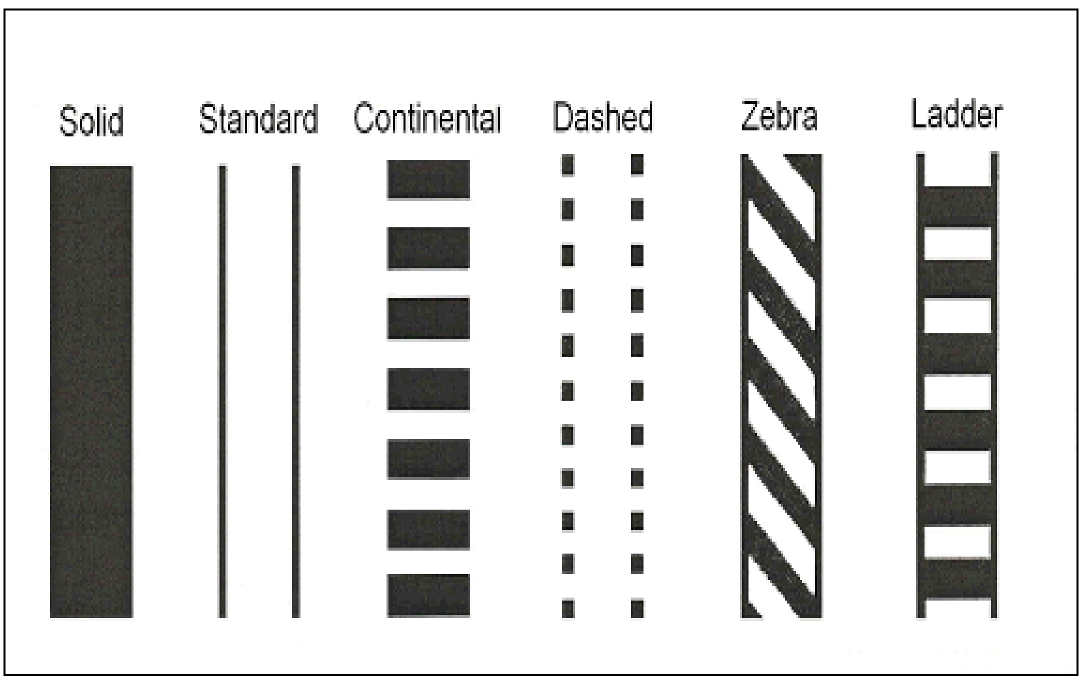
A3-1. Definition of Traffic Control Device (TCD) Variables

Traffic Control Devices	**Definition**
Stop Bar	The MUTCD indicates that a stop bar (line) is a solid white line, normally 12 to 24 inches wide, extending across all approach lanes to a STOP sign or traffic signal. A stop bar is often placed parallel to the centerline of the intersecting street. MUTCD also indicates that a stop bar is placed where it is important to indicate the point, behind which vehicles are required to stop, in compliance with a STOP sign, traffic signal, officer's direction, or other legal requirement (The Federal Highway Administration, 2009).
Puppy Tracks	Small dotted intersection markings that continue through the intersection on the mainline.
Rumble Strip	Centerline rumble strips are used on undivided highways to reduce cross-over incidents and resultant head-on collisions. Shoulder rumble strips are used primarily to reduce run-off-road collisions. They alert distracted or drowsy drivers that they are leaving the roadway or crossing the centerline (Source: Wikipedia).
Lane Divider	A divider in the middle of two lanes to separate the lanes (they are often used to divide inner lanes); more number of lane divider means that there are simply more lanes in the intersection.
Parking Space Marking	Painted on-street parking space(s)
Signalized Intersection	For the purpose of this study, the number of signalized intersections within a 100ft. buffer from an observed intersection.
Traffic poles	A thick post found in the intersection that holds either traffic signals or some sort of traffic control devices (e.g. speed, yield, pedestrian crossing signs). This was counted per 100ft. intersection buffer in this study to measure the influence of traffic signals and traffic control devices on pedestrian-vehicle collisions.
Other Traffic Signs	This indicates any traffic control signs found in the intersection buffer (100ft. from an intersection). This can include anything warning signs like 'no u-turn,' 'no turn on red,' speed limit, and yield signs. This does not include parking signs or bus stop signs.

A3-2. Pictionary of Traffic Control Device (TCD) Variables

a. Camera Enforcement

b. Types of Crosswalk



c. Raised Crosswalk

d. Continental Crossing

e. Diagonal Crossing

f. Lane Divider

g. Other Traffic Signs

h. Overpass

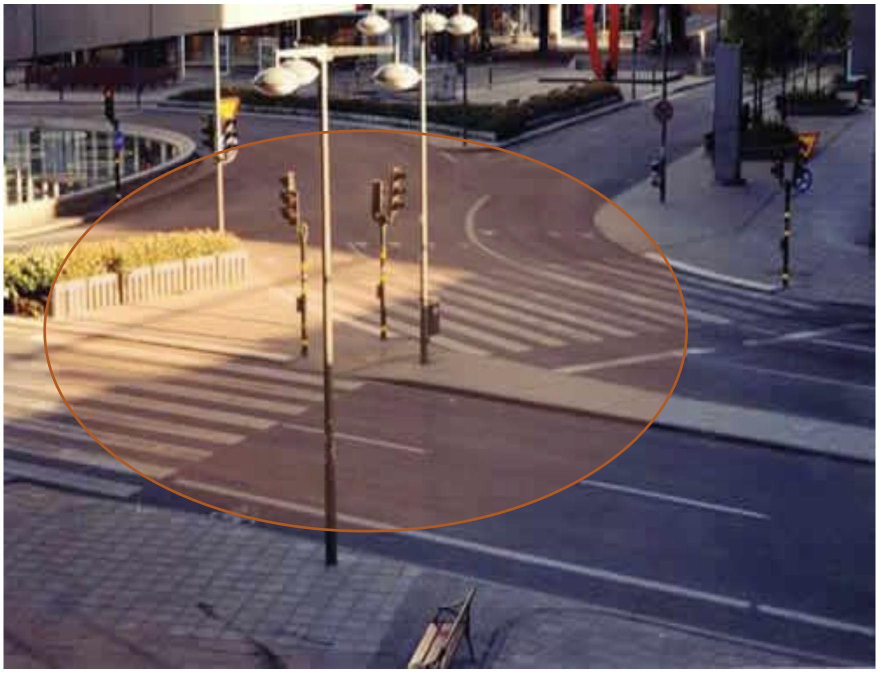
i. Parking Space Marking

j. Puppy Tracks

k. Rumble Strip

l. School Crossing Guard

m. Signalized Intersection



n. Speed Hump

o. Streetlights

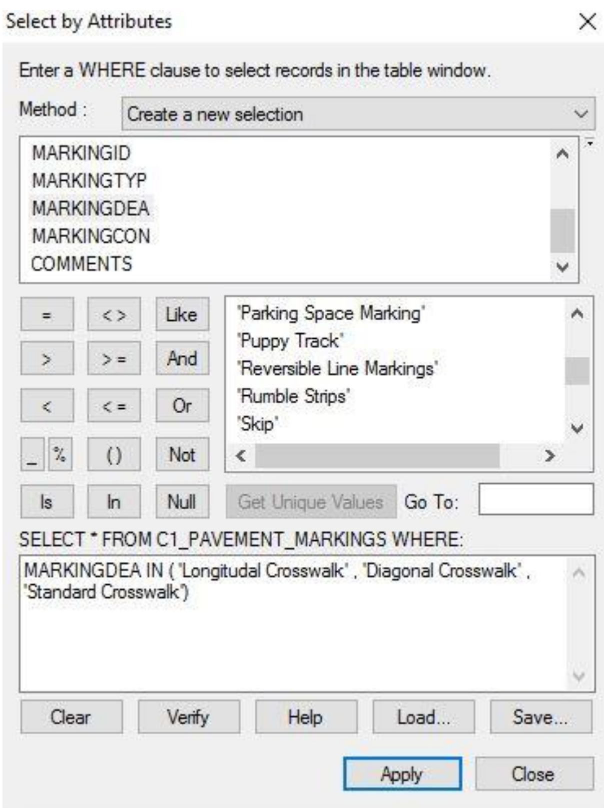
p. Traffic poles

q. Underpass

A3-3. The Types of Crosswalks Examined in This Study

Type of Crosswalks Included in the 'Crosswalk' Variable	
1	Longitudinal Crosswalk
2	Diagonal Crosswalk
3	Standard Crosswalk

Attribute selection in GIS to create the 'crosswalk' variable:



A3-4. Counting Signalized Intersections Within a Buffer

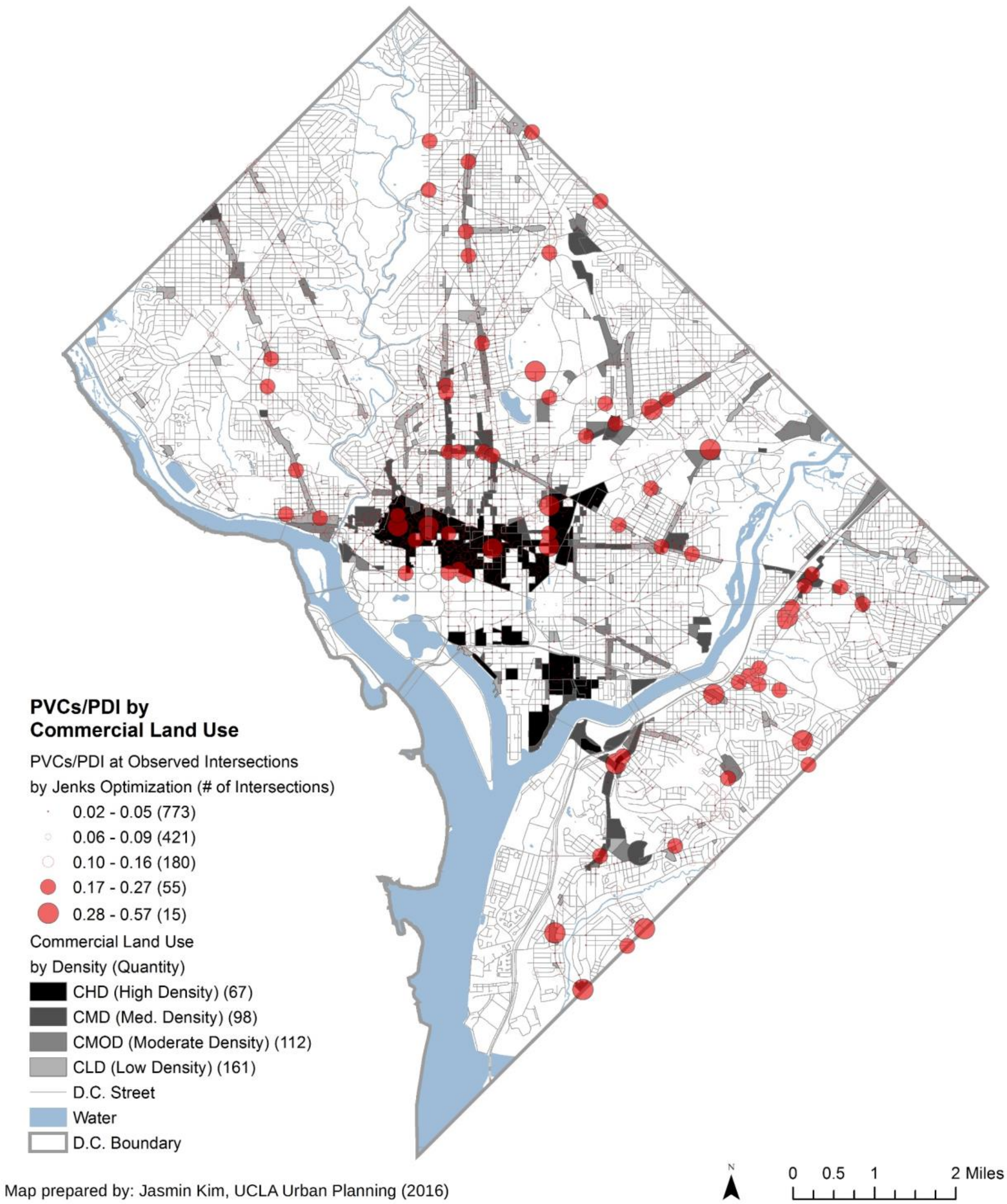
Porter St. SW& Connecticut Ave. NW

(Intersection Buffer with Two Signalized Intersection)

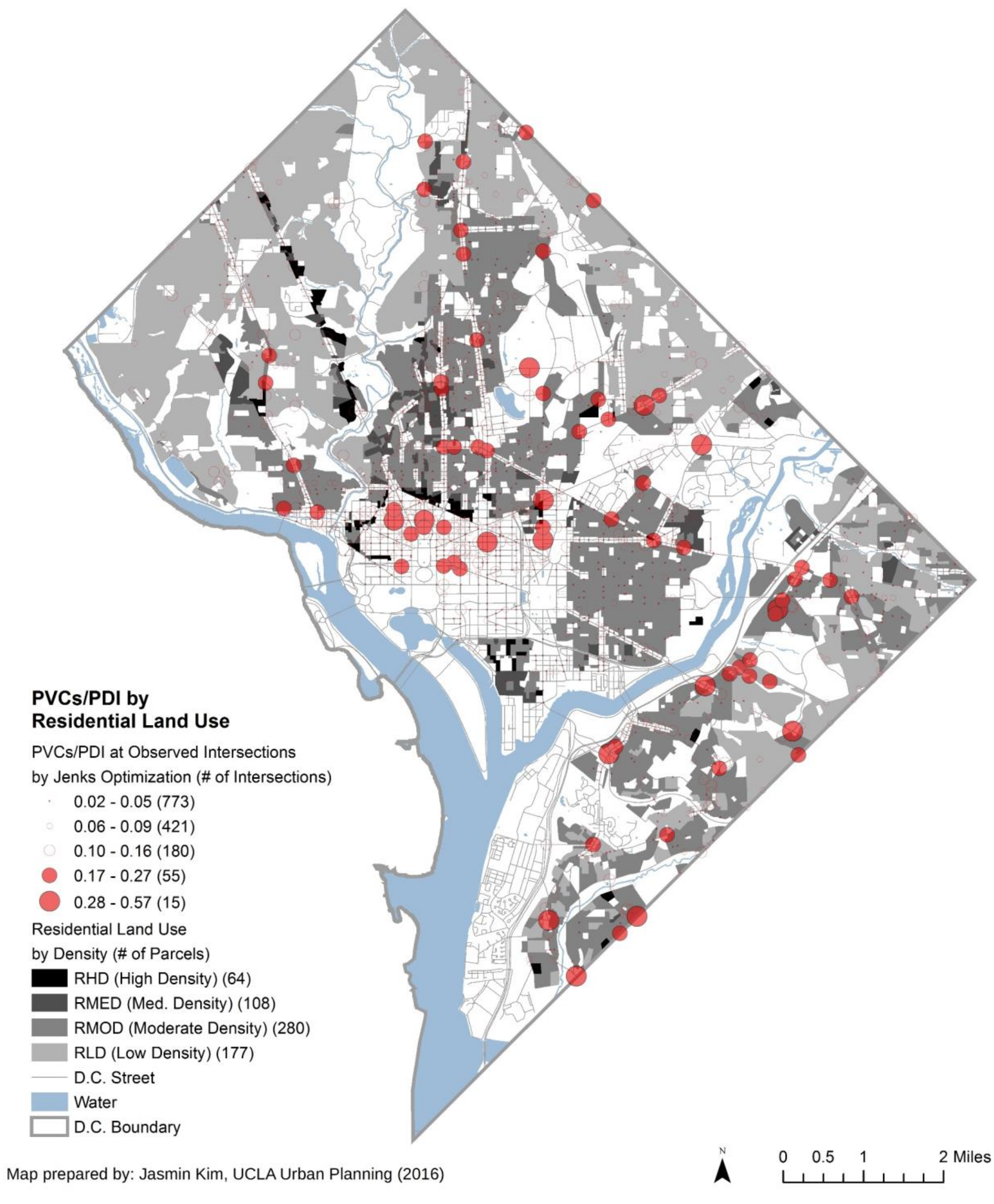
As shown in the figure above, some intersection buffers (100ft. from intersection) had two signalized intersections within the buffer when two different signalized intersections were located right next to each another. (Note: this buffer is just an ideal buffer and not to scale.)

