THE EFFECT OF CRIME ON RIDERSHIP

AN IN-DEPTH ANALYSIS OF HOW TRANSIT STATION NEIGHBORHOOD CHARACTERISTICS PREVENT CRIME AND ENCOURAGE RIDERSHIP

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Abstract

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Factors influencing public transit ridership have been widely explored in recent decades. While planners believe that density and mixed land use around transit stations will increase public transit ridership, criminology studies claim that transit stations and their surrounding environments are more prone to criminal activities due to high levels of movement and interaction between unknown persons. This study aims to investigate the impact of crime on Light Rail Transit (LRT) ridership.

Using the geo-locating technique, this study analyzes the spatial distribution of crimes in the half- mile buffer around stations in six Metropolitan Statistical Areas (MSAs): Dallas, Miami, Salt Lake City, Minneapolis, San Diego, and San Francisco. The research also applies Path analysis using Structural Equation Modeling to model the effects of station neighborhoods characteristics, built environment factors and land use

attributes and crimes on LRT ridership. The unit of analysis is the half mile buffer around transit stations.

The results show mixed land use has a direct positive significant effect on ridership. Additionally, density has an indirect positive influence on ridership and a direct positive effect on crime as well. Also, there is a full mediation exists between density, crime, and ridership. The model outcome indicates crime has a positive impact on ridership. This positive effect reflects a rise in ridership associated with an increase of criminal incidents due to high activity and high demand of public transit use by captive riders.

The additional analytical section compares regions on factors including walkability and the vegetation around the LRT stations. The ANOVA and Post Hoc test results indicate that Salt Lake City has the lowest walk score among other regions with Dallas having the next lowest walk score region compared to San Francisco and Minneapolis. Miami and San Diego do not have any apparent significant difference in mean score compared to other regions.

This study's contribution is examining the role of crime on ridership. Although transit-oriented development policies encourage density around the stations, density may threaten the area by attracting criminal activities. Crime prevention through environmental design guidelines could be followed that could change the impact of density on crime attraction around stations and deter crime. However, the most important step is creating a sense of community through an all-inclusive approach to physical, social, and economic development.

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Chapter One

Introduction

Public transit is a vital component to the social and economic development of a metropolitan area. Public transit supports social integration and access to services by playing an important role in the life of a city and its citizens (D'Alessandro, 2003). While cities experience day to day changes, significant developments result from investments in transportation infrastructure (Cervero et al., 2002). The mutual and tied relationships between transportation investments and potential economic growth have encouraged city planners, transit officials, and citizens to welcome mass transit into their neighborhoods as a tool to achieve economic development in their cities (Loukaitou-Sideris, 2000).

It is a common reality that some transit passengers face and tolerate the fear of crime when using mass transit. The fear of crime is influenced by the actual and indirect victimization experiences reported by the media and other people. Social and physical environments in and around mass transit systems could also contribute to fear of crime for transit users (Lusk, 2001). People may be deterred from using public transit due to concerns of potential threats—disorderly conduct, robbery, etc.— at, or around, transit stations (Loukaitou-Sideris, Liggett & Iseki, 2002).

Incidents of crime affect people's decisions to use public transit and cause a loss in ridership and transit demand. Such losses threaten the long-term viability of metropolitan areas, limiting the growth of transit systems and economic development (Guinn, 2013). Thus, increasing passenger safety and security is a top priority of many transit agencies (Cobb and Needle, 1997). Hazaymeh (2009) noted the perception of safety is just as important as personal safety in choosing whether to use transit. A transit system that reduces perceived fear could potentially lead to increased ridership (Hazaymeh, 2009).

Public transit authorities often inform the public of improvements in station safety to attract ridership. For example, in 2012 the Massachusetts Bay Transportation Authority reported a drop of 11% in serious crime rates at stations and along transit lines, which was associated with an average increase of 1.3 million passengers per day (Zhang, 2016). Additionally, crime is tied to the physical distribution of individuals, the routines of everyday life, and the perception and use of information about the environment (Brantingham and Brantingham, 1993). Criminology studies could help to discover the more in-depth relationship between location and crime.

Theorists see transit stations and their close neighborhoods as prime platforms where crime against persons can be facilitated. Stations concentrate large numbers of people that can become targets for pickpocketing, purse snatching, and robbery (Guinn, 2013). In transit nodes, the potential for transitory clustering of individuals, paths of travel, and destinations create settings for crime opportunities to take place. Therefore, transit stations tend to attract and generate crime due to their ability to gather large crowds of people travelling to work, shopping, or enjoying recreation along a limited number of pathways (Brantingham et al, 1991; Loukaitou-Sideris et al., 2002).

Certain physical and social characteristics, such as shrubbery (vegetation) and high density development, found at transport nodes may draw the attention of criminally motivated persons. (Ceccato, 2014). Built environment and socioeconomic characteristics of neighborhoods around the transit station play an important role in exposing transit nodes to crime. Social interactions, including those that result in victimization, are dependent on multiscale conditions in an urban environment (Ceccato, and Uittenbogaard, 2014).

These conditions are determined by the environmental attributes of the transport node (e.g., a station), the type of neighborhood in which the station is located, and the relative position of both the station and the neighborhood in the city (Ceccato et al., 2013).

The high possibility of crime incidents and reported crime occurrences at transit stations increase fear of using public transportation, which lead to ridership reduction. Therefore, it is important to further investigate this concern for a better understanding of the factors that constitute transit crime and their effect on ridership.

Despite the many recognized studies that explore the interconnections between crimes and neighborhood built environments, as well as safety concerns of public transit (Loukaitou-Sideris et al., 2002; Irvin-Erickson and La Vigne, 2015), limited studies investigate the effect of crime on transit decisions or ridership (Zhang, 2016). Furthermore, the few studies that have examined the effect of crime on mode choice, claim the causal relationship between reported crime and transit use remains ambiguous (Gallison, 2012). Moreover, most studies have documented transit crime in heavy-rail systems, buses, or underground stations. There is very little documentation of transit crime around light-rail systems, even though such systems have mushroomed in North American cities in the past two decades (Loukaitou-Sideris et al., 2002).

Research Objectives

As previously mentioned, public transit is a vital component of social and economic development; however, public transportation is still not the preferred choice for commuting among average Americans (American Community Survey, 2010). Safe access to transit is one of the most crucial components for fostering public transportation use. Crime incidents undoubtedly affect people’s decisions to use public transit and cause a loss in ridership and transit demand.

According to the criminology studies, crime is tied to individual’s physical locations, the routines of everyday life, and the perception and use of information about the environment. Based on this theoretical assumption, studying built environment and social characteristics related to crime around light rail transit (LRT) stations are important. As Zhang (2016) claims, studies addressing the effects of crime on transit decisions or ridership are limited and very little documentation of transit crime around light-rail systems exists.

Moreover, researchers often use people’s perceived fear of crime to measure safety (Berra, 2009), and perception as compared to actual crime incidents. According to Zhang (2016), the association between the objective reported crime level and the subjective feeling of crime is not strong. As such, in this study, the crime incidents at the station level were selected to have more actual data on criminal activities (Zhang, 2016).

This study not only tries to measure the impact of crime incidents around the LRT stations and its influence on ridership, but also, it aims to examine transportation policies including built environment characteristics, especially density. There are several studies on density and design to encourage public transportation ridership (Cervero and Kockelman, 1997; Cervero et al., 2002; Ewing and Cervero, 2010; Cervero and Sullivan, 2011); however, there are fewer studies on crime as an influential factor in transportation use.

With a focus on the impact of crime on LRT ridership, the main questions examined in this research to comprehensively analyze the impact of crime on ridership are the following:

- How does crime affect LRT ridership?

- Does density affect crime and ridership?
- Does density increase crime rates around the LRT stations?
- Is crime a mediation factor between socioeconomic characteristics of the neighborhood around the station and ridership?
- How does walkability influence ridership with mediation of crime?
- How does mixed land use influence ridership with mediation of crime?
- How does walkability affect crime?
- Does vegetation or tree canopy have an effect on crime?

To answer the research question statistically, the following hypotheses may frame the research methodology:

- Crime incidents around transit stations impact ridership.
- Crime in high density areas around transit stations has a positive impact on ridership.
- Crime in mixed land use neighborhoods around transit has a positive impact on ridership.
- The low socioeconomic status of neighborhoods around the stations has direct and indirect effects on ridership and crime.
- Vegetation has a negative impact on crime.
- Walkability has an impact on crime.

Testing these hypotheses could provide great insight into the factors influencing ridership with a focus of the impact of crime on ridership and factors influencing crime within a half-mile buffer around LRT stations.

Empirical Analysis

This study is distinct from other studies in its attempt to fill the gaps of previous research.

First, the Structural Equation Modeling (SEM) provides the best view of the causality relationship between crime and ridership. Second, the case study of LRT stations in the metropolitan statistical areas (MSA) level has not been examined in other studies.

The development and application of a statistical model explaining crime incidence around stations (half-mile buffer) attempts to measure the strength of relationships between crime and selected characteristics of the socioeconomic demographic and physical environment with LRT ridership.

Data

Independent variables include the population and employment around the station within a half-mile buffer radius, land use, average block size in acres, socioeconomic characteristics of the population around the station, density, vegetation, and walkability derived from the literature review.