APPENDIX 4. LAND USE COVERAGE MAPS (COMMERCIAL AND RESIDENTIAL)

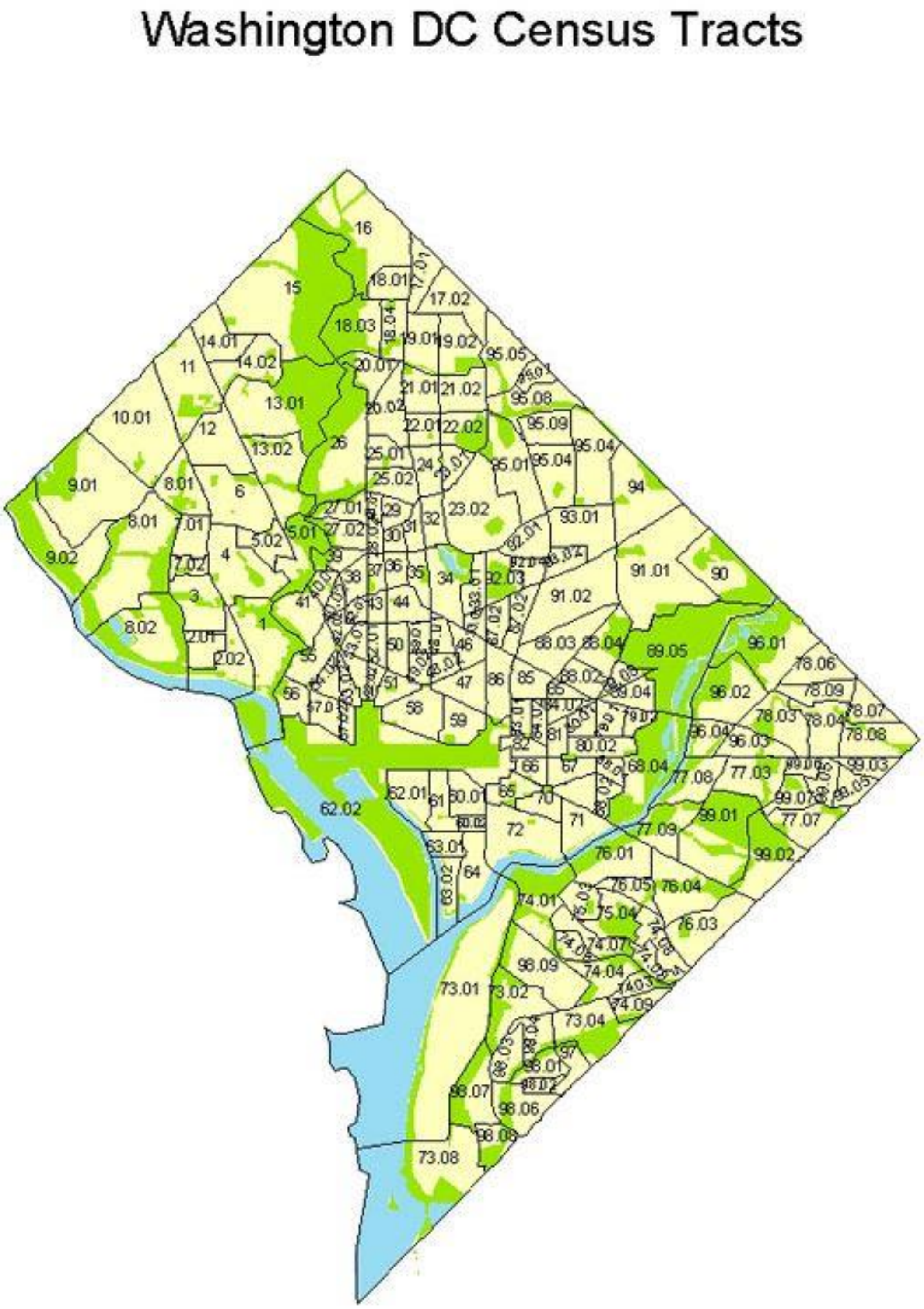
A4-1. DISTRICT OF COLUMBIA'S COMMERCIAL DENSITY LAND USE MAP



A4-2. DISTRICT OF COLUMBIA'S RESIDENTIAL DENSITY LAND USE MAP



APPENDIX 5. MAP OF D.C. CENSUS TRACTS



APPENDIX 6. LAND COVERAGE MAPS

1. POLICE DISTRICTS MAP (D.C.)

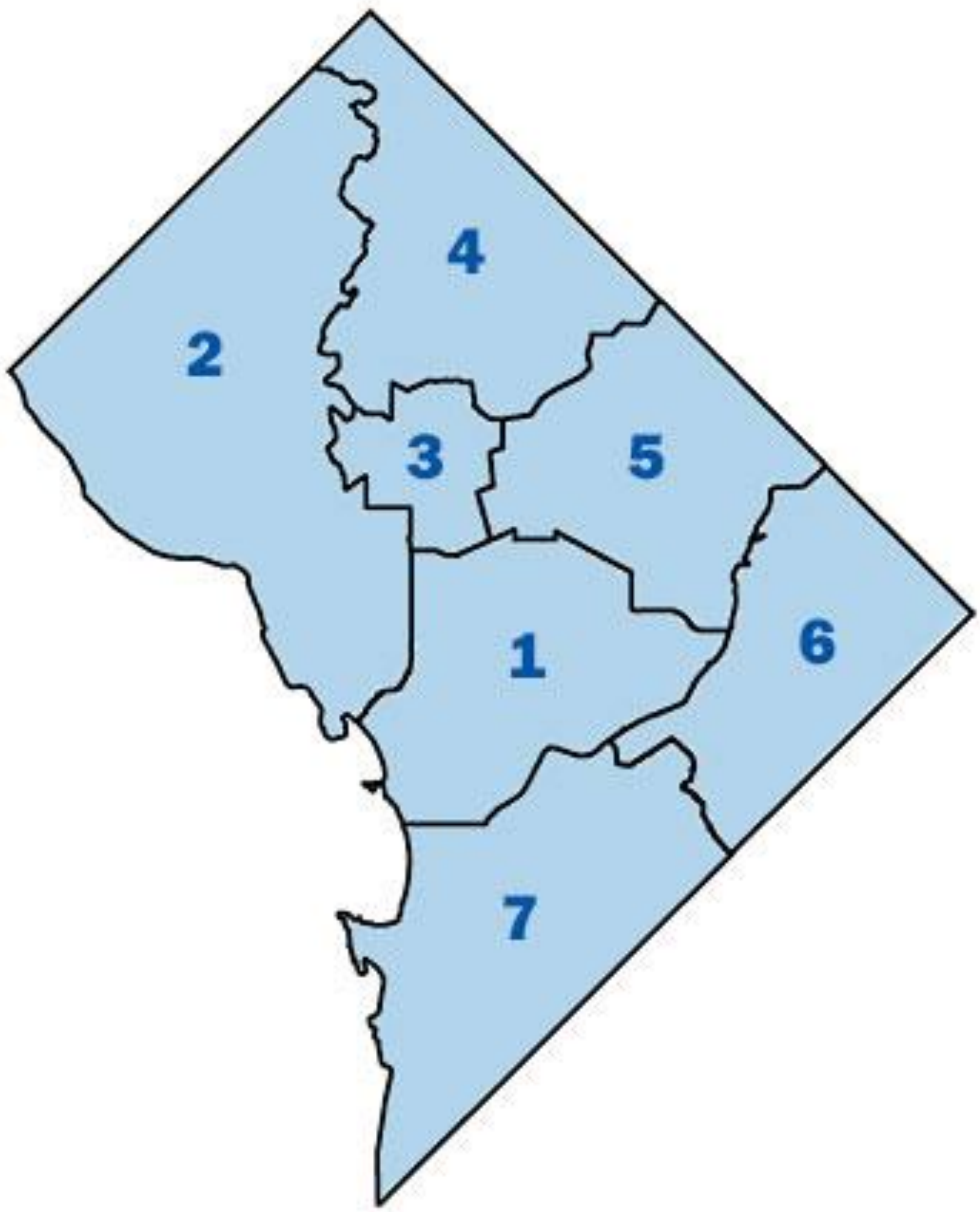


Image Source : http://mpdc.dc.gov/page/police-districts-and-police-service-areas

2. D.C. QUADRANTS MAP

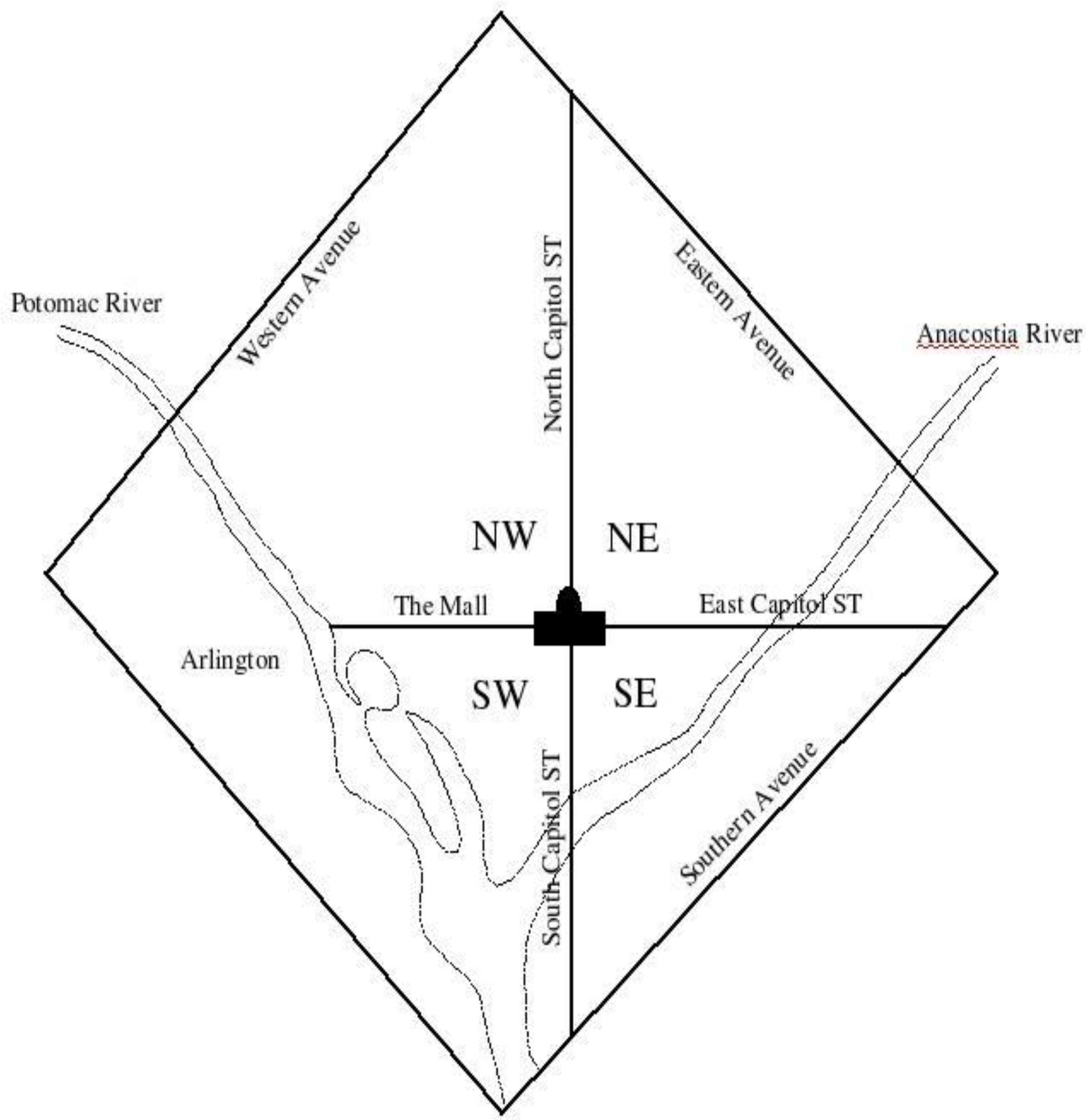


Image Source : http://badercondominium.org/Bader_Streets

APPENDIX 7. ARCHIVAL ANALYSIS: DESCRIPTIVE STATISTICS

Table A7-1. Descriptive Statistics of PVCs in D.C. from 2010 to 2014 (*n*=3,572)

Variables	# PVCs	% PVCs	Variables	# PVCs	% PVCs	Variables	# PVCs	% PVCs
Year			***City Quadrant***			***Number of Persons Injured***		
2010	602	16.9%	NE	726	20.3%	0	8	0.2%
2011	639	17.9%	NW	1942	54.4%	1	3337	93.4%
2012	712	19.9%	SE	643	18.0%	2	186	5.2%
2013	787	22.0%	SW	92	2.6%	3	23	0.6%
2014	832	23.3%	Other	2	0.1%	4	11	0.3%
			Unknown	167	4.7%	5	3	0.1%
Month						7	1	0.0%
Jan.	240	6.7%	***Police District***			9	1	0.0%
Feb.	335	9.4%	1	727	20.4%	16	1	0.0%
Mar.	355	9.9%	2	776	21.7%	20	1	0.0%
Apr.	255	7.1%	3	512	14.3%			
May	259	7.3%	4	385	10.8%	***Number of Disabling Injuries***		
Jun.	198	5.5%	5	404	11.3%	0	3205	89.7%
Jul.	169	4.7%	6	398	11.1%	1	355	9.9%
Aug.	400	11.2%	7	351	9.8%	2	8	0.2%
Sept.	386	10.8%	Special Division	19	0.5%	3	3	0.1%
Oct.	243	6.8%				4	1	0.0%
Nov.	405	11.3%	***Type of Collisions***					
Dec.	327	9.2%	Right Turn	348	9.7%	***Number of Fatalities***		
			Left Turn	913	25.6%	0	3531	98.9%
Day of Week			Straight	1563	43.8%	1	41	1.1%
Mon.	486	13.6%	Head On	96	2.7%			
Tues.	571	16.0%	Backing	251	7.0%	***Type of Pedestrian Accidents***		
Wed.	596	16.7%	Side Swiped	109	3.1%	Against Signal in Crosswalk	208	5.8%
Thurs.	568	15.9%	Rear End	27	0.8%	From Between Parked Cars	238	6.7%
Fri.	593	16.6%	Other	232	6.5%	With Signal in Crosswalk	941	26.3%
Sat.	444	12.4%	Unknown	33	0.9%	Without Signal in Crosswalk	521	14.6%
Sun.	314	8.8%				In Unmarked Crosswalk	48	1.3%
						Not in Crosswalk	738	20.7%
						Other	543	15.2%
						Unknown	335	9.4%

Table A7-1. Continued Descriptive Statistics of PVCs in D.C. from 2010 to 2014 (*n*=3,572)

Variables	# PVCs	% PVCs	Variables	# PVCs	% PVCs	Variables	# PVCs	% PVCs
Light Conditions			***Weather***			***Type of Roadway***		
Dawn	39	1.1%	Clear	2835	79.4%	One-Way, Not Divided	475	13.3%
Daylight	2258	63.2%	Fog/Mist	34	1.0%	Two-Way, Divided Protected	320	9.0%
Dusk	55	1.5%	Other	40	1.1%	Two-Way, Divided Unprotected	1014	28.4%
Dark	1134	31.7%	Rain	471	13.2%	Two-Way, Not Divided	1417	39.7%
Other	7	0.2%	Severe Crosswind	15	0.4%	Other	256	7.2%
Unknown	79	2.2%	Snow	43	1.2%	Unknown	90	2.5%
			Unknown	134	3.8%			
Presence of Streetlights			Total	3572	100.0%	***Road Surface***		
Streetlights On	1201	33.6%				Asphalt	3141	87.9%
Streetlights Off	1991	55.7%	***Road Geometry***			Concrete	313	8.8%
Defective	3	0.1%	Straight	2468	69.1%	Brick	17	0.5%
None	207	5.8%	Curve	91	2.5%	Gravel	4	0.1%
Unknown	170	4.8%	Grade	144	4.0%	Other	4	0.1%
			Level	171	4.8%	Unknown	93	2.6%
Road Conditions			Other	43	1.2%			
Dry	2856	80.0%	Ramp	6	0.2%			
Repairing	10	0.3%	Crest	4	0.1%			
Snow / Icy	42	1.2%	Bridge	3	0.1%			
Wet	558	15.6%	Unknown	642	18.0%			
Other	12	0.3%						
Unknown	94	2.6%	***Traffic Controls***					
Total	3572	100.0%	Signal	1621	45.4%			
			Stop Sign	377	10.6%			
Traffic Volume			Yield	22	0.6%			
Light	1133	31.7%	Flashing	15	0.4%			
Medium	1287	36.0%	Officer	17	0.5%			
Heavy	542	15.2%	Restricted Turn	3	0.1%			
Other	60	1.7%	Other	81	2.3%			
Unknown	550	15.4%	None	1349	37.8%			
			Unknown	87	2.4%			

APPENDIX 8. MAP OF NEIGHBORHOODS IN D.C.