The data records for monthly LRT ridership and all crime incidents were obtained for the following six MSAs selected as sample targets:

1. Dallas-Fort Worth-Arlington (Dallas Area Rapid Transit [DART])
2. San Francisco-Oakland-Fremont (Bay Area Rapid Transit [BART])
3. San Diego (Metropolitan Transit system)
4. Salt Lake City (Utah Light Rail [UTA])
5. Minneapolis (Metro Transit)
6. Miami (Metrorail)

These MSAs were selected based on close rates of ridership per year.

Statistical Approach

This research adopts a comprehensive framework for analyzing factors influencing LRT ridership with a focus on the impact of crime on ridership, the built environment, and socioeconomic characteristics of the neighborhoods around the stations.

Path analysis was used to break down the correlations among variables into casual and non-casual components. Path analysis helps researchers disentangle the complex interrelationships among variables and identify the most significant pathways involved in predicting an outcome (Kline, 2011).

To conduct the path analysis, Structural Equation Modeling (SEM)—a powerful multivariate technique—was applied to test the interactive relationships between variables as a confirmatory, rather than exploratory method (Golob, 2003). The positive and unique feature of SEM is the ability to test network structure (Gargoum and El-Basyouny, 2016). In other words, SEM tests whether the effect of independent variables on ridership is direct or crime has a mediator role in the model.

Applications of Research

This study first evaluates the impact of crime on ridership and then examines whether crime is a mediator factor between the independent variables—built environment and socioeconomic characteristics—and the dependent variable, ridership. By including vegetation and walkability factors in the model and studying the impact of these factors on crime, this study uses a holistic approach to include neighborhoods characteristics and structure around the stations and their impact on ridership. The goal of this research is to add another perspective to Transit Oriented Development (TOD) policies and add an in-depth analysis on the impact of high density areas around the stations by focusing on crime.

As mentioned in the criminology literature review, the possibility of crime incidents in high density areas is higher especially around the stations. Therefore, it is important to focus on built environment factors around the station for sustainable growth and ridership. This research explores the relationships between important factors effecting ridership considering crime as a mediating factor.

Dissertation Structure

This study includes six chapters. Chapter one is an introduction to crime and ridership. This chapter briefly explains the related background and theories. It then discusses the gap in the literature review, questions, hypotheses, and how to address the problem.

Chapter two presents the literature review and previous studies on different factors influencing ridership with a focus on the relationship between crime and LRT ridership. It discusses why transit stations are prone to criminal activities and how it affects ridership. The last part of this chapter is dedicated to crime and locational theories such as rational choice theory, routine activity theory, geometry of crime theory, and crime prevention through environmental design.

Chapter three begins with the theoretical framework and factors affecting ridership, such as crime and built environment and socioeconomic factors followed by vegetation and walkability scores.

Chapter four explains research methodology and the process of data gathering and cleansing. This chapter explains the data sources and data integration to the research model, as well as identifies the hypotheses and factors to examine. Additionally, the remainder of the chapter details the analytical methodology explaining the statistical methods, their weakness and strengths. This section describes the MSAs that were studied in the research. The comparison between demographic status, ridership, and crime is made to garner a better picture of sample data.

Chapter 5 provides the empirical analysis and begins by describing the results of the SEM model. This is followed by a summary of the criteria for model validation and an explanation of the relationships and effects of factors on each other, including direct, indirect, and total effects. The mediation relationship is also explained in this chapter. The second part is about ANOVA test to see which region has different walkability and density than the other regions.

Chapter 6 summarizes the major results of this study. It discusses the policies related to the crime prevention through environmental design and transit-oriented development (TOD) polices. In addition, the final chapter includes detailed explanation on the research limitations and the study's contribution to the literature. Also, explains future research recommendation on increasing ridership and protecting people from possible criminal activity through environmental design and create safe and sustainable growth around transit stations.

Chapter Two

Introduction

This chapter reviews the literature on factors influencing ridership followed by a background study of public transportation and crime. It highlights crime's impact on public transit ridership. Moreover, the chapter reviews relevant theories supporting the rational choice theory and the occurrence of crime in public spaces. Against that backdrop, this study is interested in crime that occurs within a half-mile buffer around public transit stations.

Taking crime into account, the study will also explain the reasons offenders choose this platform to commit their criminal activities.

It also considers the environmental role in the occurrence of crime by incorporating the approach of Crime Prevention Through Environmental Design (CPTED) to understand crime and its respective built environment. Moreover, the study conceptually links the notion of crime to established locational theories such as rational choice theory (RCT), routine activity theory (RAT) and geometry of crime theory (GOC), to get a comprehensive insight of crime.

The aforementioned concepts of crime discussed and the social factors of crime examined below underpin this dissertation's theoretical framework.

In addition, this chapter develops the conceptual definitions of crime and its occurrences related to public transit, specifically light rail systems (LRT) stations, by describing related theories on crime and ridership. Studying crime incidents limited to burglary, theft, robbery, and assault affords greater insight into social and built environment factors in the context of transit stations and their surrounding neighborhoods.

Travel behavior, transit stations and crime

To this end, the environment plays an essential role shaping crime patterns around transit stations. Previous studies and relevant criminological theory demonstrate the important role of environmental factors of crime incidents around stations. Recent Studies show transit environments, such as transit stations, are more prone to crime (Block and Davis, 1996; Clarke, 1996; La Vigne, 1997).

That being said, interchanging large flows of users and fast pace motion with potential criminal incidents, transit stations are considered to be crime generators and crime attractors. In fact, some physical and social characteristics found at transport nodes pull motivated offenders towards them and may also draw the attention of people with high levels of criminal motivation (Brantingham and Brantingham, 1993, 1995).

Reducing automobile use has been a long-standing goal among transportation planning and engineering professions for environmental, economic, and public health reasons (Ferrel and Mathur, 2012). To achieve this goal, numerous studies have been conducted to travel behavior with respect to travel mode choice.

The term “mode choice” refers to the type of transportation mode (i.e., bus, rail, walking, and driving) that people choose for individual trips from one point to another. According to transportation theory, individual mode choice depends on the usefulness and costs involved in using a travel mode (Taylor et al., 2009). This research focuses on LRT among all public transportation modes.

In a 2007 study conducted by Kim, Ulfarsson, and Hennessy, they explored the decisions people make when choosing a mode of transportation. They focused on LRT passenger of St Louis MetroLink light rail system (Metro) and analyzed the mode choice to transit stations among LRT riders. They emphasized travel mode and the choice of trips that originated from and traveled to as destination.

The analysis of mode choice is Multinomial Logit model as a discrete choice modeling approach. The model results show that reported crime frequency discourages the use of pick-up or drop-off at stations and passengers' fear of crime may be the most important reason for LRT and bus ridership reduction (Kim et al., 2007).

In recent years, LRT systems have gained growing popularity in American cities and have been developed as a safe and reliable high-capacity public transit system compared to heavy-rail transit. In fact, one of the main goals for cities and transit agencies is to maintain sustainable mobility and promote smart growth by increasing transit ridership on LRT (Kim, Ulfarsson, and Hennessy, 2007). As compared to heavy-rail, LRT systems have a significantly lower capital cost, which is appealing to many cities across the United States.

Furthermore, many additional factors influence ridership on LRT, such as density and socioeconomic characteristics (Kim, Ulfarsson, and Hennessy, 2007). According to previous studies, factors influencing mode choice and ridership can include proximity to transit, income, employment type, cars per household, size of family, and cost of housing (i.e., the tradeoff between transportation and rent costs).

Crime and Ridership

Kim (2007) contends that passengers' fear of crime may be the most important reason for the absence of an increase in LRT ridership. In fact, many passengers choose not to use transit due to personal safety concerns (Loukaitou-Sideris et al., 2002; Irvin-Erickson and La Vigne, 2015; Delbosc and Currie, 2019).

Similarly, both criminology and transportation literature identify a range of factors that can influence whether people believe they are at risk of being a victim of crime including gender, age, socioeconomic status, ethnic background, and neighborhood conditions.

The criminology literature discusses the considerable importance of neighborhood and psychological characteristics as it relates to safety and security (Delbosc and Currie, 2012).

The real and perceived risks of victimization are an important consideration when making travel decisions. Crime patterns for pick-pocketing, bag-opening and low-level sex crimes occur most often in high-target densities (Clarke et al., 1996).

The type of crime that public transit riders experience is usually called quality-of-life offences, which include such acts as fare evasion, vandalism, graffiti, littering, and various disorderly conducts. Comparing to other public places around the city, crime incidents around transit stations includes high levels of minor or quality-of life offences (Loukaitou-Sideris et al., 2002). These crimes were traditionally thought to be victimless and thus not serious crimes. However, it was recently recognized that the quality-of-life offences have huge impacts on fear levels and desirability of the services (Morgan and Cornish, 2006).

Although relatively few studies have directly examined the effect of crime incidents around stations on light rail ridership, all suggest a complex interaction between urban environments, perception of crime, and travel behavior. For example, a survey of adults carried out by Ingalls, Hartgen, and Owens (1994) applied different methods to ascertain the factors affecting personal safety perceptions on transit use such as, structural equation modelling and personal interviews. The researchers discovered that the fear of using public transit mainly came from people feeling unsafe feeling about their living communities and not transit itself.