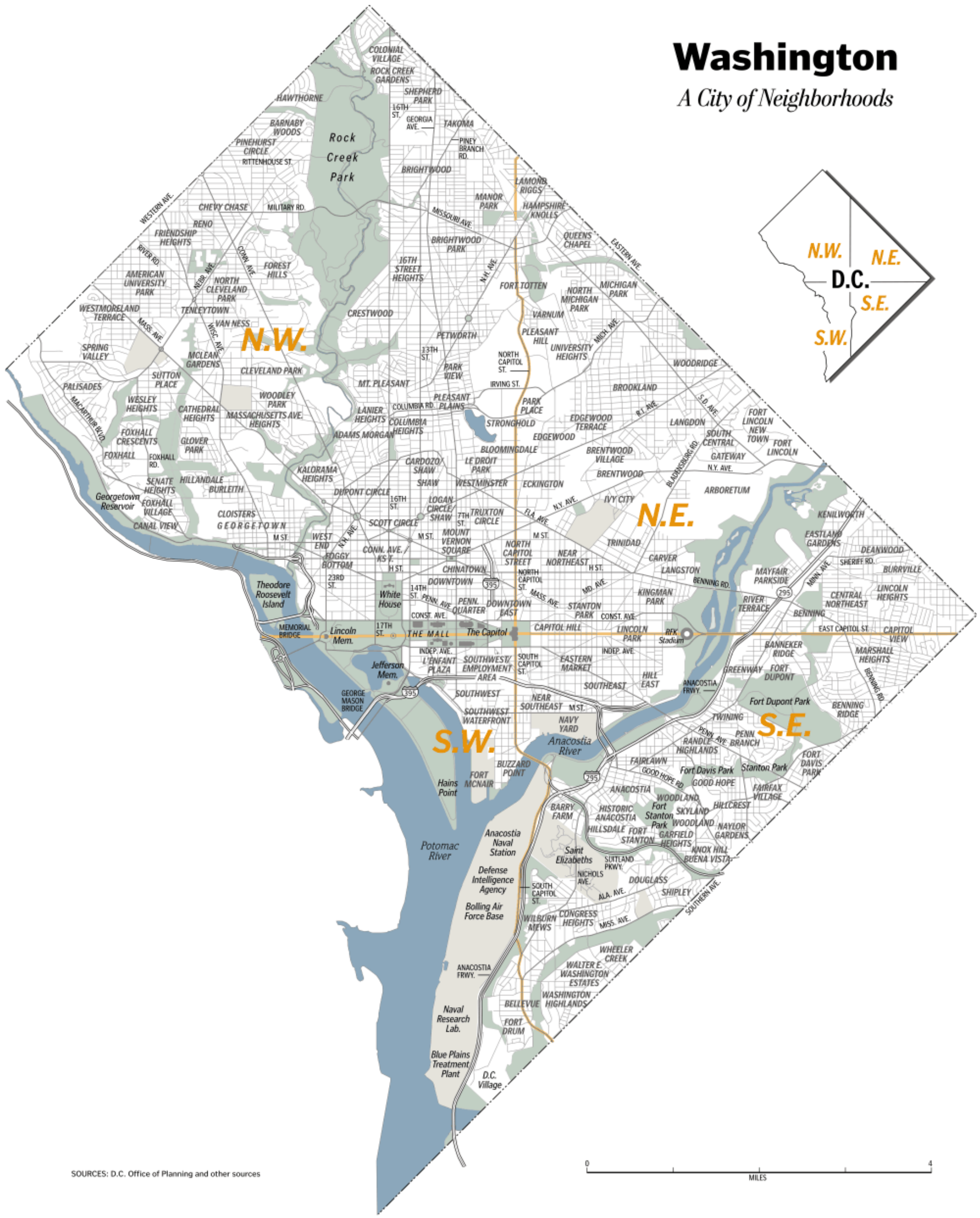


Image Source : http://media.washingtonpost.com/wp-srv/metro/specials/theguide/maps

APPENDIX 9. SELECTING VARIABLES FOR THE NB MODELS

Table A9-1. Explanatory Variables Included in the NB regression Models

Manual Elimination (r ≥ 0.5)		Stepwise Backward Elimination		
No.	*y, yint, ymid*	*y*	*yint*	*ymid*
1	(X3) PUPPY TRACK	(X3) PUPPY TRACK	(X1) STOP BAR	(X1) STOP BAR
2	(X4) RUMBLE STRIP	(X5) LANE DIVIDER	(X5) LANE DIVIDER	(X3) PUPPY TRACK
3	(X5) LANE DIVIDER	(X7) PARKING SPACE MARKING	(X8) SIGNALIZED INTERSECTION	(X8) SIGNALIZED INTERSECTION
4	(X7) PARKING SPACE MARKING	(X8) SIGNALIZED INTERSECTION	(X10) CAMERA ENFORCEMENT	(X10) CAMERA ENFORCEMENT
5	(X8) SIGNALIZED INTERSECTION	(X10) CAMERA ENFORCEMENT	(X12) OTHER TRAFFIC SIGNS	(X11) STREETLIGHT
6	(X9) TRAFFIC POLES	(X11) STREETLIGHT	(X13) SCHOOL CROSSING GUARD	(X12) OTHER TRAFFIC SIGNS
7	(X10) CAMERA ENFORCEMENT	(X13) SCHOOL CROSSING GUARD	(X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE)	(X13) SCHOOL CROSSING GUARD
8	(X11) STREETLIGHT	(X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE)	(X18) NUMBER OF BUS STOP (WITHIN 300FT)	(X18) NUMBER OF BUS STOP (WITHIN 300FT)
9	(X12) OTHER TRAFFIC SIGNS	(X18) NUMBER OF BUS STOP (WITHIN 300FT)	(X19) COMMERCIAL LAND USE (BY DENSITY)	(X19) COMMERCIAL LAND USE (BY DENSITY)
10	(X13) SCHOOL CROSSING GUARD	(X19) COMMERCIAL LAND USE (BY DENSITY)	(X22) STREET CLASSIFICATION	(X20) RESIDENTIAL LAND USE (BY DENSITY)
11	(X14) SPEED HUMP	(X20) RESIDENTIAL LAND USE (BY DENSITY)	(X23) HOUSEHOLD INCOME	(X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)
12	(X15) AREA OF SIDEWALK (SQ. FT)	(X22) STREET CLASSIFICATION	(X29) (% OF TOTAL POPULATION: AGE 15 TO 24)	
13	(X16) NUMBER 0 WITHIN 25 (WITHIN 0.25 MILE)	(X23) HOUSEHOLD INCOME	(X30) (% OF TOTAL POPULATION: AGE 25 TO 44)	
14	(X18) NUMBER 300 WITHIN 300 (WITHIN 300FT)	(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)		
15	(X19) COMMERCIAL LAND USE (CLU)			
16	(X20) RESIDENTIAL LAND USE (RLU)			
17	(X21) STREET DIRECTION			
18	(X22) STREET CLASSIFICATION			
19	(X26) % OTHER THAN BLACK OR WHITE (CT)			
20	(X30) AGE 25 to 44 (CT)			
21	(X31) AGE 45 to 64 (CT)			

* Pearson's correlation matrices were used to remove any explanatory variables that were low in significance with the dependent variables but had high correlation coefficient (*r*) of more than 0.5 with other explanatory variables.

Table A9-2. Pearson's Correlation Matrix for PVCs 'at' and 'near' Intersections (Y)

Correlations

		PVCs per Intersection	(X1) STOPBAR	(X2) CROSSWALK	(X3) PUPPY TRACK	(X4) RUMBLE STRIP	(X5) LANE DIVIDER	(X6) LANE REDUCTION ARROW	(X7) PARKING SPACE MARKING	(X8) SIGNALIZED INTERSECTION	(X9) TRAFFIC POLE	(X10) CAMERA ENFORCEMENT	(X11) STREET LIGHT	(X12) OTHER TRAFFIC SIGNS	(X13) SCHOOL CROSSING GUARD	(X14) SPEED HUMP	(X15) AREA OF SIDEWALK (SQFT)	(X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE)	(X17) NUMBER OF BUS STOP (WITHIN 100FT)	(X18) NUMBER OF BUS STOP (WITHIN 300FT)	(X19) COMMERCIAL LAND USE (BY DENSITY)	(X20) RESIDENTIAL LAND USE (BY DENSITY)	(X21) STREET DIRECTION (ONE OR TWO-WAY)	(X22) STREET CLASSIFICATION	(X23) HOUSEHOLD INCOME	(X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP)	(X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)	(X26) OTHER (% OF TOTAL CENSUS TRACT POP)	(X27) MEDIAN AGE OF NEAREST CENSUS TRACT	(X28) (% OF TOTAL POPULATION - AGE 0 TO 14)	(X29) (% OF TOTAL POPULATION - AGE 15 TO 24)	(X30) (% OF TOTAL POPULATION - AGE 25 TO 44)	(X31) (% OF TOTAL POPULATION - AGE 45 TO 64)	(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)	(X34) PEDESTRIAN DEMAND INDEX
PVCs per Intersection	Pearson Correlation	1	.159**	.132**	.098**	-.026	.300**	.b	-.018	.330**	.191**	.154**	.193**	.080**	.086**	-.026	.134**	.204**	.129**	.231**	.313**	.049	-.031	.243**	-.030	.055*	-.083**	.162**	-.089**	-.146**	.027	.168**	-.124**	-.103**	.163**
	Sig. (2-tailed)		.000	.000	.000	.325	.000		.498	.000	.000	.000	.000	.003	.001	.338	.000	.000	.000	.000	.000	.065	.248	.000	.262	.039	.002	.000	.001	.000	.310	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X1) STOPBAR	Pearson Correlation	.159**	1	.716**	.046	-.048	.393**	.b	.043	.419**	.703**	.094**	.114**	.234**	.090**	-.023	.101**	.153**	.110**	.141**	.073**	-.028	.135**	-.005	.146**	.139**	-.154**	.139**	.002	-.076**	-.062*	.120**	-.044	.027	.077**
	Sig. (2-tailed)	.000		.000	.082	.069	.000		.105	.000	.000	.000	.000	.000	.001	.383	.000	.000	.000	.000	.006	.300	.000	.844	.000	.000	.000	.000	.947	.004	.019	.000	.099	.311	.004
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X2) CROSSWALK	Pearson Correlation	.132**	.716**	1	.059*	-.025	.386**	.b	.102**	.284**	.663**	.071**	.106**	.181**	.073**	-.035	.190**	.151**	.078**	.103**	.070**	.010	-.026	.001	.129**	.160**	-.184**	.192**	.011	-.149**	-.055*	.176**	-.057*	-.005	.141**
	Sig. (2-tailed)	.000	.000		.026	.353	.000		.000	.000	.000	.007	.000	.000	.006	.187	.000	.000	.003	.000	.008	.702	.321	.974	.000	.000	.000	.000	.687	.000	.038	.000	.032	.837	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X3) PUPPY TRACK	Pearson Correlation	.098**	.046	.059*	1	-.013	.176**	.b	.006	.101**	.132**	.015	.015	-.029	-.028	.007	.006	.093**	-.004	.032	.028	-.055*	-.039	.097**	.033	.078**	-.095**	.115**	.006	-.109**	.005	.090**	-.054*	-.001	.066*
	Sig. (2-tailed)	.000	.082	.026		.626	.000		.818	.000	.000	.562	.580	.281	.299	.794	.810	.000	.881	.234	.286	.038	.140	.000	.221	.003	.000	.000	.827	.000	.854	.001	.041	.965	.013
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X4) RUMBLE STRIP	Pearson Correlation	-.026	-.048	-.025	-.013	1	-.014	.b	.031	-.038	-.014	-.008	-.022	-.037	-.015	-.006	.008	-.014	-.001	-.020	-.010	.032	-.052*	-.011	.005	.003	.005	-.034	.019	.001	-.021	.012	.043	-.024	.012
	Sig. (2-tailed)	.325	.069	.353	.626		.593		.237	.150	.607	.750	.412	.163	.566	.832	.759	.590	.964	.460	.706	.234	.049	.676	.847	.904	.858	.201	.479	.981	.434	.662	.105	.373	.641
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X5) LANE DIVIDER	Pearson Correlation	.300**	.393**	.386**	.176**	-.014	1	.b	.228**	.489**	.485**	.145**	.187**	.081**	.021	-.057*	.179**	.279**	.017	.164**	.325**	-.064*	-.167**	.278**	.171**	.306**	-.343**	.329**	-.093**	-.339**	.007	.338**	-.209**	-.084**	.234**
	Sig. (2-tailed)	.000	.000	.000	.000	.593			.000	.000	.000	.000	.000	.002	.424	.031	.000	.000	.527	.000	.000	.016	.000	.000	.000	.000	.000	.000	.000	.000	.783	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X6) LANE REDUCTION ARROW	Pearson Correlation	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b	.b
	Sig. (2-tailed)																																		
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X7) PARKING SPACE MARKING	Pearson Correlation	-.018	.043	.102**	.006	.031	.228**	.b	1	.053*	.083**	-.031	.127**	-.044	.053*	-.028	.112**	.125**	-.060*	-.120**	-.017	.064*	-.079**	.011	.154**	.128**	-.128**	.066*	-.014	-.082**	-.094**	.192**	-.048	-.061*	.157**
	Sig. (2-tailed)	.498	.105	.000	.818	.237	.000			.047	.002	.243	.000	.101	.048	.291	.000	.000	.024	.000	.535	.015	.003	.678	.000	.000	.000	.013	.594	.002	.000	.000	.072	.022	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X8) SIGNALIZED INTERSECTION	Pearson Correlation	.330**	.419**	.284**	.101**	-.038	.489**	.b	.053*	1	.489**	.105**	.222**	.214**	.134**	-.076**	.199**	.200**	.178**	.261**	.277**	-.021	-.023	.340**	.107**	.198**	-.227**	.237**	-.056*	-.232**	-.008	.242**	-.145**	-.044	.188**
	Sig. (2-tailed)	.000	.000	.000	.000	.150	.000		.047		.000	.000	.000	.000	.000	.004	.000	.000	.000	.000	.000	.428	.390	.000	.000	.000	.000	.000	.035	.000	.758	.000	.000	.099	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X9) TRAFFIC POLE	Pearson Correlation	.191**	.703**	.663**	.132**	-.014	.485**	.b	.083**	.489**	1	.076**	.186**	.245**	.113**	-.049	.135**	.163**	.085**	.161**	.123**	-.018	-.052	.123**	.151**	.212**	-.243**	.248**	-.005	-.194**	-.023	.175**	-.098**	.030	.119**
	Sig. (2-tailed)	.000	.000	.000	.000	.607	.000		.002	.000		.004	.000	.000	.000	.065	.000	.000	.001	.000	.000	.495	.051	.000	.000	.000	.000	.000	.844	.000	.393	.000	.000	.255	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X10) CAMERA ENFORCEMENT	Pearson Correlation	.154**	.094**	.071**	.015	-.008	.145**	.b	-.031	.105**	.076**	1	.017	.040	.025	-.013	-.055*	.017	-.018	.039	.027	-.026	.005	.107**	-.040	-.025	.024	-.010	-.014	.047	-.003	-.016	-.030	.009	-.015
	Sig. (2-tailed)	.000	.000	.007	.562	.750	.000		.243	.000	.004		.528	.129	.339	.629	.039	.519	.500	.141	.317	.321	.855	.000	.133	.347	.372	.701	.601	.078	.903	.550	.252	.728	.581
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X11) STREET LIGHT	Pearson Correlation	.193**	.114**	.106**	.015	-.022	.187**	.b	.127**	.222**	.186**	.017	1	.031	-.005	-.042	.281**	.166**	.017	.047	.279**	.069**	-.131**	.180**	.163**	.233**	-.253**	.208**	-.134**	-.267**	.077**	.234**	-.226**	-.092**	.255**
	Sig. (2-tailed)	.000	.000	.000	.580	.412	.000		.000	.000	.000	.528		.238	.841	.119	.000	.000	.511	.079	.000	.010	.000	.000	.000	.000	.000	.000	.000	.000	.004	.000	.000	.001	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X12) OTHER TRAFFIC SIGNS	Pearson Correlation	.080**	.234**	.181**	-.029	-.037	.081**	.b	-.044	.214**	.245**	.040	.031	1	.065*	-.049	-.051	-.045	.083**	.103**	-.014	-.037	.096**	.072**	.023	-.069**	.041	.098**	.104**	.068*	-.034	-.117**	.102**	.138**	-.155**
	Sig. (2-tailed)	.003	.000	.000	.281	.163	.002		.101	.000	.000	.129	.238		.015	.067	.057	.088	.002	.000	.593	.160	.000	.007	.380	.010	.127	.000	.000	.010	.202	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X13) SCHOOL CROSSING GUARD	Pearson Correlation	.086**	.090**	.073**	-.028	-.015	.021	.b	.053*	.134**	.113**	.025	-.005	.065*	1	.009	.002	-.061*	.064*	.010	-.056*	.038	.016	.013	-.054*	-.064*	.068*	-.050	-.002	.080**	-.053*	.003	.016	-.017	.067*
	Sig. (2-tailed)	.001	.001	.006	.299	.566	.424		.048	.000	.000	.339	.841	.015		.737	.943	.022	.016	.695	.034	.150	.557	.637	.042	.016	.011	.059	.953	.002	.048	.907	.559	.512	.012
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X14) SPEED HUMP	Pearson Correlation	-.026	-.023	-.035	.007	-.006	-.057*	.b	-.028	-.076**	-.049	-.013	-.042	-.049	.009	1	-.024	-.024	-.007	-.025	-.030	-.022	-.011	-.072**	-.053*	-.071**	.069**	-.025	-.029	.051	.011	-.028	-.004	-.028	-.011
	Sig. (2-tailed)	.338	.383	.187	.794	.832	.031		.291	.004	.065	.629	.119	.067	.737		.357	.361	.790	.354	.259	.402	.675	.007	.046	.008	.010	.341	.282	.057	.689	.294	.890	.289	.689
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X15) AREA OF SIDEWALK (SQFT)	Pearson Correlation	.134**	.101**	.190**	.006	.008	.179**	.b	.112**	.199**	.135**	-.055*	.281**	-.051	.002	-.024	1	.297**	.043	.019	.340**	.027	-.135**	.060*	.224**	.337**	-.362**	.289**	-.156**	-.362**	.033	.398**	-.265**	-.184**	.394**
	Sig. (2-tailed)	.000	.000	.000	.810	.759	.000		.000	.000	.000	.039	.000	.057	.943	.357		.000	.109	.466	.000	.315	.000	.024	.000	.000	.000	.000	.000	.000	.210	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE)	Pearson Correlation	.204**	.153**	.151**	.093**	-.014	.279**	.b	.125**	.200**	.163**	.017	.166**	-.045	-.061*	-.024	.297**	1	-.041	.038	.411**	-.073**	-.056*	.123**	.152**	.272**	-.319**	.364**	-.072**	-.347**	.010	.322**	-.190**	-.057*	.408**
	Sig. (2-tailed)	.000	.000	.000	.000	.590	.000		.000	.000	.000	.519	.000	.088	.022	.361	.000		.127	.156	.000	.006	.035	.000	.000	.000	.000	.000	.007	.000	.714	.000	.000	.031	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X17) NUMBER OF BUS STOP (WITHIN 100FT)	Pearson Correlation	.129**	.110**	.078**	-.004	-.001	.017	.b	-.060*	.178**	.085**	-.018	.017	.083**	.064*	-.007	.043	-.041	1	.529**	.024	.046	.077**	.124**	-.011	-.055*	.051	-.006	.010	.055*	-.026	-.011	.023	-.016	-.018
	Sig. (2-tailed)	.000	.000	.003	.881	.964	.527		.024	.000	.001	.500	.511	.002	.016	.790	.109	.127		.000	.361	.083	.004	.000	.678	.038	.054	.827	.720	.037	.320	.693	.393	.557	.503
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X18) NUMBER OF BUS STOP (WITHIN 300FT)	Pearson Correlation	.231**	.141**	.103**	.032	-.020	.164**	.b	-.120**	.261**	.161**	.039	.047	.103**	.010	-.025	.019	.038	.529**	1	.134**	.040	.100**	.220**	-.047	-.079**	.074**	-.009	.007	.044	-.022	-.022	.024	.013	-.007
	Sig. (2-tailed)	.000	.000	.000	.234	.460	.000		.000	.000	.000	.141	.079	.000	.695	.354	.466	.156	.000		.000	.133	.000	.000	.079	.003	.005	.723	.791	.101	.407	.415	.362	.613	.781
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X19) COMMERCIAL LAND USE (BY DENSITY)	Pearson Correlation	.313**	.073**	.070**	.028	-.010	.325**	.b	-.017	.277**	.123**	.027	.279**	-.014	-.056*	-.030	.340**	.411**	.024	.134**	1	.058*	-.066*	.192**	.095**	.196**	-.238**	.300**	-.116**	-.327**	.005	.342**	-.200**	-.113**	.284**
	Sig. (2-tailed)	.000	.006	.008	.286	.706	.000		.535	.000	.000	.317	.000	.593	.034	.259	.000	.000	.361	.000		.030	.013	.000	.000	.000	.000	.000	.000	.000	.841	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X20) RESIDENTIAL LAND USE (BY DENSITY)	Pearson Correlation	.049	-.028	.010	-.055*	.032	-.064*	.b	.064*	-.021	-.018	-.026	.069**	-.037	.038	-.022	.027	-.073**	.046	.040	.058*	1	-.008	-.016	-.048	-.026	.025	-.004	-.060*	.070**	-.162**	.172**	-.006	-.125**	.212**
	Sig. (2-tailed)	.065	.300	.702	.038	.234	.016		.015	.428	.495	.321	.010	.160	.150	.402	.315	.006	.083	.133	.030		.753	.544	.070	.324	.346	.866	.025	.008	.000	.000	.809	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X21) STREET DIRECTION (ONE OR TWO-WAY)	Pearson Correlation	-.031	.135**	-.026	-.039	-.052*	-.167**	.b	-.079**	-.023	-.052	.005	-.131**	.096**	.016	-.011	-.135**	-.056*	.077**	.100**	-.066*	-.008	1	.060*	-.013	-.178**	.195**	-.170**	.142**	.234**	-.107**	-.182**	.171**	.151**	-.194**
	Sig. (2-tailed)	.248	.000	.321	.140	.049	.000		.003	.390	.051	.855	.000	.000	.557	.675	.000	.035	.004	.000	.013	.753		.023	.637	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X22) STREET CLASSIFICATION	Pearson Correlation	.243**	-.005	.001	.097**	-.011	.278**	.b	.011	.340**	.123**	.107**	.180**	.072**	.013	-.072**	.060*	.123**	.124**	.220**	.192**	-.016	.060*	1	.092**	.162**	-.189**	.207**	-.041	-.171**	.035	.128**	-.126**	.009	.090**
	Sig. (2-tailed)	.000	.844	.974	.000	.676	.000		.678	.000	.000	.000	.000	.007	.637	.007	.024	.000	.000	.000	.000	.544	.023		.001	.000	.000	.000	.123	.000	.187	.000	.000	.728	.001
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X23) HOUSEHOLD INCOME	Pearson Correlation	-.030	.146**	.129**	.033	.005	.171**	.b	.154**	.107**	.151**	-.040	.163**	.023	-.054*	-.053*	.224**	.152**	-.011	-.047	.095**	-.048	-.013	.092**	1	.780**	-.750**	.232**	.166**	-.374**	-.179**	.320**	.008	.180**	.079**
	Sig. (2-tailed)	.262	.000	.000	.221	.847	.000		.000	.000	.000	.133	.000	.380	.042	.046	.000	.000	.678	.079	.000	.070	.637	.001		.000	.000	.000	.000	.000	.000	.000	.759	.000	.003
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP)	Pearson Correlation	.055*	.139**	.160**	.078**	.003	.306**	.b	.128**	.198**	.212**	-.025	.233**	-.069**	-.064*	-.071**	.337**	.272**	-.055*	-.079**	.196**	-.026	-.178**	.162**	.780**	1	-.982**	.395**	-.106**	-.613**	.035	.523**	-.327**	-.074**	.322**
	Sig. (2-tailed)	.039	.000	.000	.003	.904	.000		.000	.000	.000	.347	.000	.010	.016	.008	.000	.000	.038	.003	.000	.324	.000	.000	.000		0.000	.000	.000	.000	.188	.000	.000	.006	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X25) BLACK OR AFRICAN AMERICAN ALONE	Pearson Correlation	-.083**	-.154**	-.184**	-.095**	.005	-.343**	.b	-.128**	-.227**	-.243**	.024	-.253**	.041	.068*	.069**	-.362**	-.319**	.051	.074**	-.238**	.025	.195**	-.189**	-.750**	-.982**	1	-.563**	.109**	.654**	-.038	-.561**	.347**	.084**	-.366**
	Sig. (2-tailed)	.002	.000	.000	.000	.858	.000		.000	.000	.000	.372	.000	.127	.011	.010	.000	.000	.054	.005	.000	.346	.000	.000	.000	0.000		.000	.000	.000	.152	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X26) OTHER (% OF TOTAL CENSUS TRACT	Pearson Correlation	.162**	.139**	.192**	.115**	-.034	.329**	.b	.066*	.237**	.248**	-.010	.208**	.098**	-.050	-.025	.289**	.364**	-.006	-.009	.300**	-.004	-.170**	.207**	.232**	.395**	-.563**	1	-.057*	-.496**	.023	.439**	-.249**	-.083**	.373**
	Sig. (2-tailed)	.000	.000	.000	.000	.201	.000		.013	.000	.000	.701	.000	.000	.059	.341	.000	.000	.827	.723	.000	.866	.000	.000	.000	.000	.000		.031	.000	.384	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X27) MEDIAN AGE OF NEAREST CENSUS TRACT	Pearson Correlation	-.089**	.002	.011	.006	.019	-.093**	.b	-.014	-.056*	-.005	-.014	-.134**	.104**	-.002	-.029	-.156**	-.072**	.010	.007	-.116**	-.060*	.142**	-.041	.166**	-.106**	.109**	-.057*	1	.016	-.614**	-.134**	.786**	.807**	-.346**
	Sig. (2-tailed)	.001	.947	.687	.827	.479	.000		.594	.035	.844	.601	.000	.000	.953	.282	.000	.007	.720	.791	.000	.025	.000	.123	.000	.000	.000	.031		.549	.000	.000	.000	0.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X28) (% OF TOTAL POPULATION - AGE 0 TO 14)	Pearson Correlation	-.146**	-.076**	-.149**	-.109**	.001	-.339**	.b	-.082**	-.232**	-.194**	.047	-.267**	.068*	.080**	.051	-.362**	-.347**	.055*	.044	-.327**	.070**	.234**	-.171**	-.374**	-.613**	.654**	-.496**	.016	1	-.239**	-.517**	.287**	.030	-.389**
	Sig. (2-tailed)	.000	.004	.000	.000	.981	.000		.002	.000	.000	.078	.000	.010	.002	.057	.000	.000	.037	.101	.000	.008	.000	.000	.000	.000	.000	.000	.549		.000	.000	.000	.257	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X29) (% OF TOTAL POPULATION - AGE 15 TO 24)	Pearson Correlation	.027	-.062*	-.055*	.005	-.021	.007	.b	-.094**	-.008	-.023	-.003	.077**	-.034	-.053*	.011	.033	.010	-.026	-.022	.005	-.162**	-.107**	.035	-.179**	.035	-.038	.023	-.614**	-.239**	1	-.401**	-.583**	-.383**	.063*
	Sig. (2-tailed)	.310	.019	.038	.854	.434	.783		.000	.758	.393	.903	.004	.202	.048	.689	.210	.714	.320	.407	.841	.000	.000	.187	.000	.188	.152	.384	.000	.000		.000	.000	.000	.017
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X30) (% OF TOTAL POPULATION - AGE 25 TO 44)	Pearson Correlation	.168**	.120**	.176**	.090**	.012	.338**	.b	.192**	.242**	.175**	-.016	.234**	-.117**	.003	-.028	.398**	.322**	-.011	-.022	.342**	.172**	-.182**	.128**	.320**	.523**	-.561**	.439**	-.134**	-.517**	-.401**	1	-.302**	-.321**	.558**
	Sig. (2-tailed)	.000	.000	.000	.001	.662	.000		.000	.000	.000	.550	.000	.000	.907	.294	.000	.000	.693	.415	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X31) (% OF TOTAL POPULATION - AGE 45 TO 64)	Pearson Correlation	-.124**	-.044	-.057*	-.054*	.043	-.209**	.b	-.048	-.145**	-.098**	-.030	-.226**	.102**	.016	-.004	-.265**	-.190**	.023	.024	-.200**	-.006	.171**	-.126**	.008	-.327**	.347**	-.249**	.786**	.287**	-.583**	-.302**	1	.508**	-.448**
	Sig. (2-tailed)	.000	.099	.032	.041	.105	.000		.072	.000	.000	.252	.000	.000	.559	.890	.000	.000	.393	.362	.000	.809	.000	.000	.759	.000	.000	.000	.000	.000	.000	.000		.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)	Pearson Correlation	-.103**	.027	-.005	-.001	-.024	-.084**	.b	-.061*	-.044	.030	.009	-.092**	.138**	-.017	-.028	-.184**	-.057*	-.016	.013	-.113**	-.125**	.151**	.009	.180**	-.074**	.084**	-.083**	.807**	.030	-.383**	-.321**	.508**	1	-.382**
	Sig. (2-tailed)	.000	.311	.837	.965	.373	.002		.022	.099	.255	.728	.001	.000	.512	.289	.000	.031	.557	.613	.000	.000	.000	.728	.000	.006	.002	.002	0.000	.257	.000	.000	.000		.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X34) PEDESTRIAN DEMAND INDEX	Pearson Correlation	.163**	.077**	.141**	.066*	.012	.234**	.b	.157**	.188**	.119**	-.015	.255**	-.155**	.067*	-.011	.394**	.408**	-.018	-.007	.284**	.212**	-.194**	.090**	.079**	.322**	-.366**	.373**	-.346**	-.389**	.063*	.558**	-.448**	-.382**	1
	Sig. (2-tailed)	.000	.004	.000	.013	.641	.000		.000	.000	.000	.581	.000	.000	.012	.689	.000	.000	.503	.781	.000	.000	.000	.001	.003	.000	.000	.000	.000	.000	.017	.000	.000	.000	
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