The relationship between fear of crime and travel behavior has been studied in many scholarly papers (Zhang, 2016; Ingalls et al.,1994).

They surveyed the riders and residents in Greensboro, North Carolina and found that that fear of crime on buses and near bus stops is a critical factor that deters transit use (Ingalls et al., 1994).

Barrera (2009) also studied the perception and fear of crime on transit in Houston, Texas. He concluded a positive correlation between the people who had been crime victims on transit and people concerned about their safety on transit.

In a recent case study of the City of Chicago, IL, Halat et al. (2015) modeled transit access mode choice as a function of socio-demographics, neighborhood crime density, and walk score (as a measure of walkability).

Their results show both built environment (walk score) and their crime index at the destination can be meaningful predictors of individuals' mode usage. Also, Ferrell and Mathur (2012) found high-crime neighborhoods were "positively associated with transit mode choice," while they were negatively associated with walking. Using a multi-nominal logistic model, the authors suggest both positive and negative associations could exist in the crime–ridership connection.

Moreover, Zhang (2016) used a path analysis method to study crime in more compact land use areas and their impact on public transit use. The results demonstrate higher population density and more mixed land use have significant and positive association with more crimes near the bus stops. Also, his research concluded that the level of crime has a nonlinear effect on ridership. He explained that when the number of incidents crosses a threshold, ridership is negatively affected.

In and around the transit stations, safety is dependent on multi-level conditions in an urban environment. These conditions are determined by the environmental attributes of the station, the characteristics of the immediate environment, the type of neighborhood in which the station is located, and the relative position of both the station and its neighborhood in the city (Loukaitou-Sideris et al, 2002; Ceccato, 2013).

Providing safety around transit stations as public and semi-public urban spaces are amongthe priorities of urban planners and security forces. Transit stations are especially disposed to crime because of the large number of potential targets available for offenders to victimize.

Commuters represent easy targets for an offender to commit a crime against. Most commuters are tired, preoccupied, and usually tend to carry purses, bags, and other small packages with valuable objects within them (Myhre and Rosso, 1996). As transit stations supply many targets, there are optimal settings for criminal opportunities (Gallison, 2012).

As outlined in crime pattern theory, criminal decisions are affected by the environmental backcloth (the elements of an environment such as land use, design features, physical infrastructure of buildings, and transit hubs) that can influence people's criminal behaviors (Brantingham and Brantingham 1981).

In the node-place model of Bertolini (1996), the first node variable, "Connectedness," measures the connectedness of each station to the rest of the transit system. The better a station is connected to the rest of the transit system, the more potential victims and targets it will converge spatiotemporally. Thus, this nodal characteristic is assumed to be a crime-generating characteristic.

The second node variable, "Remoteness," measures the remoteness of the station from the center of the transit system. This nodal characteristic is assumed to be a crime attracting elements. Remote stations are reported to have higher rates of crimes, because they provide unique opportunities for crimes such as disorderly conduct, graffiti, and vandalism (Ceccato et al. 2013). These types of crimes are more likely to attract offenders who are seeking targets that lack guardianship.

Why Transit stations?

Many factors influence crime in general, but crime related to transit stations are typically influenced by certain characteristics of a specific location. The question is how to define the boundaries around the station to have the best analysis of crime patterns in and around transit stations.

The environment plays an essential role shaping crime patterns around transit stations. Previous studies and relevant criminological theory demonstrate the important role of the environmental factors of crime incidents around stations. Recent studies showed some transit environments—such as transit stations—are more prone to crime (Block and Davis, 1996; Clarke, 1996; La Vigne, 1997). The interchange of a large flow and past face of users at a transit station tend to attract crime and generate criminal incidents. In fact, some physical and social characteristics such as density, income level, and unemployment draw motivated offenders to commit crime around stations (Brantingham and Brantingham, 1993, 1995).

Chorus and Bertolini (2011) studied train stations, the type of train connections, proximity to central business district, and number of bus lines from a station to identify the node value of a station. Their work is based on the node-place model of Bertolini (1996), which identifies the relationship between transit and land use factors of station area development. They claim the place value of a station is defined by the population, economic clusters, and degree of multi-functionality around the stations.

Block and Davis (1996) examined spatial patterns of street robbery in four Chicago Police Districts. In two districts with low robbery rates, street robberies were concentrated near rapid transit stations; whereas, in the two high crime districts the concentrations were less noticeable. In high crime areas, robberies were most likely to occur along main streets. In a separate study, Block and Block (2000) examined street robberies in the surrounding areas of rapid transit stations in Chicago and the Bronx, NYC, and found that street robberies were concentrated around the stations. The authors claimed that the existence of both legal and illegal activities around the transit stations explained clustering of street robberies around the stations (Block and Block, 2000). They also examined the crime cluster distance from the stations and found that street robberies happened in a short distance (650 feet) away from the stations rather than the immediate neighborhoods of the stations. Comparing to further distance (1,200 feet), the existence of a rapid transit station did not seem to influence occurrences of street robberies. Therefore, it could be concluded that neighborhood characteristics play an important role in creating crime patterns around the stations (Yu, 2009).

For the same reason, in affluent areas a persistent belief that public transit will provide access for inner-city offenders to suburban areas where undiscovered attractive crime opportunities are abundant; therefore, expanding light rail or subway systems to affluent areas often raise concerns about crime and property values in the neighborhoods (Liggett et al., 2003). Also, Loukaiyou-Sideris studied the relationship between the social and physical characteristics of their neighborhoods and crime rates of the Green Line in Los Angeles, California. The data analysis showed that the low crime stations were in wealthy suburban communities with low crime rates. They found that except for motor vehicle theft, the station crime rates were directly related to the crime rates in the station neighborhoods. It is also important to mention that the Green Line is a light rail system employing an honor system without any barriers to the stations (Loukaitou-Sideris et al, 2002).

Guardianship is another important factor to control crime rate. Crimes are more conducive when the areas are relatively isolated, which leads to lack of guardianship (Block and Davis, 1996). Decreased levels of guardianship are often used to explain increased risks of victimization where the levels of population or density are low. For instance, Clarke and his associates (1996) examined robberies on the NYC subway platforms. The authors found that the risks of robberies increase as the densities of passenger decreased in 206 NYC subway stations.

Subway station parking lots are also an issue of concern with reported higher rates of crime incidents. Parking facilities can also provide opportunities to commit other types of crime such as an assault or robbery. As found by Loukaitou-Sideris and her colleagues (2002), in one of two high crime Green Line Stations, 60 percent of Type I crime—homicide, rape/attempted rape, assault, larceny, grand theft, and burglary—occurred in the park-and-ride lots, while only twenty percent of them occurred on the platform.

However, there is a difference between above the ground transit stations and under ground stations. LaVinge (1997) claimed that there would be enough differences in crime rates between above and below ground if the public transit system were able to keep criminals from entering to the underground transit environments. He said well-designed transit stations with access control can prevent criminals from the above-ground transit stations. In his study, he compared Washington D.C. Metro systems and crime rates of above-ground area. The study showed that assault was the only crime type displaying significant positive correlations with the above-ground crime levels. Meanwhile, Clarke and his colleagues (1996) reported a similar finding. They found that the NYC Subway station robbery rates were not correlated with the above-ground robbery rates at the precinct level. However, they also found substantial variations in robbery rates among the stations within each precinct (Clarke et al., 1996). Because NYC subway systems were not designed uniformly as the Washington D.C. Metro, this finding is probably not surprising.

Theoretical Perspective on Location and Crime

In this study, both ecological and non-ecological approaches are applied to examine the relationship between crime and transit station and their impact on ridership. This chapter covers theories explaining how to perceive crime and location linkage.

Historically, some theoretical approaches explain the concept of crime and location. Loukaitou-Sideris (2002) in her study of “Geography of Transit Crime”, divided crime theories in two main categories: compositional (or non-ecological) theories and ecological theories. She explained that non-ecological theorists typically argue that crime rates can be adequately explained by the socio-demographic characteristics of urban residents (age, ethnicity, class, social mobility, etc.) and economic factors affecting their neighborhoods (e.g., poverty, unemployment, inequality, etc.). Ecological theorists, on the other hand, attend to the context in which a crime takes place. Consequently, their emphasis is concentrated on analyzing where, when, and how crime occurs (Brantingham and Brantingham 1981).

Rational Choice Theory

Becker (1968) stated that criminal behavior can be examined similar to how economists analyze consumer choice. Just like business owners, criminals consider the costs and benefits of using their assets and time and will decide whether crime is the most profitable occupation or hobby. Therefore, studies on criminal decision-making assume that criminals are “rational” beings. For each attempt, they decide whether a crime is worth the risk of getting caught or not by weighing the costs and benefits associated with the crime (Cornish and Clarke, 1986).

Rational choice theory (RCT) was stablished by Cornish and Clarke. they published Reasoning Criminal in 1986 and outlining the conscious decision-making of offenders who choose to commit crime. The theory assumes that when an offender makes a ‘rational’ decision as to whether to commit a crime, individual processes information from both their physical and social environments (Cornish and Clarke, 1986). This behavior is influenced by a wide spectrum of factors, such as previous experiences and background, assessment of general needs, evaluation of real and perceived solutions, chance events, readiness, and decisions.