b. Cannot be computed because at least one of the variables is constant.

Table A9-3. Pearson's Correlation Matrix for PVCs 'at' Intersections (Yint)

Correlations

		PVCs 'at' Intersection Only	(X1) STOPBAR	(X2) CROSSWALK	(X3) PUPPY TRACK	(X4) RUMBLE STRIP	(X5) LANE DIVIDER	(X6) LANE REDUCTION ARROW	(X7) PARKING SPACE MARKING	(X8) SIGNALIZED INTERSECTION	(X9) TRAFFIC POLE	(X10) CAMERA ENFORCEMENT	(X11) STREET LIGHT	(X12) OTHER TRAFFIC SIGNS	(X13) SCHOOL CROSSING GUARD	(X14) SPEED HUMP	(X15) AREA OF SIDEWALK (SQFT)	(X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE)	(X17) NUMBER OF BUS STOP (WITHIN 100FT)	(X18) NUMBER OF BUS STOP (WITHIN 300FT)	(X19) COMMERCIAL LAND USE (BY DENSITY)	(X20) RESIDENTIAL LAND USE (BY DENSITY)	(X21) STREET DIRECTION (ONE OR TWO-WAY)	(X22) STREET CLASSIFICATION	(X23) HOUSEHOLD INCOME	(X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP)	(X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)	(X26) OTHER (% OF TOTAL CENSUS TRACT POP)	(X27) MEDIAN AGE OF NEAREST CENSUS TRACT	(X28) (% OF TOTAL POPULATION - AGE 0 TO 14)	(X29) (% OF TOTAL POPULATION - AGE 15 TO 24)	(X30) (% OF TOTAL POPULATION - AGE 25 TO 44)	(X31) (% OF TOTAL POPULATION - AGE 45 TO 64)	(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)	(X34) PEDESTRIAN DEMAND INDEX
PVCs 'at' Intersection Only	Pearson Correlation	1	.198**	.164**	.082**	-.040	.310**	.[b]	-.002	.309**	.221**	.144**	.160**	.121**	.062*	-.020	.139**	.195**	.089**	.187**	.267**	.016	-.008	.243**	.020	.105**	-.131**	.177**	-.075**	-.170**	.029	.171**	-.125**	-.077**	.157**
	Sig. (2-tailed)		.000	.000	.002	.133	.000		.953	.000	.000	.000	.000	.000	.020	.460	.000	.000	.001	.000	.000	.557	.759	.000	.462	.000	.000	.000	.005	.000	.277	.000	.000	.004	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X1) STOPBAR	Pearson Correlation	.198**	1	.716**	.046	-.048	.393**	.[b]	.043	.419**	.703**	.094**	.114**	.234**	.090**	-.023	.101**	.153**	.110**	.141**	.073**	-.028	.135**	-.005	.146**	.139**	-.154**	.139**	.002	-.076**	-.062*	.120**	-.044	.027	.077**
	Sig. (2-tailed)	.000		.000	.082	.069	.000		.105	.000	.000	.000	.000	.000	.001	.383	.000	.000	.000	.000	.006	.300	.000	.844	.000	.000	.000	.000	.947	.004	.019	.000	.099	.311	.004
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X2) CROSSWALK	Pearson Correlation	.164**	.716**	1	.059*	-.025	.386**	.[b]	.102**	.284**	.663**	.071**	.106**	.181**	.073**	-.035	.190**	.151**	.078**	.103**	.070**	.010	-.026	.001	.129**	.160**	-.184**	.192**	.011	-.149**	-.055*	.176**	-.057*	-.005	.141**
	Sig. (2-tailed)	.000	.000		.026	.353	.000		.000	.000	.000	.007	.000	.000	.006	.187	.000	.000	.003	.000	.008	.702	.321	.974	.000	.000	.000	.000	.687	.000	.038	.000	.032	.837	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X3) PUPPY TRACK	Pearson Correlation	.082**	.046	.059*	1	-.013	.176**	.[b]	.006	.101**	.132**	.015	.015	-.029	-.028	.007	.006	.093**	-.004	.032	.028	-.055*	-.039	.097**	.033	.078**	-.095**	.115**	.006	-.109**	.005	.090**	-.054*	-.001	.066*
	Sig. (2-tailed)	.002	.082	.026		.626	.000		.818	.000	.000	.562	.580	.281	.299	.794	.810	.000	.881	.234	.286	.038	.140	.000	.221	.003	.000	.000	.827	.000	.854	.001	.041	.965	.013
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X4) RUMBLE STRIP	Pearson Correlation	-.040	-.048	-.025	-.013	1	-.014	.[b]	.031	-.038	-.014	-.008	-.022	-.037	-.015	-.006	.008	-.014	-.001	-.020	-.010	.032	-.052*	-.011	.005	.003	.005	-.034	.019	.001	-.021	.012	.043	-.024	.012
	Sig. (2-tailed)	.133	.069	.353	.626		.593		.237	.150	.607	.750	.412	.163	.566	.832	.759	.590	.964	.460	.706	.234	.049	.676	.847	.904	.858	.201	.479	.981	.434	.662	.105	.373	.641
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X5) LANE DIVIDER	Pearson Correlation	.310**	.393**	.386**	.176**	-.014	1	.[b]	.228**	.489**	.485**	.145**	.187**	.081**	.021	-.057*	.179**	.279**	.017	.164**	.325**	-.064*	-.167**	.278**	.171**	.306**	-.343**	.329**	-.093**	-.339**	.007	.338**	-.209**	-.084**	.234**
	Sig. (2-tailed)	.000	.000	.000	.000	.593			.000	.000	.000	.000	.000	.002	.424	.031	.000	.000	.527	.000	.000	.016	.000	.000	.000	.000	.000	.000	.000	.000	.783	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X6) LANE REDUCTION ARROW	Pearson Correlation	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]	.[b]
	Sig. (2-tailed)																																		
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X7) PARKING SPACE MARKING	Pearson Correlation	-.002	.043	.102**	.006	.031	.228**	.[b]	1	.053*	.083**	-.031	.127**	-.044	.053*	-.028	.112**	.125**	-.060*	-.120**	-.017	.064*	-.079**	.011	.154**	.128**	-.128**	.066*	-.014	-.082**	-.094**	.192**	-.048	-.061*	.157**
	Sig. (2-tailed)	.953	.105	.000	.818	.237	.000			.047	.002	.243	.000	.101	.048	.291	.000	.000	.024	.000	.535	.015	.003	.678	.000	.000	.000	.013	.594	.002	.000	.000	.072	.022	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X8) SIGNALIZED INTERSECTION	Pearson Correlation	.309**	.419**	.284**	.101**	-.038	.489**	.[b]	.053*	1	.489**	.105**	.222**	.214**	.134**	-.076**	.199**	.200**	.178**	.261**	.277**	-.021	-.023	.340**	.107**	.198**	-.227**	.237**	-.056*	-.232**	-.008	.242**	-.145**	-.044	.188**
	Sig. (2-tailed)	.000	.000	.000	.000	.150	.000		.047		.000	.000	.000	.000	.000	.004	.000	.000	.000	.000	.000	.428	.390	.000	.000	.000	.000	.000	.035	.000	.758	.000	.000	.099	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X9) TRAFFIC POLE	Pearson Correlation	.221**	.703**	.663**	.132**	-.014	.485**	.[b]	.083**	.489**	1	.076**	.186**	.245**	.113**	-.049	.135**	.163**	.085**	.161**	.123**	-.018	-.052	.123**	.151**	.212**	-.243**	.248**	-.005	-.194**	-.023	.175**	-.098**	.030	.119**
	Sig. (2-tailed)	.000	.000	.000	.000	.607	.000		.002	.000		.004	.000	.000	.000	.065	.000	.000	.001	.000	.000	.495	.051	.000	.000	.000	.000	.000	.844	.000	.393	.000	.000	.255	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X10) CAMERA ENFORCEMENT	Pearson Correlation	.144**	.094**	.071**	.015	-.008	.145**	.[b]	-.031	.105**	.076**	1	.017	.040	.025	-.013	-.055*	.017	-.018	.039	.027	-.026	.005	.107**	-.040	-.025	.024	-.010	-.014	.047	-.003	-.016	-.030	.009	-.015
	Sig. (2-tailed)	.000	.000	.007	.562	.750	.000		.243	.000	.004		.528	.129	.339	.629	.039	.519	.500	.141	.317	.321	.855	.000	.133	.347	.372	.701	.601	.078	.903	.550	.252	.728	.581
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X11) STREET LIGHT	Pearson Correlation	.160**	.114**	.106**	.015	-.022	.187**	.[b]	.127**	.222**	.186**	.017	1	.031	-.005	-.042	.281**	.166**	.017	.047	.279**	.069**	-.131**	.180**	.163**	.233**	-.253**	.208**	-.134**	-.267**	.077**	.234**	-.226**	-.092**	.255**
	Sig. (2-tailed)	.000	.000	.000	.580	.412	.000		.000	.000	.000	.528		.238	.841	.119	.000	.000	.511	.079	.000	.010	.000	.000	.000	.000	.000	.000	.000	.000	.004	.000	.000	.001	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X12) OTHER TRAFFIC SIGNS	Pearson Correlation	.121**	.234**	.181**	-.029	-.037	.081**	.[b]	-.044	.214**	.245**	.040	.031	1	.065*	-.049	-.051	-.045	.083**	.103**	-.014	-.037	.096**	.072**	.023	-.069**	.041	.098**	.104**	.068*	-.034	-.117**	.102**	.138**	-.155**
	Sig. (2-tailed)	.000	.000	.000	.281	.163	.002		.101	.000	.000	.129	.238		.015	.067	.057	.088	.002	.000	.593	.160	.000	.007	.380	.010	.127	.000	.000	.010	.202	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X13) SCHOOL CROSSING GUARD	Pearson Correlation	.062*	.090**	.073**	-.028	-.015	.021	.[b]	.053*	.134**	.113**	.025	-.005	.065*	1	.009	.002	-.061*	.064*	.010	-.056*	.038	.016	.013	-.054*	-.064*	.068*	-.050	-.002	.080**	-.053*	.003	.016	-.017	.067*
	Sig. (2-tailed)	.020	.001	.006	.299	.566	.424		.048	.000	.000	.339	.841	.015		.737	.943	.022	.016	.695	.034	.150	.557	.637	.042	.016	.011	.059	.953	.002	.048	.907	.559	.512	.012
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X14) SPEED HUMP	Pearson Correlation	-.020	-.023	-.035	.007	-.006	-.057*	.[b]	-.028	-.076**	-.049	-.013	-.042	-.049	.009	1	-.024	-.024	-.007	-.025	-.030	-.022	-.011	-.072**	-.053*	-.071**	.069**	-.025	-.029	.051	.011	-.028	-.004	-.028	-.011
	Sig. (2-tailed)	.460	.383	.187	.794	.832	.031		.291	.004	.065	.629	.119	.067	.737		.357	.361	.790	.354	.259	.402	.675	.007	.046	.008	.010	.341	.282	.057	.689	.294	.890	.289	.689
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X15) AREA OF SIDEWALK (SQFT)	Pearson Correlation	.139**	.101**	.190**	.006	.008	.179**	.[b]	.112**	.199**	.135**	-.055*	.281**	-.051	.002	-.024	1	.297**	.043	.019	.340**	.027	-.135**	.060*	.224**	.337**	-.362**	.289**	-.156**	-.362**	.033	.398**	-.265**	-.184**	.394**
	Sig. (2-tailed)	.000	.000	.000	.810	.759	.000		.000	.000	.000	.039	.000	.057	.943	.357		.000	.109	.466	.000	.315	.000	.024	.000	.000	.000	.000	.000	.000	.210	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X16) NUMBER OF METRO STOP (WITHIN	Pearson Correlation	.195**	.153**	.151**	.093**	-.014	.279**	.[b]	.125**	.200**	.163**	.017	.166**	-.045	-.061*	-.024	.297**	1	-.041	.038	.411**	-.073**	-.056*	.123**	.152**	.272**	-.319**	.364**	-.072**	-.347**	.010	.322**	-.190**	-.057*	.408**
	Sig. (2-tailed)	.000	.000	.000	.000	.590	.000		.000	.000	.000	.519	.000	.088	.022	.361	.000		.127	.156	.000	.006	.035	.000	.000	.000	.000	.000	.007	.000	.714	.000	.000	.031	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X17) NUMBER OF BUS STOP (WITHIN 100FT)	Pearson Correlation	.089**	.110**	.078**	-.004	-.001	.017	.[b]	-.060*	.178**	.085**	-.018	.017	.083**	.064*	-.007	.043	-.041	1	.529**	.024	.046	.077**	.124**	-.011	-.055*	.051	-.006	.010	.055*	-.026	-.011	.023	-.016	-.018
	Sig. (2-tailed)	.001	.000	.003	.881	.964	.527		.024	.000	.001	.500	.511	.002	.016	.790	.109	.127		.000	.361	.083	.004	.000	.678	.038	.054	.827	.720	.037	.320	.693	.393	.557	.503
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X18) NUMBER OF BUS STOP (WITHIN 300FT)	Pearson Correlation	.187**	.141**	.103**	.032	-.020	.164**	.[b]	-.120**	.261**	.161**	.039	.047	.103**	.010	-.025	.019	.038	.529**	1	.134**	.040	.100**	.220**	-.047	-.079**	.074**	-.009	.007	.044	-.022	-.022	.024	.013	-.007
	Sig. (2-tailed)	.000	.000	.000	.234	.460	.000		.000	.000	.000	.141	.079	.000	.695	.354	.466	.156	.000		.000	.133	.000	.000	.079	.003	.005	.723	.791	.101	.407	.415	.362	.613	.781
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X19) COMMERCIAL LAND USE (BY DENSITY)	Pearson Correlation	.267**	.073**	.070**	.028	-.010	.325**	.[b]	-.017	.277**	.123**	.027	.279**	-.014	-.056*	-.030	.340**	.411**	.024	.134**	1	.058*	-.066*	.192**	.095**	.196**	-.238**	.300**	-.116**	-.327**	.005	.342**	-.200**	-.113**	.284**
	Sig. (2-tailed)	.000	.006	.008	.286	.706	.000		.535	.000	.000	.317	.000	.593	.034	.259	.000	.000	.361	.000		.030	.013	.000	.000	.000	.000	.000	.000	.000	.841	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X20) RESIDENTIAL LAND USE (BY DENSITY)	Pearson Correlation	.016	-.028	.010	-.055*	.032	-.064*	.[b]	.064*	-.021	-.018	-.026	.069**	-.037	.038	-.022	.027	-.073**	.046	.040	.058*	1	-.008	-.016	-.048	-.026	.025	-.004	-.060*	.070**	-.162**	.172**	-.006	-.125**	.212**
	Sig. (2-tailed)	.557	.300	.702	.038	.234	.016		.015	.428	.495	.321	.010	.160	.150	.402	.315	.006	.083	.133	.030		.753	.544	.070	.324	.346	.866	.025	.008	.000	.000	.809	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X21) STREET DIRECTION (ONE OR TWO-WAY)	Pearson Correlation	-.008	.135**	-.026	-.039	-.052*	-.167**	.[b]	-.079**	-.023	-.052	.005	-.131**	.096**	.016	-.011	-.135**	-.056*	.077**	.100**	-.066*	-.008	1	.060*	-.013	-.178**	.195**	-.170**	.142**	.234**	-.107**	-.182**	.171**	.151**	-.194**
	Sig. (2-tailed)	.759	.000	.321	.140	.049	.000		.003	.390	.051	.855	.000	.000	.557	.675	.000	.035	.004	.000	.013	.753		.023	.637	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X22) STREET CLASSIFICATION	Pearson Correlation	.243**	-.005	.001	.097**	-.011	.278**	.[b]	.011	.340**	.123**	.107**	.180**	.072**	.013	-.072**	.060*	.123**	.124**	.220**	.192**	-.016	.060*	1	.092**	.162**	-.189**	.207**	-.041	-.171**	.035	.128**	-.126**	.009	.090**
	Sig. (2-tailed)	.000	.844	.974	.000	.676	.000		.678	.000	.000	.000	.000	.007	.637	.007	.024	.000	.000	.000	.000	.544	.023		.001	.000	.000	.000	.123	.000	.187	.000	.000	.728	.001
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X23) HOUSEHOLD INCOME	Pearson Correlation	.020	.146**	.129**	.033	.005	.171**	.[b]	.154**	.107**	.151**	-.040	.163**	.023	-.054*	-.053*	.224**	.152**	-.011	-.047	.095**	-.048	-.013	.092**	1	.780**	-.750**	.232**	.166**	-.374**	-.179**	.320**	.008	.180**	.079**
	Sig. (2-tailed)	.462	.000	.000	.221	.847	.000		.000	.000	.000	.133	.000	.380	.042	.046	.000	.000	.678	.079	.000	.070	.637	.001		.000	.000	.000	.000	.000	.000	.000	.759	.000	.003
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X24) WHITE ALONE (% OF TOTAL CENSUS TRACT	Pearson Correlation	.105**	.139**	.160**	.078**	.003	.306**	.[b]	.128**	.198**	.212**	-.025	.233**	-.069**	-.064*	-.071**	.337**	.272**	-.055*	-.079**	.196**	-.026	-.178**	.162**	.780**	1	-.982**	.395**	-.106**	-.613**	.035	.523**	-.327**	-.074**	.322**
	Sig. (2-tailed)	.000	.000	.000	.003	.904	.000		.000	.000	.000	.347	.000	.010	.016	.008	.000	.000	.038	.003	.000	.324	.000	.000	.000		0.000	.000	.000	.000	.188	.000	.000	.006	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X25) BLACK OR AFRICAN AMERICAN ALONE	Pearson Correlation	-.131**	-.154**	-.184**	-.095**	.005	-.343**	.[b]	-.128**	-.227**	-.243**	.024	-.253**	.041	.068*	.069**	-.362**	-.319**	.051	.074**	-.238**	.025	.195**	-.189**	-.750**	-.982**	1	-.563**	.109**	.654**	-.038	-.561**	.347**	.084**	-.366**
	Sig. (2-tailed)	.000	.000	.000	.000	.858	.000		.000	.000	.000	.372	.000	.127	.011	.010	.000	.000	.054	.005	.000	.346	.000	.000	.000	0.000		.000	.000	.000	.152	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X26) OTHER (% OF TOTAL CENSUS TRACT	Pearson Correlation	.177**	.139**	.192**	.115**	-.034	.329**	.[b]	.066*	.237**	.248**	-.010	.208**	.098**	-.050	-.025	.289**	.364**	-.006	-.009	.300**	-.004	-.170**	.207**	.232**	.395**	-.563**	1	-.057*	-.496**	.023	.439**	-.249**	-.083**	.373**
	Sig. (2-tailed)	.000	.000	.000	.000	.201	.000		.013	.000	.000	.701	.000	.000	.059	.341	.000	.000	.827	.723	.000	.866	.000	.000	.000	.000	.000		.031	.000	.384	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X27) MEDIAN AGE OF NEAREST CENSUS TRACT	Pearson Correlation	-.075**	.002	.011	.006	.019	-.093**	.[b]	-.014	-.056*	-.005	-.014	-.134**	.104**	-.002	-.029	-.156**	-.072**	.010	.007	-.116**	-.060*	.142**	-.041	.166**	-.106**	.109**	-.057*	1	.016	-.614**	-.134**	.786**	.807**	-.346**
	Sig. (2-tailed)	.005	.947	.687	.827	.479	.000		.594	.035	.844	.601	.000	.000	.953	.282	.000	.007	.720	.791	.000	.025	.000	.123	.000	.000	.000	.031		.549	.000	.000	.000	0.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X28) (% OF TOTAL POPULATION - AGE 0 TO 14)	Pearson Correlation	-.170**	-.076**	-.149**	-.109**	.001	-.339**	.[b]	-.082**	-.232**	-.194**	.047	-.267**	.068*	.080**	.051	-.362**	-.347**	.055*	.044	-.327**	.070**	.234**	-.171**	-.374**	-.613**	.654**	-.496**	.016	1	-.239**	-.517**	.287**	.030	-.389**
	Sig. (2-tailed)	.000	.004	.000	.000	.981	.000		.002	.000	.000	.078	.000	.010	.002	.057	.000	.000	.037	.101	.000	.008	.000	.000	.000	.000	.000	.000	.549		.000	.000	.000	.257	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X29) (% OF TOTAL POPULATION - AGE 15 TO 24)	Pearson Correlation	.029	-.062*	-.055*	.005	-.021	.007	.[b]	-.094**	-.008	-.023	-.003	.077**	-.034	-.053*	.011	.033	.010	-.026	-.022	.005	-.162**	-.107**	.035	-.179**	.035	-.038	.023	-.614**	-.239**	1	-.401**	-.583**	-.383**	.063*
	Sig. (2-tailed)	.277	.019	.038	.854	.434	.783		.000	.758	.393	.903	.004	.202	.048	.689	.210	.714	.320	.407	.841	.000	.000	.187	.000	.188	.152	.384	.000	.000		.000	.000	.000	.017
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X30) (% OF TOTAL POPULATION - AGE 25 TO 44)	Pearson Correlation	.171**	.120**	.176**	.090**	.012	.338**	.[b]	.192**	.242**	.175**	-.016	.234**	-.117**	.003	-.028	.398**	.322**	-.011	-.022	.342**	.172**	-.182**	.128**	.320**	.523**	-.561**	.439**	-.134**	-.517**	-.401**	1	-.302**	-.321**	.558**
	Sig. (2-tailed)	.000	.000	.000	.001	.662	.000		.000	.000	.000	.550	.000	.000	.907	.294	.000	.000	.693	.415	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X31) (% OF TOTAL POPULATION - AGE 45 TO 64)	Pearson Correlation	-.125**	-.044	-.057*	-.054*	.043	-.209**	.[b]	-.048	-.145**	-.098**	-.030	-.226**	.102**	.016	-.004	-.265**	-.190**	.023	.024	-.200**	-.006	.171**	-.126**	.008	-.327**	.347**	-.249**	.786**	.287**	-.583**	-.302**	1	.508**	-.448**
	Sig. (2-tailed)	.000	.099	.032	.041	.105	.000		.072	.000	.000	.252	.000	.000	.559	.890	.000	.000	.393	.362	.000	.809	.000	.000	.759	.000	.000	.000	.000	.000	.000	.000		.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)	Pearson Correlation	-.077**	.027	-.005	-.001	-.024	-.084**	.[b]	-.061*	-.044	.030	.009	-.092**	.138**	-.017	-.028	-.184**	-.057*	-.016	.013	-.113**	-.125**	.151**	.009	.180**	-.074**	.084**	-.083**	.807**	.030	-.383**	-.321**	.508**	1	-.382**
	Sig. (2-tailed)	.004	.311	.837	.965	.373	.002		.022	.099	.255	.728	.001	.000	.512	.289	.000	.031	.557	.613	.000	.000	.000	.728	.000	.006	.002	.002	0.000	.257	.000	.000	.000		.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X34) PEDESTRIAN DEMAND INDEX	Pearson Correlation	.157**	.077**	.141**	.066*	.012	.234**	.[b]	.157**	.188**	.119**	-.015	.255**	-.155**	.067*	-.011	.394**	.408**	-.018	-.007	.284**	.212**	-.194**	.090**	.079**	.322**	-.366**	.373**	-.346**	-.389**	.063*	.558**	-.448**	-.382**	1
	Sig. (2-tailed)	.000	.004	.000	.013	.641	.000		.000	.000	.000	.581	.000	.000	.012	.689	.000	.000	.503	.781	.000	.000	.000	.001	.003	.000	.000	.000	.000	.000	.017	.000	.000	.000	
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

b. Cannot be computed because at least one of the variables is constant.