RCT reflects the complexity of the decision-making process when an offender chooses to commit any action (Gallison, 2012). Thus, the rational choice perspective assumes criminals are motivated, but they might be discouraged from committing a crime if they perceive a potential target to be too risky due to the effort involved (La Vigne, 1997).

RCT outlines the conscious decision-making process of offenders who choose to commit crimes by evaluating the situation. They make the decision based on physical and social environments (Cornish and Clarke, 1986). According to this theory, criminals choose their target and target area, including transit stations, based on their prior experiments.

Routine Activity Theory

Lawrence Cohen and Marcus Felson (1979) proposed Routine Activities Theory (RAT) to explain crime through the structural changes within the daily routines of offenders and victims. They claimed that the temporal and spatial patterns of interaction with different people through changing routines increased the likelihood of becoming a victim of a crime (Gallison, 2012).

They propose that three minimal elements must be present for a crime to occur. Elements include a suitable target (a person or a piece of property), a motivated offender, and a lack of a capable guardian (anyone who engages in protective behaviors for family, friends, strangers, and property). According to the RAT, criminal incidents happen based upon three key principles:

1- Participant Principle: Each type of crime depends upon presence or absences of certain participants.

2- Behavior Settings Principle: The community Is divided into many behavior settings: slices of time and place where various activities occur, whether legal or Illegal, orderly, or disorderly.

3- Flows Principle: People flow from one behavior setting to another. In the process, a legal behavior setting sets the stage for an illegal behavior setting nearby in time and space. (Felson et al, 1996; p: 75)

Individuals who use public transportation tend to travel based on regular schedules. Most people are traveling based on regular commuting times during the early morning and late afternoon to and from work. Foreseeable commuting times can lead to several criminal opportunities. This notion draws on Cohen and Felson’s (1979) Routine Activities Theory. Additionally,

The influential environmental factors for criminals to make decisions are the context, the elements of an environment such as land uses, design features, and physical structure of buildings around transit stations (Brantingham and Brantingham 1981).

Crime occurs as a result of daily routines templates of both offenders and victims. This template creates people's awareness space (Gallison, 2012), which is studied in crime pattern theory (CPT).

CPT, an extension of RAT, explains the way people conceptualize their surroundings and human activity and is a significant consideration for understanding crime patterns (Irvin-Erickson and La Vigne, 2015).

These mentioned theories view criminals as rational individuals likely to act when opportunity arises but reluctant to commit crimes when there is a high likelihood of being caught (Cornish and Clarke 1986).

Geometry of Crime Theory

The third important theory in this approach is the geometric theory of crime (GCT), which clearly explains the relationship between crime and place. This theory, first expressed by Brantingham and Brantingham in 1981, claimed that as criminals seek targets, they go through a multi-stage decision-making process.

The environment emits signals that indicate good, safe, easy, or bad, unprofitable, and risky situations. Based on these factors and their experience, criminals create the templates to compare victims and targets to those known to be acceptable. When they establish the template, it becomes relatively fixed and self-reinforcing. Individual templates have similarities since the spatial and temporal distribution of victims and proper situation is patterned or clustered. Environmental criminologists apply micro spatial decision-making process to different types of crimes in variety of geographical scopes (La Vigne, 1997).

In a transit setting, offenders rationalize their decision to commit a crime based on several circumstances including the type of crime they want to commit, ease of targets, level of surveillance, and ease of escape (D'Alessandro, 2003). The absence of social guardianship, sense of property ownership, and low risk of being witnessed are the additional circumstances for possible criminal activity (Buckley, 1996).

Crime Prevention through Environmental Design

The theory of crime prevention using design was originally was based on crime prevention around public housing (Newman, 1973). Newman argued that built environment is a facilitator for criminal activities (Cozens and Love, 2015).

Along with crime and locational theories and based on research by Jacobs and Newman, there is an approach to crime control known as crime prevention through environmental design (CPTED) (Greenberg & Rohe, 2007). Jeffery (1969) introduced CPTED as proper design and effective use of the built environment to reduce fear and the incidence of crime. CPTED also plays an important role in strategies to address crime in transit systems (Loukaitou-Sideris et al., 2006).

There are four main principles in CPTED about build environment design to prevent crime: territoriality, natural surveillance, activity support, and access control.

Territoriality: This is a design concept that separates private space from public space ownership. It claims that people protect their own space and respect the territory of others (Sohn, 2016).

Natural surveillance: This refers to landscape and proper location and use of windows and lighting to increase the visibility of activities occurring in the area (Peak, 2013). This concept has been supported by the “defensible space” theory (Poyner, 1983).

Activity support: This is about encouraging outdoor activities through offering public spaces for safe activities (Sohn, 2016). It is expected to attract ordinary individuals to participate in normal outdoor activities as a part of the natural surveillance system to discourage potential offenders from committing crimes (Cozens, Saville, & Hiller, 2005).

Accessibility: This is a design concept for crime prevention strategies through limiting the access of criminals to targets (Cozens et al., 2005).

The same concept could be adopted around transit stations as well. Promoting all the CPTED concepts—territoriality, natural surveillance, activity support, and access control—could play an important role in creating safety and preventing crime around transit stations. Promoting CPTED as a conceptual built environment framework in transit stations is mostly aligned with TOD concepts such as increasing density and walkability density.

It could be concluded that LRT stations are subject to daily routine activities and send signals about their conduciveness as places to commit crime. In the other words, according to rational choice theory, transit stations give cues to offenders on whether to commit crime in these areas.

There are combinations of a motivated offender, a lack of a capable guardian and a suitable target at LRT stations. Based on routine activities theory, the conjunction of targets and offenders combined with a lack of protection from capable guardians could result in a potential increase in the number of crimes incidents within the surrounding neighborhood. Moreover, the geometric theory framework explains how LRT Stations can facilitate crime through the movements of offenders based on node characteristics.

Summary

This chapter covered the scholarly studies on the topic of crime and public transit and summarized relevant theoretical frameworks, including rational choice theory, routine activity theory, geometry of crime social theories, and crime prevention through environmental design. These theories demonstrate why and how criminal activities can accrue around transit stations and finally, how we can control or prevent dangerous behavior through environmental design based on CPTED. In the next chapter, the interaction between supportive theories and the theoretical framework is explained.

Chapter Three

Introduction

As mentioned in the previous chapter, crime and public transportation have a complex relationship associated with different factors such as environmental characteristics and density. Moreover, travel behavior is a complex phenomenon. Crime incidents around public transit stations, individual preferences, socioeconomic status, and urban structures play important roles in travel behavior. The following chapter begins with a description of the framework between factors affecting crime and ridership and their interactions. The next section includes literature reviews that support this study's theoretical framework. Lastly, this chapter summarizes the literature based on key elements, addressing the: (1) theoretical framework, (2) factors affecting ridership, and (3) factors affecting crime.

Theoretical Framework

To have a comprehensive analysis about the impact of crime incidents on LRT ridership, one needs to establish an empirical method of analysis that can effectively measure the impacts of indicators around LRT stations. Based on a review of previous literature studies, there are generally two approaches to crime theory that can explain LRT station crime: compositional and ecological.

The compositional approach focuses on the local social climate of the station neighborhood around LRT stations, including the characteristics of residents that explain inter-city variation in crime (Loukaitou-Sideris et al., 2002). Taylor argues "local social ties may have a direct and indirect impact on crime and related outcomes." (Taylor et al., 1984, p. 307) Social connection variables include age composition, population density, ownership level, and income level. Correlations between these social indicators within a population are related to possible causes of criminal activity (Cullen and Agnew, 2003). A limitation to this approach is the underlying social context of station neighborhoods—it does not include physical attributes that may have potential for crime influence (Byrne, 1986). Therefore, a solely composition-based approach disregards the impact of the physical environment and the potential crime opportunity areas.

Conversely, the ecological approach emphasizes various physical characteristics of an area, such as land use and physical features, including their impact on crime (Byrne, 1986). The environmental setting of crime occurrences and ecological models analyze the interactions of offenders with their surroundings emphasizing the role of local physical attributes on ridership (Loukaitou-Sideris et al, 2002; Taylor et al, 1984). However, the ecological perspective on transit crime context is limited in terms of social characteristics.

Both compositional and ecological dimensions offer incomplete explanations of city-crime correlation (Byrne, 1986). To address this issue, Loukaitou-Sideris et al. (2002) developed an integrated theoretical framework encompassing both compositional and ecological elements. Following the principal of the integrated theoretical framework, this study implements the combination of social and physical variables and their interaction with crime incidence within a half-mile buffer around public transit stations.

Based on the integrated theoretical framework, the following chapter delves further into the appropriate variables to address the impact of crime on LRT ridership.