Table A9-4. Pearson's Correlation Matrix for PVCs 'Near' Intersections (Ymid)

Correlations

		PVCs 'near' Intersection Only	(X1) STOPBAR	(X2) CROSSWALK	(X3) PUPPY TRACK	(X4) RUMBLE STRIP	(X5) LANE DIVIDER	(X6) LANE REDUCTION ARROW	(X7) PARKING SPACE MARKING	(X8) SIGNALIZED INTERSECTION	(X9) TRAFFIC POLE	(X10) CAMERA ENFORCEMENT	(X11) STREET LIGHT	(X12) OTHER TRAFFIC SIGNS	(X13) SCHOOL CROSSING GUARD	(X14) SPEED HUMP	(X15) AREA OF SIDEWALK (SQFT)	(X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE)	(X17) NUMBER OF BUS STOP (WITHIN 100FT)	(X18) NUMBER OF BUS STOP (WITHIN 300FT)	(X19) COMMERCIAL LAND USE (BY DENSITY)	(X20) RESIDENTIAL LAND USE (BY DENSITY)	(X21) STREET DIRECTION (ONE OR TWO-WAY)	(X22) STREET CLASSIFICATION	(X23) HOUSEHOLD INCOME	(X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP)	(X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)	(X26) OTHER (% OF TOTAL CENSUS TRACT POP)	(X27) MEDIAN AGE OF NEAREST CENSUS TRACT	(X28) (% OF TOTAL POPULATION - AGE 0 TO 14)	(X29) (% OF TOTAL POPULATION - AGE 15 TO 24)	(X30) (% OF TOTAL POPULATION - AGE 25 TO 44)	(X31) (% OF TOTAL POPULATION - AGE 45 TO 64)	(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)	(X34) PEDESTRIAN DEMAND INDEX
PVCs 'near' Intersection Only	Pearson Correlation	1	-.006	-.004	.058*	.012	.089**	.c	-.031	.145**	.020	.069**	.117**	-.035	.065*	-.018	.038	.085**	.105**	.147**	.179**	.068*	-.045	.084**	-.086**	-.058*	.046	.033	-.052	-.013	.006	.053*	-.041	-.075**	.066*
	Sig. (2-tailed)		.819	.889	.030	.649	.001		.238	.000	.448	.009	.000	.189	.014	.506	.155	.001	.000	.000	.000	.011	.089	.002	.001	.028	.083	.215	.052	.636	.812	.045	.125	.005	.014
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X1) STOPBAR	Pearson Correlation	-.006	1	.716**	.046	-.048	.393**	.c	.043	.419**	.703**	.094**	.114**	.234**	.090**	-.023	.101**	.153**	.110**	.141**	.073**	-.028	.135**	-.005	.146**	.139**	-.154**	.139**	.002	-.076**	-.062*	.120**	-.044	.027	.077**
	Sig. (2-tailed)	.819		.000	.082	.069	.000		.105	.000	.000	.000	.000	.000	.001	.383	.000	.000	.000	.000	.006	.300	.000	.844	.000	.000	.000	.000	.947	.004	.019	.000	.099	.311	.004
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X2) CROSSWALK	Pearson Correlation	-.004	.716**	1	.059*	-.025	.386**	.c	.102**	.284**	.663**	.071**	.106**	.181**	.073**	-.035	.190**	.151**	.078**	.103**	.070**	.010	-.026	.001	.129**	.160**	-.184**	.192**	.011	-.149**	-.055*	.176**	-.057*	-.005	.141**
	Sig. (2-tailed)	.889	.000		.026	.353	.000		.000	.000	.000	.007	.000	.000	.006	.187	.000	.000	.003	.000	.008	.702	.321	.974	.000	.000	.000	.000	.687	.000	.038	.000	.032	.837	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X3) PUPPY TRACK	Pearson Correlation	.058*	.046	.059*	1	-.013	.176**	.c	.006	.101**	.132**	.015	.015	-.029	-.028	.007	.006	.093**	-.004	.032	.028	-.055*	-.039	.097**	.033	.078**	-.095**	.115**	.006	-.109**	.005	.090**	-.054*	-.001	.066*
	Sig. (2-tailed)	.030	.082	.026		.626	.000		.818	.000	.000	.562	.580	.281	.299	.794	.810	.000	.881	.234	.286	.038	.140	.000	.221	.003	.000	.000	.827	.000	.854	.001	.041	.965	.013
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X4) RUMBLE STRIP	Pearson Correlation	.012	-.048	-.025	-.013	1	-.014	.c	.031	-.038	-.014	-.008	-.022	-.037	-.015	-.006	.008	-.014	-.001	-.020	-.010	.032	-.052*	-.011	.005	.003	.005	-.034	.019	.001	-.021	.012	.043	-.024	.012
	Sig. (2-tailed)	.649	.069	.353	.626		.593		.237	.150	.607	.750	.412	.163	.566	.832	.759	.590	.964	.460	.706	.234	.049	.676	.847	.904	.858	.201	.479	.981	.434	.662	.105	.373	.641
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X5) LANE DIVIDER	Pearson Correlation	.089**	.393**	.386**	.176**	-.014	1	.c	.228**	.489**	.485**	.145**	.187**	.081**	.021	-.057*	.179**	.279**	.017	.164**	.325**	-.064*	-.167**	.278**	.171**	.306**	-.343**	.329**	-.093**	-.339**	.007	.338**	-.209**	-.084**	.234**
	Sig. (2-tailed)	.001	.000	.000	.000	.593			.000	.000	.000	.000	.000	.002	.424	.031	.000	.000	.527	.000	.000	.016	.000	.000	.000	.000	.000	.000	.000	.000	.783	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X6) LANE REDUCTION ARROW	Pearson Correlation	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c	.c
	Sig. (2-tailed)																																		
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X7) PARKING SPACE MARKING	Pearson Correlation	-.031	.043	.102**	.006	.031	.228**	.c	1	.053*	.083**	-.031	.127**	-.044	.053*	-.028	.112**	.125**	-.060*	-.120**	-.017	.064*	-.079**	.011	.154**	.128**	-.128**	.066*	-.014	-.082**	-.094**	.192**	-.048	-.061*	.157**
	Sig. (2-tailed)	.238	.105	.000	.818	.237	.000			.047	.002	.243	.000	.101	.048	.291	.000	.000	.024	.000	.535	.015	.003	.678	.000	.000	.000	.013	.594	.002	.000	.000	.072	.022	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X8) SIGNALIZED INTERSECTION	Pearson Correlation	.145**	.419**	.284**	.101**	-.038	.489**	.c	.053*	1	.489**	.105**	.222**	.214**	.134**	-.076**	.199**	.200**	.178**	.261**	.277**	-.021	-.023	.340**	.107**	.198**	-.227**	.237**	-.056*	-.232**	-.008	.242**	-.145**	-.044	.188**
	Sig. (2-tailed)	.000	.000	.000	.000	.150	.000		.047		.000	.000	.000	.000	.000	.004	.000	.000	.000	.000	.000	.428	.390	.000	.000	.000	.000	.000	.035	.000	.758	.000	.000	.099	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X9) TRAFFIC POLE	Pearson Correlation	.020	.703**	.663**	.132**	-.014	.485**	.c	.083**	.489**	1	.076**	.186**	.245**	.113**	-.049	.135**	.163**	.085**	.161**	.123**	-.018	-.052	.123**	.151**	.212**	-.243**	.248**	-.005	-.194**	-.023	.175**	-.098**	.030	.119**
	Sig. (2-tailed)	.448	.000	.000	.000	.607	.000		.002	.000		.004	.000	.000	.000	.065	.000	.000	.001	.000	.000	.495	.051	.000	.000	.000	.000	.000	.844	.000	.393	.000	.000	.255	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X10) CAMERA ENFORCEMENT	Pearson Correlation	.069**	.094**	.071**	.015	-.008	.145**	.c	-.031	.105**	.076**	1	.017	.040	.025	-.013	-.055*	.017	-.018	.039	.027	-.026	.005	.107**	-.040	-.025	.024	-.010	-.014	.047	-.003	-.016	-.030	.009	-.015
	Sig. (2-tailed)	.009	.000	.007	.562	.750	.000		.243	.000	.004		.528	.129	.339	.629	.039	.519	.500	.141	.317	.321	.855	.000	.133	.347	.372	.701	.601	.078	.903	.550	.252	.728	.581
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X11) STREET LIGHT	Pearson Correlation	.117**	.114**	.106**	.015	-.022	.187**	.c	.127**	.222**	.186**	.017	1	.031	-.005	-.042	.281**	.166**	.017	.047	.279**	.069**	-.131**	.180**	.163**	.233**	-.253**	.208**	-.134**	-.267**	.077**	.234**	-.226**	-.092**	.255**
	Sig. (2-tailed)	.000	.000	.000	.580	.412	.000		.000	.000	.000	.528		.238	.841	.119	.000	.000	.511	.079	.000	.010	.000	.000	.000	.000	.000	.000	.000	.000	.004	.000	.000	.001	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X12) OTHER TRAFFIC SIGNS	Pearson Correlation	-.035	.234**	.181**	-.029	-.037	.081**	.c	-.044	.214**	.245**	.040	.031	1	.065*	-.049	-.051	-.045	.083**	.103**	-.014	-.037	.096**	.072**	.023	-.069**	.041	.098**	.104**	.068*	-.034	-.117**	.102**	.138**	-.155**
	Sig. (2-tailed)	.189	.000	.000	.281	.163	.002		.101	.000	.000	.129	.238		.015	.067	.057	.088	.002	.000	.593	.160	.000	.007	.380	.010	.127	.000	.000	.010	.202	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X13) SCHOOL CROSSING GUARD	Pearson Correlation	.065*	.090**	.073**	-.028	-.015	.021	.c	.053*	.134**	.113**	.025	-.005	.065*	1	.009	.002	-.061*	.064*	.010	-.056*	.038	.016	.013	-.054*	-.064*	.068*	-.050	-.002	.080**	-.053*	.003	.016	-.017	.067*
	Sig. (2-tailed)	.014	.001	.006	.299	.566	.424		.048	.000	.000	.339	.841	.015		.737	.943	.022	.016	.695	.034	.150	.557	.637	.042	.016	.011	.059	.953	.002	.048	.907	.559	.512	.012
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X14) SPEED HUMP	Pearson Correlation	-.018	-.023	-.035	.007	-.006	-.057*	.c	-.028	-.076**	-.049	-.013	-.042	-.049	.009	1	-.024	-.024	-.007	-.025	-.030	-.022	-.011	-.072**	-.053*	-.071**	.069**	-.025	-.029	.051	.011	-.028	-.004	-.028	-.011
	Sig. (2-tailed)	.506	.383	.187	.794	.832	.031		.291	.004	.065	.629	.119	.067	.737		.357	.361	.790	.354	.259	.402	.675	.007	.046	.008	.010	.341	.282	.057	.689	.294	.890	.289	.689
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X15) AREA OF SIDEWALK (SQFT)	Pearson Correlation	.038	.101**	.190**	.006	.008	.179**	.c	.112**	.199**	.135**	-.055*	.281**	-.051	.002	-.024	1	.297**	.043	.019	.340**	.027	-.135**	.060*	.224**	.337**	-.362**	.289**	-.156**	-.362**	.033	.398**	-.265**	-.184**	.394**
	Sig. (2-tailed)	.155	.000	.000	.810	.759	.000		.000	.000	.000	.039	.000	.057	.943	.357		.000	.109	.466	.000	.315	.000	.024	.000	.000	.000	.000	.000	.000	.210	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X16) NUMBER OF METRO STOP (WITHIN	Pearson Correlation	.085**	.153**	.151**	.093**	-.014	.279**	.c	.125**	.200**	.163**	.017	.166**	-.045	-.061*	-.024	.297**	1	-.041	.038	.411**	-.073**	-.056*	.123**	.152**	.272**	-.319**	.364**	-.072**	-.347**	.010	.322**	-.190**	-.057*	.408**
	Sig. (2-tailed)	.001	.000	.000	.000	.590	.000		.000	.000	.000	.519	.000	.088	.022	.361	.000		.127	.156	.000	.006	.035	.000	.000	.000	.000	.000	.007	.000	.714	.000	.000	.031	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X17) NUMBER OF BUS STOP (WITHIN 100FT)	Pearson Correlation	.105**	.110**	.078**	-.004	-.001	.017	.c	-.060*	.178**	.085**	-.018	.017	.083**	.064*	-.007	.043	-.041	1	.529**	.024	.046	.077**	.124**	-.011	-.055*	.051	-.006	.010	.055*	-.026	-.011	.023	-.016	-.018
	Sig. (2-tailed)	.000	.000	.003	.881	.964	.527		.024	.000	.001	.500	.511	.002	.016	.790	.109	.127		.000	.361	.083	.004	.000	.678	.038	.054	.827	.720	.037	.320	.693	.393	.557	.503
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X18) NUMBER OF BUS STOP (WITHIN 300FT)	Pearson Correlation	.147**	.141**	.103**	.032	-.020	.164**	.c	-.120**	.261**	.161**	.039	.047	.103**	.010	-.025	.019	.038	.529**	1	.134**	.040	.100**	.220**	-.047	-.079**	.074**	-.009	.007	.044	-.022	-.022	.024	.013	-.007
	Sig. (2-tailed)	.000	.000	.000	.234	.460	.000		.000	.000	.000	.141	.079	.000	.695	.354	.466	.156	.000		.000	.133	.000	.000	.079	.003	.005	.723	.791	.101	.407	.415	.362	.613	.781
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X19) COMMERCIAL LAND USE (BY DENSITY)	Pearson Correlation	.179**	.073**	.070**	.028	-.010	.325**	.c	-.017	.277**	.123**	.027	.279**	-.014	-.056*	-.030	.340**	.411**	.024	.134**	1	.058*	-.066*	.192**	.095**	.196**	-.238**	.300**	-.116**	-.327**	.005	.342**	-.200**	-.113**	.284**
	Sig. (2-tailed)	.000	.006	.008	.286	.706	.000		.535	.000	.000	.317	.000	.593	.034	.259	.000	.000	.361	.000		.030	.013	.000	.000	.000	.000	.000	.000	.000	.841	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X20) RESIDENTIAL LAND USE (BY DENSITY)	Pearson Correlation	.068*	-.028	.010	-.055*	.032	-.064*	.c	.064*	-.021	-.018	-.026	.069**	-.037	.038	-.022	.027	-.073**	.046	.040	.058*	1	-.008	-.016	-.048	-.026	.025	-.004	-.060*	.070**	-.162**	.172**	-.006	-.125**	.212**
	Sig. (2-tailed)	.011	.300	.702	.038	.234	.016		.015	.428	.495	.321	.010	.160	.150	.402	.315	.006	.083	.133	.030		.753	.544	.070	.324	.346	.866	.025	.008	.000	.000	.809	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X21) STREET DIRECTION (ONE OR TWO-WAY)	Pearson Correlation	-.045	.135**	-.026	-.039	-.052*	-.167**	.c	-.079**	-.023	-.052	.005	-.131**	.096**	.016	-.011	-.135**	-.056*	.077**	.100**	-.066*	-.008	1	.060*	-.013	-.178**	.195**	-.170**	.142**	.234**	-.107**	-.182**	.171**	.151**	-.194**
	Sig. (2-tailed)	.089	.000	.321	.140	.049	.000		.003	.390	.051	.855	.000	.000	.557	.675	.000	.035	.004	.000	.013	.753		.023	.637	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X22) STREET CLASSIFICATION	Pearson Correlation	.084**	-.005	.001	.097**	-.011	.278**	.c	.011	.340**	.123**	.107**	.180**	.072**	.013	-.072**	.060*	.123**	.124**	.220**	.192**	-.016	.060*	1	.092**	.162**	-.189**	.207**	-.041	-.171**	.035	.128**	-.126**	.009	.090**
	Sig. (2-tailed)	.002	.844	.974	.000	.676	.000		.678	.000	.000	.000	.000	.007	.637	.007	.024	.000	.000	.000	.000	.544	.023		.001	.000	.000	.000	.123	.000	.187	.000	.000	.728	.001
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X23) HOUSEHOLD INCOME	Pearson Correlation	-.086**	.146**	.129**	.033	.005	.171**	.c	.154**	.107**	.151**	-.040	.163**	.023	-.054*	-.053*	.224**	.152**	-.011	-.047	.095**	-.048	-.013	.092**	1	.780**	-.750**	.232**	.166**	-.374**	-.179**	.320**	.008	.180**	.079**
	Sig. (2-tailed)	.001	.000	.000	.221	.847	.000		.000	.000	.000	.133	.000	.380	.042	.046	.000	.000	.678	.079	.000	.070	.637	.001		.000	.000	.000	.000	.000	.000	.000	.759	.000	.003
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X24) WHITE ALONE (% OF TOTAL CENSUS TRACT	Pearson Correlation	-.058*	.139**	.160**	.078**	.003	.306**	.c	.128**	.198**	.212**	-.025	.233**	-.069**	-.064*	-.071**	.337**	.272**	-.055*	-.079**	.196**	-.026	-.178**	.162**	.780**	1	-.982**	.395**	-.106**	-.613**	.035	.523**	-.327**	-.074**	.322**
	Sig. (2-tailed)	.028	.000	.000	.003	.904	.000		.000	.000	.000	.347	.000	.010	.016	.008	.000	.000	.038	.003	.000	.324	.000	.000	.000		0.000	.000	.000	.000	.188	.000	.000	.006	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X25) BLACK OR AFRICAN AMERICA N ALONE	Pearson Correlation	.046	-.154**	-.184**	-.095**	.005	-.343**	.c	-.128**	-.227**	-.243**	.024	-.253**	.041	.068*	.069**	-.362**	-.319**	.051	.074**	-.238**	.025	.195**	-.189**	-.750**	-.982**	1	-.563**	.109**	.654**	-.038	-.561**	.347**	.084**	-.366**
	Sig. (2-tailed)	.083	.000	.000	.000	.858	.000		.000	.000	.000	.372	.000	.127	.011	.010	.000	.000	.054	.005	.000	.346	.000	.000	.000	0.000		.000	.000	.000	.152	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X26) OTHER (% OF TOTAL CENSUS TRACT	Pearson Correlation	.033	.139**	.192**	.115**	-.034	.329**	.c	.066*	.237**	.248**	-.010	.208**	.098**	-.050	-.025	.289**	.364**	-.006	-.009	.300**	-.004	-.170**	.207**	.232**	.395**	-.563**	1	-.057*	-.496**	.023	.439**	-.249**	-.083**	.373**
	Sig. (2-tailed)	.215	.000	.000	.000	.201	.000		.013	.000	.000	.701	.000	.000	.059	.341	.000	.000	.827	.723	.000	.866	.000	.000	.000	.000	.000		.031	.000	.384	.000	.000	.002	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X27) MEDIAN AGE OF NEAREST CENSUS TRACT	Pearson Correlation	-.052	.002	.011	.006	.019	-.093**	.c	-.014	-.056*	-.005	-.014	-.134**	.104**	-.002	-.029	-.156**	-.072**	.010	.007	-.116**	-.060*	.142**	-.041	.166**	-.106**	.109**	-.057*	1	.016	-.614**	-.134**	.786**	.807**	-.346**
	Sig. (2-tailed)	.052	.947	.687	.827	.479	.000		.594	.035	.844	.601	.000	.000	.953	.282	.000	.007	.720	.791	.000	.025	.000	.123	.000	.000	.000	.031		.549	.000	.000	.000	0.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X28) (% OF TOTAL POPULATION - AGE 0 TO 14)	Pearson Correlation	-.013	-.076**	-.149**	-.109**	.001	-.339**	.c	-.082**	-.232**	-.194**	.047	-.267**	.068*	.080**	.051	-.362**	-.347**	.055*	.044	-.327**	.070**	.234**	-.171**	-.374**	-.613**	.654**	-.496**	.016	1	-.239**	-.517**	.287**	.030	-.389**
	Sig. (2-tailed)	.636	.004	.000	.000	.981	.000		.002	.000	.000	.078	.000	.010	.002	.057	.000	.000	.037	.101	.000	.008	.000	.000	.000	.000	.000	.000	.549		.000	.000	.000	.257	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X29) (% OF TOTAL POPULATION - AGE 15 TO 24)	Pearson Correlation	.006	-.062*	-.055*	.005	-.021	.007	.c	-.094**	-.008	-.023	-.003	.077**	-.034	-.053*	.011	.033	.010	-.026	-.022	.005	-.162**	-.107**	.035	-.179**	.035	-.038	.023	-.614**	-.239**	1	-.401**	-.583**	-.383**	.063*
	Sig. (2-tailed)	.812	.019	.038	.854	.434	.783		.000	.758	.393	.903	.004	.202	.048	.689	.210	.714	.320	.407	.841	.000	.000	.187	.000	.188	.152	.384	.000	.000		.000	.000	.000	.017
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X30) (% OF TOTAL POPULATION - AGE 25 TO 44)	Pearson Correlation	.053*	.120**	.176**	.090**	.012	.338**	.c	.192**	.242**	.175**	-.016	.234**	-.117**	.003	-.028	.398**	.322**	-.011	-.022	.342**	.172**	-.182**	.128**	.320**	.523**	-.561**	.439**	-.134**	-.517**	-.401**	1	-.302**	-.321**	.558**
	Sig. (2-tailed)	.045	.000	.000	.001	.662	.000		.000	.000	.000	.550	.000	.000	.907	.294	.000	.000	.693	.415	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X31) (% OF TOTAL POPULATION - AGE 45 TO 64)	Pearson Correlation	-.041	-.044	-.057*	-.054*	.043	-.209**	.c	-.048	-.145**	-.098**	-.030	-.226**	.102**	.016	-.004	-.265**	-.190**	.023	.024	-.200**	-.006	.171**	-.126**	.008	-.327**	.347**	-.249**	.786**	.287**	-.583**	-.302**	1	.508**	-.448**
	Sig. (2-tailed)	.125	.099	.032	.041	.105	.000		.072	.000	.000	.252	.000	.000	.559	.890	.000	.000	.393	.362	.000	.809	.000	.000	.759	.000	.000	.000	.000	.000	.000	.000		.000	.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X32) (% OF TOTAL POPULATION - AGE 65 PLUS)	Pearson Correlation	-.075**	.027	-.005	-.001	-.024	-.084**	.c	-.061*	-.044	.030	.009	-.092**	.138**	-.017	-.028	-.184**	-.057*	-.016	.013	-.113**	-.125**	.151**	.009	.180**	-.074**	.084**	-.083**	.807**	.030	-.383**	-.321**	.508**	1	-.382**
	Sig. (2-tailed)	.005	.311	.837	.965	.373	.002		.022	.099	.255	.728	.001	.000	.512	.289	.000	.031	.557	.613	.000	.000	.000	.728	.000	.006	.002	.002	0.000	.257	.000	.000	.000		.000
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414
(X34) PEDESTRIAN DEMAND INDEX	Pearson Correlation	.066*	.077**	.141**	.066*	.012	.234**	.c	.157**	.188**	.119**	-.015	.255**	-.155**	.067*	-.011	.394**	.408**	-.018	-.007	.284**	.212**	-.194**	.090**	.079**	.322**	-.366**	.373**	-.346**	-.389**	.063*	.558**	-.448**	-.382**	1
	Sig. (2-tailed)	.014	.004	.000	.013	.641	.000		.000	.000	.000	.581	.000	.000	.012	.689	.000	.000	.503	.781	.000	.000	.000	.001	.003	.000	.000	.000	.000	.000	.017	.000	.000	.000	
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414	1414

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

c. Cannot be computed because at least one of the variables is constant.

Table A9-5. Stepwise Backward Elimination Process Using SPSS

A9-5 (a) Identifying Model Predictors Using Stepwise Backward Elimination for *y*

a. for y (all PVCs per Intersection)

b. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X2) CROSSWALK, (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

c. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

d. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

e. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

f. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET

CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

g. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

h. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

i. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

j. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

k. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

l. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

m. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

n. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT

o. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT

p. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT

q. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER

r. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER

A9-5 (b) Identifying Model Predictors Using Stepwise Backward Elimination for *yint*

a. for *yint* (all PVCs per Intersection that occurred 'at' Intersections)

b. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X2) CROSSWALK, (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

c. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

d. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

e. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

f. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18)

NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

g. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

h. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

i. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

j. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

k. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

l. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

m. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

n. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

o. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

p. Predictors in the Model: (Constant), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

q. Predictors in the Model: (Constant), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

r. Predictors in the Model: (Constant), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

s. Predictors in the Model: (Constant), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X22) STREET CLASSIFICATION, (X23) HOUSEHOLD INCOME, (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44)

A9-5 (c) Identifying Model Predictors Using Stepwise Backward Elimination for *ymid*

a. for *ymid* (PVCs per Intersection that occurred 'near' Intersections)

b. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X2) CROSSWALK, (X23) HOUSEHOLD INCOME, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

c. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X2) CROSSWALK, (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

d. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X14) SPEED HUMP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

e. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X4) RUMBLE STRIP, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

f. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X5) LANE DIVIDER, (X28) (% OF TOTAL

POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

g. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X9) TRAFFIC POLES, (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

h. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X24) WHITE ALONE (% OF TOTAL CENSUS TRACT POP), (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

i. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X27) MEDIAN AGE OF NEAREST CENSUS TRACT, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

j. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X26) OTHER (% OF TOTAL CENSUS TRACT POP), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

k. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X15) AREA OF SIDEWALK (SQFT), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

l. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17)

NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X7) PARKING SPACE MARKING, (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

m. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X31) (% OF TOTAL POPULATION - AGE 45 TO 64), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

n. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X28) (% OF TOTAL POPULATION - AGE 0 TO 14), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

o. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X1) STOP BAR, (X30) (% OF TOTAL POPULATION - AGE 25 TO 44), (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

p. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X29) (% OF TOTAL POPULATION - AGE 15 TO 24), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X1) STOP BAR, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

q. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X21) STREET DIRECTION (ONE OR TWO-WAY), (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X1) STOP BAR, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

r. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X16) NUMBER OF METRO STOP (WITHIN 0.25 MILE), (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X1) STOP BAR, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

s. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X17) NUMBER OF BUS STOP (WITHIN 100FT), (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP

(WITHIN 300FT), (X1) STOP BAR, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

t. Predictors in the Model: (Constant), (X32) (% OF TOTAL POPULATION - AGE 65 PLUS), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X1) STOP BAR, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

u. Predictors in the Model: (Constant), (X3) PUPPY TRACK, (X10) CAMERA ENFORCEMENT, (X13) SCHOOL CROSSING GUARD, (X11) STREETLIGHT, (X20) RESIDENTIAL LAND USE (BY DENSITY), (X12) OTHER TRAFFIC SIGNS, (X19) COMMERCIAL LAND USE (BY DENSITY), (X8) SIGNALIZED INTERSECTION, (X18) NUMBER OF BUS STOP (WITHIN 300FT), (X1) STOP BAR, (X25) BLACK OR AFRICAN AMERICAN ALONE (% OF TOTAL CENSUS TRACT POP)

APPENDIX 10. NEGATIVE BINOMIAL REGRESSION: SUMMARY OF PARAMETERS

Table A10-1. NB Model (Manual Elimination: *r* > 0.5) Excluding Exposure Variable

NB Regression (No Offset) Manual Elimination Method		*Model 1 (y)*				*Model 2 (yint)*				*Model 3 (ymid)*			
Xi	*Explanatory Variables*	*β*	*SE*	*Sig.*	*Exp(β)*	*β*	*SE*	*Sig.*	*Exp(β)*	*β*	*SE*	*Sig.*	*Exp(β)*
-	(Intercept)	.05	0.23	.826	1.05	-.72	0.26	.005**	0.48	-.54	0.30	.073*	0.58
X3	PUPPY TRACK	.05	0.06	.400	1.05	.02	0.06	.703	1.02	.10	0.07	.179	1.10
X4	RUMBLE STRIP	-.08	0.29	.780	0.92	-.60	0.56	.286	0.55	.15	0.31	.620	1.16
X5	LANE DIVIDER	.02	0.01	.138	1.02	.02	0.01	.086*	1.03	.01	0.02	.702	1.01
X7	PARKING SPACE MARKING	-.05	0.05	.250	0.95	-.04	0.05	.426	0.96	-.07	0.06	.265	0.93
X8	SIGNALIZED INTERSECTION	.23	0.09	.008**	1.26	.23	0.10	.018**	1.26	.28	0.11	.015**	1.32
X9	TRAFFIC POLES	-.4E-2	0.01	.778	1.00	.02	0.02	.277	1.02	-.04	0.02	.038**	0.96
X10	CAMERA ENFORCEMENT	.19	0.13	.143	1.21	.21	0.14	.135	1.23	.17	0.15	.262	1.19
X11	STREETLIGHT	.02	0.02	.236	1.02	.02	0.02	.420	1.02	.04	0.02	.119	1.04
X12	OTHER TRAFFIC SIGNS	.01	0.02	.469	1.01	.04	0.02	.063*	1.04	-.04	0.02	.134	0.96
X13	SCHOOL CROSSING GUARD	.22	0.14	.114	1.24	.19	0.15	.209	1.21	.31	0.17	.074*	1.36
X14	SPEED HUMP	.05	0.39	.900	1.05	.16	0.43	.710	1.17	-.15	0.51	.772	0.86
X15	AREA OF SIDEWALK (SQFT)	.00	0.00	.937	1.00	.00	0.00	.394	1.00	-.2E-4	0.00	.329	1.00
X16	NUMBER OF METRO STOP (WITHIN 0.25 MILE)	.08	0.07	.245	1.09	.08	0.08	.319	1.08	.08	0.09	.397	1.08
X18	NUMBER OF BUS STOP (WITHIN 300FT)	.06	0.03	.025**	1.06	.05	0.03	.077*	1.05	.07	0.03	.031**	1.07
X19	COMMERCIAL LAND USE (CLU)			.079*				.079*				.009**	
X19=4.00	CLU (HIGH DENSITY)	.23	0.14	.095*	1.26	.18	0.15	.222	1.20	.32	0.18	.073*	1.38
X19=3.00	CLU (MED. DENSITY)	.36	0.16	.027*	1.43	.43	0.18	.017**	1.53	.34	0.20	.092*	1.41
X19=2.00	CLU (MODERATE DENSITY)	.25	0.14	.089*	1.28	.08	0.16	.602	1.09	.56	0.17	.001***	1.74
X19=1.00	CLU (LOW DENSITY)	.16	0.11	.149	1.17	.09	0.12	.453	1.10	.29	0.14	.039**	1.34
X19=.00	NO CLU	0a			1.00	0a			1.00	0a			1.00
X20	RESIDENTIAL LAND USE (RLU)			.600				.600				.760	
X20=4.00	RLU (HIGH DENSITY)	.09	0.15	.531	1.10	.06	0.16	.708	1.06	.16	0.19	.415	1.17
X20=3.00	RLU (MED. DENSITY)	-.05	0.15	.747	0.95	-.20	0.16	.229	0.82	.14	0.18	.427	1.15
X20=2.00	RLU (MODERATE DENSITY)	.06	0.09	.539	1.06	.02	0.10	.841	1.02	.12	0.12	.296	1.13
X20=1.00	RLU (LOW DENSITY)	-.12	0.13	.360	0.88	-.20	0.15	.186	0.82	.00	0.18	.987	1.00
X20=.00	NO RLU	0a	0.14		1.00	0a			1.00	0a			1.00
X21	STREET DIRECTION (ONE OR TWO-WAY)			.704				.704				.165	
X21=2.00	TWO-WAY	-.03	0.09	.704	0.97	.06	0.10	.572	1.06	-.16	0.11	.165	0.86
X21=1.00	ONE-WAY	0a			1.00	0a			1.00	0a			1.00
X22	STREET CLASSIFICATION			.615				.615				.894	
X22=6.00	INTERSTATE	.05	0.67	.937	1.05	.49	0.70	.482	1.64	-1.04	1.14	.361	0.35
X22=5.00	OTHER FREEWAY	-.06	0.94	.951	0.94	-.55	1.29	.667	0.57	.34	1.02	.737	1.41
X22=4.00	PRINCIPAL ARTERIAL	.15	0.11	.172	1.16	.25	0.12	.035**	1.29	-.02	0.14	.877	0.98
X22=3.00	MINOR ARTERIAL	.11	0.09	.228	1.12	.17	0.10	.102*	1.19	.02	0.12	.888	1.02
X22=2.00	COLLECTOR	-.03	0.11	.773	0.97	-.09	0.12	.466	0.92	.08	0.13	.565	1.08
X22=1.00	LOCAL STREET	0a			1.00	0a			1.00	0a			1.00
X26	% OTHER THAN BLACK OR WHITE (CT)	.21	0.56	.710	1.229	.38	.612	.536	1.460	-.01	.712	.989	0.99
X30	% AGE 25 to 44 (CT)	.02	0.33	.951	1.02	.21	0.36	.560	1.24	-.30	0.43	.483	0.74
X31	% AGE 45 to 64 (CT)	-.23	0.60	.705	0.80	-.29	0.65	.662	0.75	-.09	0.78	.903	0.91

*significant at p ≤ 0.10; **significant at p ≤ 0.05; ***significant at p ≤ 0.01; Shaded numeric values represent parameters for significant variables; Dependent Variables: (Y)AllPVCs (Yint) IntPVCs, (Ymid) MidPVCs; Control Variable (offset term): AvgPDI; Negative β is highlighted in red and represents negative relationships between X and Y variables; a. Set to zero because this parameter is redundant.; (CT) refers to 'of total population or income in the census tract.'

Table A10-2. NB Model (Automatic Backwards Elimination) Excluding Exposure Variable

NB Regression (No Offset) Stepwise Backward Elimination		*Model 4 (y)*				*Model 5 (yint)*				*Model 6 (ymid)*			
Xi	*Explanatory Variables*	*β*	*Se*	*Sig.*	*Exp(β)*	*β*	*Se*	*Sig.*	*Exp(β)*	*β*	*Se*	*Sig.*	*Exp(β)*
-	(Intercept)	.18	.07	.010**	1.20	-.93	.13	.000***	.39	-1.04	.12	.000***	.35
X1	STOP BAR	-	-	-	-	.06	.02	.003**	1.06	-.05	.02	.022*	.95
X3	PUPPY TRACK	.05	.03	.081*	1.05	-	-	-	-	.10	.05	.049*	1.10
X5	LANE DIVIDER	.02	.01	.000***	1.02	.02	.01	.006**	1.02	-	-	-	-
X7	PARKING SPACE MARKING	-.05	.02	.033**	.95			-	-	-	-	-	-
X8	SIGNALIZED INTERSECTION	.24	.04	.000***	1.27	.22	.06	.000***	1.25	.30	.08	.000***	1.34
X10	CAMERA ENFORCEMENT	.17	.06	.007**	1.18	.19	.09	.028**	1.21	.18	.11	.107	1.19
X11	STREETLIGHT	.03	.01	.004**	1.03	-	-	-	-	.04	.02	.030*	1.04
X12	OTHER TRAFFIC SIGNS	-	-	-	-	.04	.01	.002**	1.04	-.04	.02	.013**	.96
X13	SCHOOL CROSSING GUARD	.20	.07	.002**	1.22	.17	.09	.075*	1.18	.23	.12	.061*	1.26
X16	NUMBER OF METRO STOP (WITHIN 0.25 MILE)	.10	.03	.002**	1.11	.09	.05	.053*	1.10	-	-	-	-
X18	NUMBER OF BUS STOP (WITHIN 300FT)	.05	.01	.000***	1.05	.05	.02	.006**	1.05	.06	.02	.010**	1.06
X19	COMMERCIAL LAND USE (CLU)	-	-	.000***	-	-	-	.000**	-	-	-	.000**	-
X19=4.00	CLU (HIGH DENSITY)	.23	.06	.000***	1.26	.24	.09	.005**	1.27	.37	.12	.002**	1.45
X19=3.00	CLU (MED. DENSITY)	.33	.08	.000***	1.40	.34	.09	.000***	1.40	.30	.14	.037*	1.35
X19=2.00	CLU (MODERATE DENSITY)	.25	.07	.000***	1.29	.07	.09	.459	1.07	.54	.12	.000***	1.72
X19=1.00	CLU (LOW DENSITY)	.19	.05	.000***	1.21	.18	.08	.015**	1.20	.25	.10	.013**	1.28
X19=.00	NO CLU	0a	-	-	-	-	-	-	-	0a	-	-	1.00
X20	RESIDENTIAL LAND USE (RLU)	-	-	.121	-	-	-	-	-	-	-	.628	-
X20=4.00	RLU (HIGH DENSITY)	.10	.07	.164	1.10	-	-	-	-	.14	.14	.298	1.15
X20=3.00	RLU (MED. DENSITY)	-.05	.07	.499	.96	-	-	-	-	.12	.13	.333	1.13
X20=2.00	RLU (MODERATE DENSITY)	.03	.04	.477	1.03	-	-	-	-	.04	.08	.596	1.04
X20=1.00	RLU (LOW DENSITY)	-.09	.06	.143	.91	-	-	-	-	-.07	.12	.584	.93
X20=.00	NO RLU	0a	-	-	1.00	-	-	-	-	0a	-	-	1.00
X22	STREET CLASSIFICATION	-	-	.004**	-	-	-	.000**	-	-	-	-	-
X22=6.00	INTERSTATE	.16	.32	.607	1.18	.61	.43	.157	1.85	-	-	-	-
X22=5.00	OTHER FREEWAY	.04	.45	.929	1.04	-.49	.83	.550	.61	-	-	-	-
X22=4.00	PRINCIPAL ARTERIAL	.17	.05	.001***	1.19	.29	.07	.000***	1.34	-	-	-	-
X22=3.00	MINOR ARTERIAL	.10	.04	.019**	1.11	.17	.07	.011**	1.18	-	-	-	-
X22=2.00	COLLECTOR	-.02	.05	.727	.98	-.08	.08	.264	.92	-	-	-	-
X22=1.00	LOCAL STREET	0a	-	-	-	-	-	-	-	-	-	-	-
X23	HOUSEHOLD INCOME (CT)	-.1E-5	.00	.002**	1.00	-.1E-5	.00	.124	1.00	-	-	-	-
X25	% BLACK (CT)	-	-	-	-	-	-	-	-	.40	.10	.000***	1.49
X29	% AGE 15 to 24 (CT)	-	-	-	-	.58	.20	.004**	1.79	-	-	-	-
X30	% AGE 25 TO 44 (CT)	-	-	-	-	.87	.24	.000***	2.39	-	-	-	-
X32	% AGE 65 PLUS (CT)	-0.75	.31	.017**	.47	-	-	-	-	-	-	-	-

*significant at p ≤ 0.10; **p ≤ 0.05; *** p ≤ 0.01; Shaded numeric values represent parameters for significant variables; Stepwise backward elimination method used to detect multicollinearity; a. Set to zero because this parameter is redundant; (CT) refers to 'of total population or income in the census tract.'