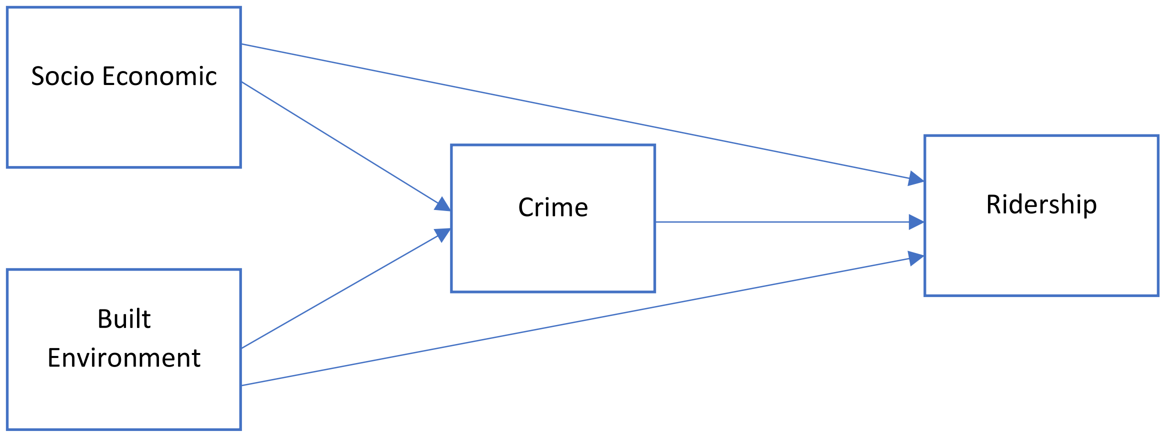

Figure 1. Theoretical Framework

Reviewing background studies proves that compositional and ecological dimensions are viewed separately and offer incomplete explanations of the city-crime correlation (Byrne, 1986).

Table 1. Compositional vs. Ecological Theories

	Compositional	Ecological
Description	Social context of station neighborhood Aggregate characteristics of populations explain variations in crime occurrence	Physical attributes of LRT stations and station neighborhoods Focus on micro environmental setting crime occurrence
Variables	Population density Ownership level Income level	Land use Physical features
Limitations	Lack of emphasis on physical correlates of crime	Lack of emphasis on social context of crime

This study proposes the development and implementation of an integrated theoretical framework encompassing both compositional and ecological elements into an analysis of crime occurrence within a half-mile buffer around public transit stations. A combination of social and physical variables, including their interaction with crime incidence at LRT stations, provides a convenient analytical and theoretical framework (Loukaitou-Sideris et al., 2002; Byrne, 1986). It also allows for a better understanding of the varying social and physical features associated with crime occurrence around transit stations and its impact on transit ridership.

Factors Influencing Ridership

Socioeconomic Factors Influencing Ridership

Transit ridership could be influenced by regional geography, metropolitan economy, population characteristics, and highway characteristics. Taylor (2009) suggests factors such as income level, employment, and car ownership have important influence on ridership.

These socioeconomic variables are included in regression analyses of transit ridership (Taylor, Miller, Iseki, and Fink, 2009). Gomez-Ibanez (1996) used a per capita income factor for the ridership models in Boston and concluded the positive effect of employment growth on ridership was balanced by the impact of increasing incomes. Therefore, the level of income has a negative influence on public transit ridership and studies consistently support the finding that car ownership and parking costs have significant positive relationship with public transit use (Kim, Ahn, and Kim, 2016).

Built Environmental Factors Affecting Ridership

The environmental factors such as density, diversity, and land use patterns around rail transit stations are among the primary factors that guarantee successful strategic planning for public transit stations and sustainable transportation system (Zemp, Stauffacher, Lang, and Scholz, 2011).

Proponents of Smart Growth and TOD strategies argue that those physical arrangements increase transit ridership by providing easy, convenient access to transit systems a short distance from the origin/destination with high concentrations of activity and well-connected street patterns (Cervero, 2002).

In addition to the single effect of density, Cervero reported that high density brings more transit ridership when it is accompanied by a mix of residential, commercial, and office uses in proximity to the station. Moreover, a pedestrian-friendly environment around stations considerably improves the accessibility to the public transit system (Ryan and Frank, 2009).

According to Cervero (2002), density is defined per unit of area as a measured variable. Density covers various topics such as population, dwelling units, employment, or building floor area. Activity density refers to the combined population and employment density and can be gross or net.

In travel behavior research, Cervero and Kockelman (1997) introduced the most influential variables on travel demand (ridership) as the original three dimensions—density, diversity, and design. Following their studies, Ewing and Cervero (2001) studies added destination accessibility and distance to transit as critical additions to the original “three Ds.” Further research found demand management and demographics to be the sixth and seventh dimensions of influence (Cervero and Kockelman, 1997).

Diversity, according to Cervero and Kockelman (1997), is a measurement of the number of different land uses in a given area and the degree to which land area, floor area, or employment is represented. Entropy—as it pertains to diversity—measures the level of mixed land use in each area. The lower entropy value indicates single-use environments and higher values represent mix land uses. Jobs to housing or jobs-to-population ratios are less frequently used.

Design measures street network characteristics and the variety of dense urban grids with several connections to straight streets and sparse suburban networks using the average block size and number of intersections per square mile. Other physical variables distinguish pedestrian-oriented environments and design includes measurement of sidewalk coverage, number of pedestrian crossings, average building obstacles, average street width, and street tree canopy (Cervero and Kockelman, 1997).

Destination accessibility measures the ease to local and regional trip attractions (Handy, 1993). The level of destination accessibility depends on the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral ones. Handy (1993) defined local accessibility by measuring the distance from home to the closest store using the gravity model.

The last factor of the "three Ds" is distance—the shortest street route from home or work to the nearest public transportation facility. It can also be measured as the range between transit stops, total stations within an area, or density of the transit route (Cervero and Kockelman, 1997).

In addition, the effects of land use mix and urban design became important factors to consider in public transit studies (Cervero, 1993; Spillar and Rutherford, 1998).

In an analysis of transit demand in Portland, Oregon, Nelson and Nygaard (1995) studied 40-land uses and demographic factors. They found that the most important factor to determine transit demand is overall housing density and employment density per acre.

Similarly, Pushkarev and Zupan (1977) found that the demand for different transit modes is defined by residential densities in transit corridors, the size of the downtown and the distance of the stations from downtown. The importance of density factor is also referenced in the Spillar and Rutherford (1998) study in which they conclude that by increasing density, public transit ridership could increase to a maximum point (Taylor and Fink, 2003).

Cervero et al. (2002), stated that a doubling of mean residential densities is related with a 3.7 percent increase in transit's commute mode share for a typical rail station setting in the San Francisco Bay Area. Also, in Arlington County, Virginia, every 100,000 square feet of additional office and retail floor space near its Metrorail stations are associated with an increase of approximately 50 customers in daily ridership.

Crime Impact on Ridership

Halat et al. (2015) modeled transit access mode choice as a function of socio-demographics, neighborhood crime density, and walk score (as a walkability measure). Results show that both built environment and crime index at the destination have a significant impact on individual's mode usage choice.

In the most recent study on crime and bus ridership, Zhang (2016) claims that higher population density and higher entropy (mixed land use) produce more crimes near bus stops. As a result, the level of crimes has a nonlinear effect on ridership around bus stops. Zhang (2016) claims that when crime rates exceed a threshold level; ridership is negatively affected.

However, some studies claim that not only transit related crimes but also crime rates in neighborhoods near the stations influenced people's transit use. Delbosc and Currie (2012) studied the personal safety perceptions on transit use. They found that the fear of using public transit mainly comes from people's unsafe feelings about their living communities, instead of based on transit itself. Low-income communities and inner-city neighborhoods with a greater percentage of non-white populations typically have higher crime rates than affluent white suburbs (Delbosc and Currie, 2012)

Considering different land uses, Ferrell et al. (2008) examined the effects of neighborhood crime on public transportation mode choice in the San Francisco Bay Area. The authors find that transit use in suburban cities significantly decreases as crime rates increase. Using similar datasets, Ferrell and Mathur (2012) declare higher rate of violent property crime relates to increased ridership.

It appears that both positive and negative associations could exist in the crime–ridership connection. The positive association between crime and ridership reflects a concurrent relationship between crime and ridership, and the negative association reflects a fall in ridership due to deterioration of community security and safety (Zhang, 2016).

Sherman (1995) claimed that in the past two decades there has been an expansion into the analysis of the spatial distribution of crime with small scale or micro level analysis as place-based research. The increased availability of spatially referenced crime data and the technological advances of software products promote the analysis of the spatial clustering of crime, or hot-spot analysis (Newton and Felson, 2015).

The existing research studies show busy places such as transit stations generate higher numbers of criminal incidents. Moreover, they are alleged to be dangerous places, causing fears for personal security (Yu, 2009). This increased probability of facing offenders influences people's decision to use public transit facilities (Gallison, 2012).

Factors Influencing Crime

Crimes, whether they occur between individuals or against properties, are known to cluster in space over an extended period. Crimes, such as robbery, burglary, and motor vehicle theft, display spatial concentrations in the context of public transit (Brantingham and Brantingham, 1998; Loukaitou-Sideris et al., 2002; Liggett et al., 2003; Newton, 2004).

Socioeconomic Status Influence on Crime

Researchers have hypothesized that crime is strongly related to the aggregate elements of the social and economic factors of the hot spots. There is a high level of correlation between crime at a station and crime in the surrounding neighborhoods, sometimes caused by the socioeconomic status of the population (Ceccato et al., 2013). Factors such as poverty, ethnicity, age composition, income, education, gender and citizenship have been studied in scholarly papers (Byrne, 1986).

Shaw and McKay (1942) studied the relationship between neighborhood conditions and crime in Chicago. They claimed that low economic status, ethnic heterogeneity, and residential instability led to community disorder. Bursik (1988) conceptualized *Social disorganization theory* as "the inability of a community structure to realize the common values of its residents and maintain effective social controls" and associated many forms of crime as a result of weak informal social controls, often present in crime attractor's area. As Loukaitou-Sideris (1999), Loukaitou-Sideris et al (2002), and Newton et al. (2004) mentioned, transportation nodes in deprived areas have higher risks of crime. Bryne (1986), an earlier researcher, focused on as poverty, ethnicity, age composition, income, education, gender, and citizenship indicators of high-risk crime areas (Ceccato et al., 2013).

Built Environment Influence on Crime

The fundamental of spatial context and crime could be explained in contemporary criminology through the socioecological explanation of criminality (Irvin-Erickson and La Vigne, 2015). The pioneers of this approach were Park and Burgess (1925) who examined how urban environments affect human criminal behavior.

Savage and Vila (2003) mentioned that Park and Burgess's notions of natural areas and concentric zones motivated members of the Chicago School to run field research on the effects of urban environments on crime and disorder. They also stated that environmental criminology theories inspired by the Chicago School emphasized explaining criminal behavior through understanding how people react to their physical environments (Savage and Vila, 2003).

Jane Jacobs (1961), the founder of the "Eyes on the Street" theory claims that compact characteristics, such as walkability, density, and land-use diversity attract more people on the streets and generate more interactions between inhabitants. These factors, Jacobs argued, create a strong sense of community with the added benefit of natural surveillance of strangers and as a result, informal social control reduces crime. However, many empirical studies found contrary results to Jacobs' observations (Anderson et al., 2013). The oppositional perspectives claim that mixed land-use policies, high street connectivity, and densification unintentionally result in undesired opportunities for crime victimization (Paulsen, 2012).

Many studies have focused on the relationship between access and crime. Comparisons between high-crime and low-crime neighborhoods indicate that blocks, or street areas with accessibility, are associated with higher crime (Eck and Weisburd, 1995). According to Taylor (1993), street designs can impact the possibility of crime incidents. He claimed that streets with grid patterns have higher potential crime rates than streets with cul-de-sacs, winding roads, or dead ends. Grid networks create an easier and quicker escape for potential offenders than areas with an organic street layout, which might be not familiar to the offender. A study by Perkins, Wandersman, Rich, and Taylor (1993) of New York City found that wider streets tended to invite more traffic, and therefore, make blocks more prone to crime incidents. In addition to street configuration, alleys and mid-block connections to open a block or a neighborhood provide an easy escape and intensify the criminal risk for residential or commercial establishments (Brantingham and Brantingham, 1993).

As summarized in the aforementioned research, the design of the built environment around the stations could lead to potential criminal activities through the level of access and easy entrance and exit (Greenberg and Rohe, 1984). Brantingham and Brantingham (1981) stated that a concentration of criminal activities occurs close to major transportation arteries and highways.

Moreover, the research of Block and Davis (1996) disclosed that most robberies did not occur at the transit station but a short distance away where it was more difficult for others to view the crime. Walkability must be considered when proposing or designing a safe transit system, whether by bus or rail.

Relationships between land uses have also been studied by scholars and identify commercial and transitional development as attractive targets for criminals. On the contrary, industrial areas mixed with residential areas are considered to be less attractive

(Loukaitou-Sideris et. al., 2000). Confirming this posit, Shaw and McKay (1929) noted that commercial and industrial areas were prominent features of neighborhoods with high residential criminal behavior.

A study conducted in the District of Colombia by Rhodes and Conly (2008) analyzed the relationship between land use and crime. They ranked high risk areas to low risk areas. In their ranking, commercial and transitional areas tended to be more attractive targets for criminals whereas industrial areas with residential properties were considered the least attractive. In residential land use categories, multifamily housing areas were more susceptible to crime than single-family housing (Rhodes and Conly, 2008).

Taylor and Harrell (1996) claimed that the higher percentage of lots zoned for commercial use was a significant predictor of higher risk for increased robbery rates. Some commercial uses are more prone to generate crime than others, especially if there is a high concentration of these in a small area (Block and Block, 1995). Pawn shops, check-cashing facilities, and ATMs are considered establishments likely to attract criminal activities (Perkins, Meeks, and Taylor, 1992). Bars, liquor stores, and abandoned buildings were also found to attract more crime in respective vicinities (Byrne 1986; Block and Block 1995, 2000).

Inner city or outer city location of a public transit station is a crucial factor regarding the safety of the transit facility itself. Ceccato and Uittenbogaard (2014) stated that city centers are more prone to crime; thus, it would be expected that the more centrally located a station is, the higher risk of criminal incidents (Ceccato and Uittenbogaard, 2014).

Moreover, the possibility of surveillance has been found to have a strong effect in reducing crime (Brantingham and Brantingham, 1993). Surveillance could be defined as visibility, such as good lighting at night. The presence of physical features that increase the visibility of a site—without the obstacles that block view—can help prevent crime in and around the stations.

For light-rail stations, the type of platform design also has an effect, depending on the neighborhood context. Street-level stations can provide an easy escape for criminals (Loukaitou-Sideris et al., 2002). On the other hand, if a station is located within dense urban environments, good visibility from its surroundings could provide natural surveillance opportunities (Felson et al., 1990). Lighting, fencing, specific security hardware, and open design could work as surveillance tools to discourage crime (Harris, 1971).

Density, as referenced earlier, is an ambiguous factor influencing crime. For instance, Jane Jacobs' (1961) theory of “Eyes on the Street” considered high density as a preventive factor for crime incidents. Conversely, many researchers claim that high levels of activity do not necessarily imply suitable surveillance (Mayhew, 1981). This is more accurate for transit-related types of crime because this crime may typically take place in situations of high density where the potential offender can easily hide in the crowd (Loukaitou-Sideris, 1999). As Glass (2011) mentioned, the busiest stations have the most serious incidents of crime on the platform.

The Impacts of Vegetation on Crime

There are few studies on potential effect of vegetation on crime incidents around transportation networks at urban areas. Nevertheless, studying vegetation, as a special aspect of the physical environment, is embedded in routine activity theory (Du and Law, 2016). Studies also exist that emphasize people’s ability to observe surroundings in their daily routine. Thus, there are two main schools of thought about the relationship between crime and vegetation.

The general belief is that vegetation enables “the cover of crime”—hiding offenders and criminal activity from view (Kuo and Sullivan, 2001). To expound on this common theme, the idea is that people cannot see their surroundings clearly in the presence of vegetation and trees, and therefore, feel more vulnerable to criminal activities as offenders use vegetation to conceal their actions (Du and Law, 2016). Kuo and Sullivan (2001) concluded that vegetation could provide cover for a criminal’s activity and increase the possibility of crime, as well as, encourage fear of crime.

Despite these conclusions, no studies have examined whether crime rates are higher in the presence of dense vegetation. Due to the possibility of masking criminal activities, most evidence links dense vegetation with fear of crime. Dense vegetation refers to large shrubs and woods that considerably reduce visibility and physically promote heightened risk of criminal activity (Kuo and Sullivan, 2001).

Conversely, the second school of thought supports the idea that a well-maintained green area certainly does not block views; high-canopy trees in widely spaced land spaces have minimal effect on visibility. Flowers and low-growing shrubs seem irrelevant to creating a dangerous environment for people and cover for criminal activities. These researchers claim that vegetation can be considered a crime deterrent (Du and Law, 2016). Wolfe and Mennis (2012) verified that vegetation is associated with lower crime rates for assault, robbery, and burglary in Philadelphia.

Kuo and Sullivan (2001) also analyzed vegetation and crime relationship across 98 buildings in a public housing complex in Chicago. They examined the vegetation concentration by visually rating it from aerial and ground-level photography. They proved that a greater concentration of vegetation was associated with lower property and violent crime while controlling for other characteristics of the buildings—a relationship that the authors attributed to increased public use and the mentally restorative effects of vegetated—as compared to barren urban landscapes.

Donovan and Prestemon's (2012) study of crime in Portland, Oregon, found that the presence of large street trees resulted in crime suppression. They claimed that the presence of big trees increases the use of public space and surveillance, and if the trees are well cared for, they may also be regarded as a neighborhood's symbol of social control. Surprisingly, they also found that smaller trees on private lots increase the chance of crime incidence by providing concealment for criminals.

Chaudhury (1994) stated that residential vegetation can act as a territorial marker. His study explained that front views of houses with a host of environmental features influenced ratings of territorial personalization. He found that having and maintaining vegetative features is the strongest predictor of territorial personalization.

Troy et al. (2012) compared private versus public lands and urban versus rural settings in Baltimore, Maryland. They found a negative relationship between tree canopy and crime.

In summary, it can be concluded that vegetation discourages crime:

Territorial personalization and social control are among the main factors in crime prevention through well-maintained vegetation. Vegetation could act as a territorial marker in residential areas and in public areas, demonstrating well observed and monitored locations (Chaudhury, 1994; Donovan and Prestemon's, 2012).