Table A10-3. NB Model (Manual Elimination: r > 0.5) Including Exposure Variable

NB Regression (Offset: Log of AvgPDI) Manual Elimination Method		*Model 7 (y)*				*Model 8 (yint)*				*Model 9 (ymid)*			
Xi	*Explanatory Variables*	*β*	*SE*	*Sig.*	*Exp(β)*	*β*	*SE*	*Sig.*	*Exp(β)*	*β*	*SE*	*Sig.*	*Exp(β)*
-	(Intercept)	-3.23	0.24	.000***	0.04	-4.05	0.26	.000***	0.02	-3.82	0.30	.000***	0.02
X3	PUPPY TRACK	.05	0.06	.349	1.05	.02	0.06	.692	1.02	.10	0.07	.151	1.11
X4	RUMBLE STRIP	-.16	0.30	.601	0.85	-.80	0.60	.186	0.45	.09	0.31	.761	1.10
X5	LANE DIVIDER	.02	0.01	.072*	1.02	.03	0.01	.032**	1.03	.01	0.02	.749	1.01
X7	PARKING SPACE MARKING	-.07	0.05	.166	0.94	-.06	0.05	.291	0.95	-.07	0.06	.248	0.93
X8	SIGNALIZED INTERSECTION	.22	0.09	.015**	1.24	.21	0.10	.035**	1.23	.27	0.11	.017**	1.32
X9	TRAFFIC POLES	-.1E-3	0.01	.994	1.00	.02	0.02	.168	1.02	-.03	0.02	.069*	0.97
X10	CAMERA ENFORCEMENT	.19	0.13	.131	1.21	.22	0.14	.118	1.24	.19	0.16	.230	1.20
X11	STREETLIGHT	.02	0.02	.419	1.02	.01	0.02	.611	1.01	.03	0.02	.219	1.03
X12	OTHER TRAFFIC SIGNS	.03	0.02	.152	1.03	.05	0.02	.013**	1.05	-.02	0.02	.369	0.98
X13	SCHOOL CROSSING GUARD	.09	0.14	.514	1.09	.07	0.15	.637	1.07	.18	0.17	.304	1.19
X14	SPEED HUMP	-.01	0.39	.970	0.99	.12	0.43	.779	1.13	-.20	0.51	.689	0.82
X15	AREA OF SIDEWALK (SQFT)	-.1E-4	0.00	.357	1.00	.00	0.00	.962	1.00	-.3E-4	0.00	.069*	1.00
X16	NUMBER OF METRO STOPS (WITHIN 0.25 MILE)	-.05	0.07	.455	0.95	-.06	0.08	.484	0.95	-.06	0.09	.494	0.94
X18	NUMBER OF BUS STOPS (WITHIN 300FT)	.05	0.03	.040**	1.06	.05	0.03	.109*	1.05	.07	0.03	.041**	1.07
X19	COMMERCIAL LAND USE (CLU)	-	-	.080*	-	-	-	.146	-	-	-	.011*	-
X19=4.00	CLU (HIGH DENSITY)	.32	0.14	.024**	1.37	.25	0.15	.100*	1.28	.44	0.18	.016**	1.55
X19=3.00	CLU (MED. DENSITY)	.30	0.16	.065*	1.35	.38	0.18	.033**	1.46	.28	0.20	.176	1.32
X19=2.00	CLU (MODERATE DENSITY)	.19	0.15	.187	1.21	.04	0.16	.815	1.04	.48	0.18	.006***	1.62
X19=1.00	CLU (LOW DENSITY)	.16	0.11	.166	1.17	.09	0.12	.470	1.09	.30	0.14	.036**	1.35
X19=.00	NO CLU	0a	-	-	1.00	0a	-	-	1.00	0a	-	-	1.00
X20	RESIDENTIAL LAND USE (RLU)	-	-	.814	-	-	-	.337	-	-	-	.995	-
X20=4.00	RLU (HIGH DENSITY)	-.04	0.15	.798	0.96	-.08	0.16	.601	0.92	.02	0.19	.913	1.02
X20=3.00	RLU (MED. DENSITY)	-.17	0.15	.235	0.84	-.33	0.16	.043**	0.72	.04	0.18	.841	1.04
X20=2.00	RLU (MODERATE DENSITY)	-.02	0.09	.823	0.98	-.06	0.10	.576	0.94	.05	0.12	.668	1.05
X20=1.00	RLU (LOW DENSITY)	-.06	0.14	.654	0.94	-.14	0.15	.376	0.87	.06	0.18	.754	1.06
X20=.00	NO RLU	0a	-	-	1.00	0a	-	-	1.00	0a	-	-	1.00
X21	STREET DIRECTION (ONE OR TWO-WAY)	-	-	.987	-	-	-	.348	-	-	-	.285	-
X21=2.00	TWO-WAY	.00	0.09	.987	1.00	.09	0.10	.348	1.10	-.12	0.11	.285	0.89
X21=1.00	ONE-WAY	0a	-	-	1.00	0a	-	-	1.00	0a	-	-	1.00
X22	STREET CLASSIFICATION	-	-	.352	-	-	-	.031**	-	-	-	.955	-
X22=6.00	INTERSTATE	.33	0.68	.631	1.39	.77	0.72	.280	2.17	-.84	1.16	.471	0.43
X22=5.00	OTHER FREEWAY	-.02	0.99	.987	0.98	-.56	1.38	.683	0.57	.27	1.05	.801	1.30
X22=4.00	PRINCIPAL ARTERIAL	.20	0.11	.077*	1.22	.30	0.12	.013**	1.35	.02	0.14	.904	1.02
X22=3.00	MINOR ARTERIAL	.14	0.09	.136	1.15	.20	0.11	.061*	1.22	.04	0.12	.714	1.05
X22=2.00	COLLECTOR	-.03	0.11	.792	0.97	-.07	0.12	.540	0.93	.08	0.13	.553	1.08
X22=1.00	LOCAL STREET	0a	-	-	1.00	0a	-	-	1.00	0a	-	-	1.00
X26	% OTHER THAN BLACK OR WHITE (CT)	-.42	0.56	.455	0.66	-.20	0.62	.751	0.82	-.65	0.72	.363	0.52
X30	% AGE 25 to 44 (CT)	-.83	0.34	.014**	0.44	-.63	0.37	.088*	0.54	-1.11	0.43	.010**	0.33
X31	% AGE 45 to 64 (CT)	1.31	0.61	.031**	3.69	1.24	0.66	.061*	3.45	1.38	0.78	.077*	3.98

*significant at $p \leq 0.10$; **$p \leq 0.05$; *** $p \leq 0.01$; Shaded numeric values represent parameters for significant variables;
Dependent Variables: (Y)AllPVCs (Yint) IntPVCs, (Ymid) MidPVCs; Control Variable (offset term): AvgPDI;
Negative β is highlighted in red and represents negative relationships between X and Y variables;
a. Set to zero because this parameter is redundant.; (CT) refers to 'of total population or income in the census tract.'

Table A10-4. NB Model (Automatic Backwards Elimination) Including Exposure Variable

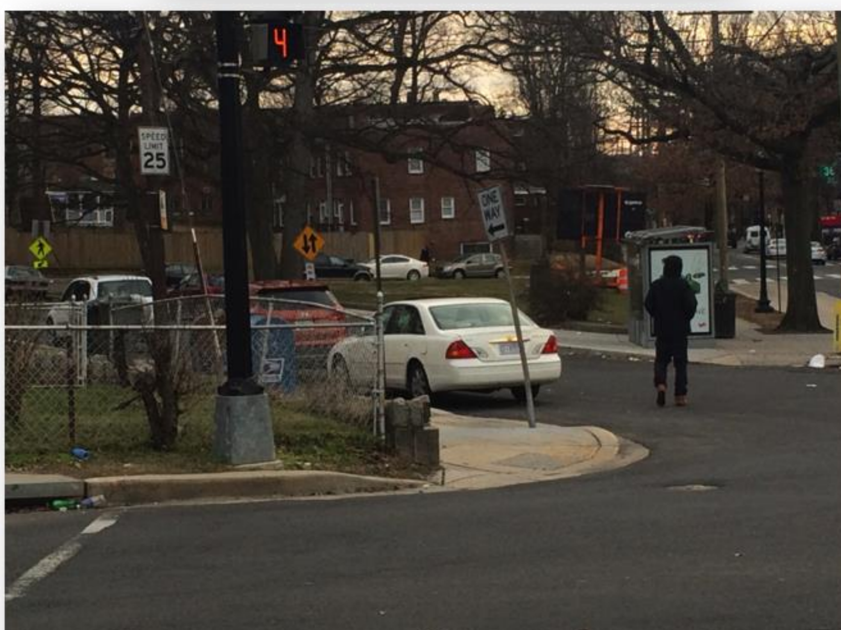
NB Regression (Offset: Log of AvgPDI) Stepwise Backward Elimination		*Model 10 (y)*				*Model 11 (yint)*				*Model 12 (ymid)*			
Xi	*Explanatory Variables*	*β*	*Se*	*Sig.*	*Exp(β)*	*β*	*Se*	*Sig.*	*Exp(β)*	*β*	*Se*	*Sig.*	*Exp(β)*
-	(Intercept)	-3.28	0.08	.000***	0.04	-3.54	0.14	.000***	0.03	-4.54	0.13	.000***	0.01
X1	STOP BAR	-	-	-	-	.05	0.02	.017**	1.05	-.06	0.03	.019**	0.94
X3	PUPPY TRACK	.04	0.03	.216	1.04	-	-	-	-	.09	0.05	.113	1.09
X5	LANE DIVIDER	.02	0.01	.005**	1.02	.03	0.01	.001***	1.03	-	-	-	-
X7	PARKING SPACE MARKING	-.07	0.03	.015**	0.94	-	-	-	-	-	-	-	-
X8	SIGNALIZED INTERSECTION	.22	0.05	.000***	1.25	.22	0.07	.002**	1.24	.27	0.08	.001***	1.31
X10	CAMERA ENFORCEMENT	.20	0.07	.005**	1.22	.22	0.10	.025**	1.24	.20	0.12	.077*	1.23
X11	STREETLIGHT	.01	0.01	.337	1.01	-	-	-	-	.02	0.02	.233	1.02
X12	OTHER TRAFFIC SIGNS	-	-	-	-	.05	0.01	.000***	1.05	-.02	0.02	.291	0.98
X13	SCHOOL CROSSING GUARD	.09	0.08	.259	1.09	.03	0.10	.776	1.03	.10	0.13	.430	1.11
X16	NUMBER OF METRO STOPS (WITHIN 0.25 MILE)	-.11	0.04	.004**	0.89	-.05	0.05	.325	0.95	-	-	-	-
X18	NUMBER OF BUS STOPS (WITHIN 300FT)	.06	0.01	.000***	1.07	.05	0.02	.014**	1.05	.06	0.03	.016**	1.06
X19	COMMERCIAL LAND USE (CLU)	-	-	.000***	-	-	-	.000***	-	-	-	.001***	-
X19=4.00	CLU (HIGH DENSITY)	.19	0.08	.011**	1.22	.31	0.10	.001***	1.36	.25	0.13	.049**	1.28
X19=3.00	CLU (MED. DENSITY)	.35	0.09	.000***	1.42	.23	0.11	.031**	1.25	.19	0.15	.210	1.21
X19=2.00	CLU (MODERATE DENSITY)	.20	0.08	.014**	1.22	-.04	0.11	.709	0.96	.45	0.13	.001***	1.57
X19=1.00	CLU (LOW DENSITY)	.19	0.06	.003**	1.20	.15	0.08	.073*	1.16	.31	0.11	.004**	1.37
X19=.00	NO CLU	0a	-	-	1.00	0a	-	-	1.00	0a	-	-	1.00
X20	RESIDENTIAL LAND USE (RLU)	-	-	.033*	-	-	-	.937	-	-	-	.775*	-
X20=4.00	RLU (HIGH DENSITY)	-.11	0.08	.208	0.90	-	-	-	-	-.01	0.15	.944	0.99
X20=3.00	RLU (MED. DENSITY)	-.25	0.08	.002**	0.78	-	-	-	-	-.05	0.14	.702	0.95
X20=2.00	RLU (MODERATE DENSITY)	-.04	0.05	.463	0.96	-	-	-	-	-.05	0.09	.581	0.95
X20=1.00	RLU (LOW DENSITY)	.02	0.08	.797	1.02	-	-	-	-	.11	0.13	.410	1.12
X20=.00	NO RLU	0a	-	-	1.00	-	-	-	-	0a	-	-	1.00
X22	STREET CLASSIFICATION	-	-	.011*	-	-	-	.101*	-	-	-	-	-
X22=6.00	INTERSTATE	.31	0.38	.413	1.37	.77	0.49	.117	2.16	-	-	-	-
X22=5.00	OTHER FREEWAY	.20	0.55	.715	1.22	-.59	0.98	.543	0.55	-	-	-	-
X22=4.00	PRINCIPAL ARTERIAL	.19	0.06	.002**	1.20	.31	0.08	.000***	1.36	-	-	-	-
X22=3.00	MINOR ARTERIAL	.11	0.05	.046**	1.11	.19	0.07	.010*	1.21	-	-	-	-
X22=2.00	COLLECTOR	-.03	0.06	.611	0.97	-.09	0.08	.283	0.91	-	-	-	-
X22=1.00	LOCAL STREET	0a	-	-	1.00	0a		-	1.00	-	-	-	-
X23	HOUSEHOLD INCOME (CT)	-.2E-5	0.00	.000***	1.00	.00	0.00	.937	1.00	-	-	-	-
X25	% BLACK (CT)	-	-	-	-	-	-	-	-	.75	0.11	.000***	2.12
X29	% AGE 15 to 24 (CT)	-	-	-	-	-.37	0.23	.101*	0.69	-	-	-	-
X30	% AGE 25 TO 44 (CT)	-	-	-	-	-1.10	0.27	.000***	0.33	-	-	-	-
X32	% AGE 65 PLUS (CT)	1.61	0.38	.000***	5.00	-	-	-	-	-	-	-	-

*significant at $p \leq 0.10$; **$p \leq 0.05$; *** $p \leq 0.01$; Shaded numeric values represent parameters for significant variables;
Stepwise backward elimination method used to detect multicollinearity;
a. Set to zero because this parameter is redundant; (CT) refers to 'of total population or income in the census tract.'

APPENDIX 11. PHOTOS OF TOP 7 CASE STUDY INTERSECTIONS

1. **Wheeler Rd. & Southern Ave. SE**

2. Minnesota Ave. & B St. SE



3. Montana Ave. & Rhode Island Ave. NE

4. Pennsylvania Ave. & Alabama Ave. SE

1. South Capitol St. SE & Atlantic St. SW

5. Minnesota Ave. & Pennsylvania Ave. SE

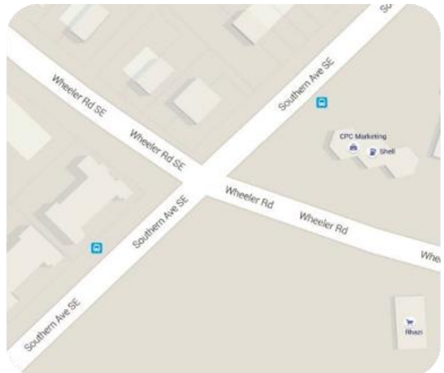
6. South Capitol St. & Southern Ave. SE


THRIFT


W19 INDIAN HEAD
S170
metrobus

APPENDIX 12. ROAD GEOMETRIES OF TOP 7 CASE STUDY INTERSECTIONS

1. **Wheeler & Southern**



2. **Minnesota & B**

3. **Montana & Rhode Island**

4. Pennsylvania & Alabama

5. South Capitol & Atlantic

6. Minnesota & Pennsylvania

7. S. Capitol & Southern

Image Credit: Google Maps

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