First, vegetation tempers psychological traits of violence through green landscape (Kuo and Sullivan, 2001). Vegetation might constrain crime through mitigating mental fatigue. Mental fatigue symptoms are irritability, inattentiveness, and decreased control over impulses which are all psychological precursors to violence (Kaplan, 1987).

The “Broken Window” theory is another explanation of how vegetation can reduce crime (Sousa and Kelling, 2006). It claims that well-maintained vegetation indicates authority and showcases that the community is under supervision by its residents (Du and Law, 2016). Well-maintained vegetation outside of a home could serves as one of the *cues to care* (Nassauer, 1988). Moreover, Brown and colleagues (Brown & Altman, 1983) supported similar findings and added that plantations and other green territorial markers make properties less attractive for burglary.

Summary

This chapter provided an overview of the theoretical model. It explained the influence of each variable on ridership and crime with reference to the literature review and scholarly findings. Specifically, this chapter reviewed literature with a focus on the interaction between built environment and socio-economic factors effecting ridership and crime. Moreover, the impact of crime on ridership was covered. Land use and vegetation are the two important factors to focus on in this study as they have significant association with crime. In conclusion, this chapter focused on the relationships between the studied variables in the research to establish the theoretical model. Strong theoretical model is the backbone of Structural Equation Modeling. The next chapter details the research methodology.

Chapter Four

Methodology and Data

This chapter presents the research statistical framework and modeling techniques . This section establishes the research questions, research hypothesis, research model and variables including gathering, cleaning and integration of data.

Increasing public transit ridership is one of the top priorities of urban and transportation planners due to its connection with other key issues: environmental, density, healthy communities, among many others. Transit agencies—with the goal of creating a worthy investment that is beneficial to the community—have an obvious interest in the growth of transit use.

Among all the possible barriers to increasing ridership, safety stands out. Fear of crime and lack of safety are important factors impacting riders' opinion and choice to use public transportation (Zhang, 2016). Many empirical studies confirmed the influence of the built environment and socioeconomic factors on travel behavior (Ewing and Cervero, 2001). However, there are few studies concerning the role of crime and safety on travel decision-making and ridership (Kim, Ahn, Choi & Kim, 2016).

Therefore, measuring the impact of crime on ridership is a crucial step for urban planners and transit agencies. To quantify the impact of crime on ridership, it is important to identify the effect of built environment and socioeconomic characteristics of the neighborhoods around the stations on ridership.

Research questions

To achieve a comprehensive approach toward analyzing the impact of crime in ridership, one should answer the following questions:

- Does crime affect LRT ridership?
- How could density affect crime and ridership?
- Does density increase crime rates around the LRT stations?
- Does crime act as a mediation factor between socioeconomic characteristics of the neighborhood around the station and ridership?
- How could walkability influence ridership with mediation of crime?
- How could mixed land use influence ridership with mediation of crime?
- How does walkability affect crime?
- Does vegetation or tree canopy coverage influence crime?

Research Hypotheses

To answer the research question statistically, the following hypothesis could help to frame the research methodology.

Crime incidents around transit stations impact ridership.

Studies on the influence of crime and travel behavior state a complex interaction between the urban environment, crime levels, and transit use (Cozens and Love, 2015). Most of these studies consider transit stations as prime settings for attracting criminal behavior. They claimed concentration of big crowds together in one place creates an accessible target for offenders to commit the offences of pickpocketing, purse snatching, and robbery (Loukaitou, 2002).

In 2017 Appleyard and Ferrel examine the Influence of crime on active and sustainable travel. They find high rates of neighborhood corridor-level and station area-level crimes diminish transit use.

The impact of neighborhood crime activities on travel mode choice varied based on the crime type, travel mode, and the city type analyzed. They claimed that in suburban areas, higher crime is associated with lower transit usage for work and non-work trips Appleyard and Ferrell (2017). Complex relationship between crime and ridership could have both positive and negative associations. Ferrell et al. (2012)

The positive association could be explained as an increase in ridership results in related rise in level of activity around the stations and thus, creates greater potential for criminal activities. The inverse may also hold with the negative association—when the community feels public transit is unsafe, a decrease in ridership occurs (Zhang, 2016). Therefore, the goal of this research is to quantify the impact of crime on ridership,

Crime in high density areas around transit stations has positive impact on ridership.

Routine Activities Theory (RAT) set forth by Cohen and Felson (1979), claims that unlawful activities often happen in parallel when potential offenders and their targets are at the same location with the absence of guardians. Consequently, large populations and high-density areas increase the numbers of potential offenders and targets; this results in more crime and formation of criminal hotspots spatially (Hipp and Roussell, 2013).

According to Jane Jacob's theory of "Eyes on the Street", commercial uses spread among residential areas increase safety due to movement of people—storekeepers, shoppers, locals. Because of this, it is believed that people are typically strong proponents of peace and order themselves. As a result, the constant movements in commercial use increases surveillance in the area (Anderson, MacDonald, Bluthenthal, and Ashwood, 2013).

LRT stations are usually located in high density areas and it is this main reason that stations should be referred to as crime generators and attraction nodes—basically places of opportunity for criminal activity (D'Alessandro, 2003).

Crime in mixed land use neighborhoods around transit has a positive impact on ridership.

People who visit a commercial-residential space for shopping or other businesses likely have only limited time for surveillance on the street and less inclination to manage neighborhood safety than residents (Taylor,1988).

Studies show that commercial uses have positive association with crime. Correspondingly, homogeneous residential neighborhoods have lower rates of crime than mixed-use neighborhoods (Anderson et al., 2013).

When non-residential land use is added to a purely residential neighborhood, it would result in an increased number of strangers and traffic which would make it difficult for the residents to distinguish who belongs in their neighborhoods and who does not (Taylor, 1998). As Taylor (1988) said, a mixed-use in a block or a neighborhood could cause interruption in residential areas and reduce informal social controls.

Moreover, the Chicago School also argues that transition from old residential to new commercial use, creates a trace of concentration of criminal neighborhoods and enterprises (Brantingham, and Brantingham, 1993). Zhang (2016) also claimed that introducing commercial use into residential neighborhoods could attract more offenders and crimes.

The presence of businesses and parks could increase crime rate and enhance people's perception of danger (Wilcox, Quisenberry, and Jones, 2003). According to Loukaitou-Sideris et al (2001), large commercial and transitional areas are attractive environments for criminals. Anderson's et al. (2013) empirical study of Los Angeles found that the average crime rate in the mixed-use neighborhoods is 15 percent higher than in the residential-only neighborhoods.

LRT transit stations and surrounding areas vary in terms of land use; hence, crime at LRT stations is affected by specific types of land uses. These stations are usually located in mixed land uses or commercial areas close to Central Business Districts (CBDs).

In accordance with the situational crime prevention literature, commercial establishments create more attractive crime opportunities as they draw strangers to the area who might be potential offenders—or criminal targets—which leads to increase of victimization. Therefore, it is be hypothesized that mixed land use neighborhoods around LRT stations have positive association with crime incidents in the same areas.

Low socioeconomic status of neighborhoods around the stations has direct and indirect effects on ridership and crime.

Cohen and Felson's (1979) RAT predicted changes in criminal activity through changes in the normal activities of the victims of crime. However, these changes in activities are highly related to different sociodemographic and socioeconomic characteristics and the various places frequented in the same period of time.

According to social disorganization theory (SDT) set forth by Shaw and McKay (1942) there are five factors causing crime: demographic, economic, social, family disruption and urbanization.

There is a strong link between poverty and crime in empirical studies. Poverty defines as income level, unemployment rates, and neighborhood stability. According to

Harries (1995) poverty has the greatest impact on crime amongst other socioeconomic factors.

In a very surprising study, Angel (1968) found that the middle-income areas—or the business areas serving middle class—had little to no robberies. This might be a result of using more security measures to deter criminals and said options may not be available to disadvantaged people due to income disparity. It could also be explained by the unfamiliarity of the offenders within these higher-income neighborhoods (Yu, 2009).

The empirical study conducted by Loukaitou-Sideris et al (2002) found a significant positive correlation exists with the proportion of low-income areas (< $25,000). In addition, high-income areas (> $75,000) have a negative relationship with crime rate.

According to social disorganization and economic deprivation theory, the next important factor to study is unemployment. Unemployment is shown to be the greatest predictor of measured crime rates (Andresen, 2006).

Income level also influences household affordability to rent or buy their dwellings. Perkins et al (1993) specified areas with many owned dwellings are expected to have less crime incidents because of increased territoriality. Thus, people with owned dwellings are more likely to cautiously maintain their property, exercising guardianship and control.

Loukaitou-Sideris et al (2002) and D'Alessandro (2003) both found negative correlation with percentage of owner-occupied dwellings within a station neighborhood and LRT station crime rate.

Therefore, based on the studies, income level, rented dwelling units, and unemployment have significant impact on crime around transit stations.

Vegetation has negative impact on crime.

According to Chaudhury (1994) and Donovan (2012), vegetation acts as territorial marker in residential areas. Moreover, vegetation in public areas demonstrates a well observed and monitored place with territorial personalization and social control.

The "Broken Window" theory explains the role vegetation can have in reducing crime (Sousa and Kelling, 2006). It claims that well-maintained vegetation shapes authority and shows the community it is under supervision by its residents (Du and Law, 2016).

In addition, vegetation has a psychological effect on people. It could moderate emotional distress—signs of violence—through green landscape (Kuo and Sullivan, 2001) by mitigating mental fatigue. Said symptoms include irritability, inattentiveness, and decreased control over impulses which are all psychological precursors to violence (Kaplan, 1987).

It could be concluded that to create safe environments around LRT stations, vegetation could work as a mediator to decrease crime.

Walkability has an impact on crime

Pedestrian routes are another choice to access transit stations. According to Cervero and Kockelman (1997), measures including average block size, proportion of four-way intersections, sidewalk coverage, number of pedestrian crossings, and other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones, helps people to access transit easier.

From a criminology perspective, high level of walkability could intensify the chance of criminal activity. According to the RAT, the low-level intensity of pedestrian traffic may offer few criminal targets. The critical intensity zones refer to the intermediate to high-level of pedestrian traffic—whereupon offenders could find their targets more easily (Zhang, 2016).

Conversely, Jane Jacob's "Eyes on the Street" theory argued for creating increased guardianship through more public interactions. Jacobs believed that urban street life promoted greater surveillance and stewardship through the ever-changing richness of community and commerce. Business owners, shoppers, and residents alike engaged by means of talking and walking—a natural born brigade (Anderson, MacDonald, Bluthenthal, and Ashwood, 2013).

Therefore, it is important to study the walkability around LRT stations since it is expected to have a high-level of interactions and walkability in close distance from transit nodes.

To examine these hypotheses, six metropolitan areas are selected as target samples to run the analysis based on their characteristics. It is worth mentioning that the aggregate of gathered data from the following regions create a reliable sample data to run the analysis. These regions have close LRT ridership per year; however, there are other factors to be considered in choosing these regions. The following sections provide a comprehensive description of these regions separately.

Study Regions

Due to their growth, population increase, and increased development activities (especially in the core), these metropolitan statistical areas (MSAs) are perfect case studies to understand the importance of ridership and factors influencing travel mode choice and crime. The following MSAs are chosen to study in this research:

- Dallas-Fort Worth-Arlington (Dallas Area Rapid Transit [DART])
- Miami (Metrorail)

- Salt Lake (Utah light rail [UTA])
- Minneapolis (Metro Transit)
- San Francisco-Oakland-Fremont (Bay Area Rapid Transit [BART]),
- San Diego (Metropolitan Transit system)

To select the target areas among US cities, there are several indicators to consider. These indicators create a holistic criterion which could be categorized in three main groups. First: demographic and geographic factors, including population, density, and affordability. Second: transit system information including daily and annual ridership, public transit use, and auto ownership. Third: crime rate. Considering these factors and the availability of data areas, these cities were selected.

The following section is a brief description of each city and its demographics and socioeconomic status.

Demographics and socioeconomic criteria

Dallas, Texas

Dallas, located in the state of Texas, is the seat of Dallas County, with an estimated 2017 population of 1,341,075. Dallas is the ninth most-populous city in the U.S. and third in Texas after Houston and San Antonio. It is also the eighteenth most-populous city in North America as of 2015 (U.S. Census Bureau, 2018. Dallas has the most populated city in the Dallas–Fort Worth Metroplex, the fourth-largest metropolitan area in the country at 7.5 million people as of 2018. The city's combined statistical area is the seventh largest in the U.S. as of 2017, with 7,846,293 residents.

According to the 2017 American Community Survey (ACS), the median income for a household in the city was $47,285. The per capita income for the city was $25,904. About 18.7% of families and 21.7% of the population were below the poverty line.

In the United States Census Bureau's 2017 estimates, 61.8% identified as White (29.1% non-Hispanic white), 24.3% Black or African American, 0.3% American Indian or Alaska Native. Hispanics or Latinos made up 41.7% of the estimated population (American Community Survey, 2017).

Miami, Florida

Miami is the county seat of Florida's Miami-Dade County and the most populous city in the Miami metropolitan area. Miami is the second most populous city in the Southern US region after Washington, D.C. It is a global city with the largest concentration of international banks in the United States. The current population is estimated to be 470,914 (World Population Review, 2019).

In 2000, the most significant ethnic/national origin in Miami was Cuban (34.1% of the population), followed by Nicaraguan (5.6%), Haitian (5.5%), Honduran (3.3%), Dominican (1.7%) and Colombian (1.6%). The United Nations Development Program also ranked Miami first in terms of its percentage of foreign-born residents at fifty-nine percent (UNDP, 2018).

According to the most recent American Community Survey (ACS), the racial composition of Miami was: White: 75.22%, Black or African American: 17.67%, Other race: 3.94%, Two or more races: 1.80%, Asian: 1.08%, Native American: 0.25%, Native Hawaiian or Pacific Islander: 0.04% (U.S. Census Bureau, 2018).

Salt Lake City, Utah

Summarized to Salt Lake, although abbreviated as SLC, this capital city is the most populated in the state of Utah. Salt Lake City is situated in Salt Lake City–Ogden–Provo Combined Statistical Area.

Salt Lake City population is 192,154 which is more than 10 percent of Utah's population with an ethnic diversity of 75.1% White, 2.6% African American, 1.2% American Indian and Alaska Native. The city's population has historically identified as white—only 22.3% of the total population is Hispanic or Latino (Census, Bureau, 2017).

Around three quarters of Utah's total population is employed with high-tech firms. Utah is a lead high-tech subsector in terms of employment and number of establishments (James, 2007).

Minneapolis, Minnesota

Minneapolis is the largest city in the state of Minnesota and 46th-largest in the United States, with an estimated population of 425,403 (United States Census Bureau, 2019) The Twin Cities metropolitan area consists of Minneapolis, its neighbor Saint Paul, and many suburbs—a total of approximately 3.63 million people.

White Americans make up about three-fifths of Minneapolis' population. The Minneapolis–St. Paul area is the third largest economic center in the Midwest, behind Chicago and Detroit (US. Metro economic, 2017), with an almost 200 billion gross metropolitan product and ranked thirteenth per capita personal income in the U.S. Minneapolis was recovering from the nation's recession in 2000 and personal income grew 3.8% in 2005, though it was behind the national average of 5%. The city returned to peak employment during the fourth quarter of that year (Bureau of Economic, 2005).

San Francisco, California

San Francisco—located in Northern California—is known as the cultural, commercial, and financial center of Northern California. San Francisco is the 13th-most populous city in the United States, and the fourth-most populous in California, with 883,305 residents as of 2018 (U.S. Census Bureau, 2019). It covers an area of about 46.89 square miles (U.S. Census Bureau), mostly at the north end of the San Francisco Peninsula in the San Francisco Bay Area.

San Francisco is the second highest-density city among US cities. As of 2017, it is the seventh-highest income county in the United States, with a per capita income of $119,868. San Francisco's Combined Statistical Area (CSA) is the country's third-largest urban economy as of 2017. San Francisco has a diversified service economy with employment spread across a wide range of professional services including financial services, tourism, and high technology (Bureau of Economic).

According to the U.S. Census Bureau (2018) San Francisco's population is 883,305 with a population density of 18,838/sq. mi. less than half of the San Francisco population is non-Hispanic with 41.9% of total population compared to 92.5% in 1940. The racial and ethnic composition consists of 390,387 whites (48%), 267,915 Asians (33%), 48,870 African Americans (6%), and others.

Median income in San Francisco places the third among American cities with a 2007 value of $65,519. Median family income is $81,136. The city's poverty rate is 12%, lower than the national average (American Community Survey).

San Diego, California

San Diego is a city in the state of California with an estimated population of 1,419,516. It is the eighth-largest city in the United States and second largest in

California. The city is the seat of San Diego County and is the economic center of the region as well as the San Diego–Tijuana metropolitan area.

San Diego's main economic engines are military and defense-related activities, tourism, international trade, and manufacturing. According to 2010 US Census data, the city had a population of 1,307,402 distributed over a land area of 372.1 square miles. As of December 2012, San Diego has the third-largest homeless population in the United States (Census Bureau, 2017).

As of May 2015, the median price of a house was $520,000. In November 2018, the median home price was $558,000. The San Diego metropolitan area had one of the worst housing affordability rankings of all metropolitan areas in the United States in 2009 (Cox, Pavletich, and Hartwich, 2017).

Public Transit Criteria

This study’s unit of analysis is the half-mile buffer around transit stations. Also, the light rail transit system does not only serve the city, but the entire designated region. The cities for this case study are considered the most important of their respective regions; therefore, they reflect the main characteristics of the transit system.

To better understand the transit performance of each city, the regional transportation data was adopted to create this measurement. The public transit criteria include daily and annual ridership of each transit system, percent of people who use public transit to go to work in the region, and the number of cars each household also owns in the region. Each city has the strongest transit system with the highest ridership in their respective regions, and they are all auto-dominated cities despite the presence of a transit system.

Following, is a brief description of each transit system.

DART[1] (Dallas)

Dallas Area Rapid Transit (DART) is a transit agency serving the Dallas-Fort Worth metropolitan area of Texas. DART was created in 1983 to replace a municipal bus system in addition to a funded expansion of the region's transit network through a sales tax levied in member cities. DART's light rail system is the longest in the United States at over 93 miles (149.7 km) and began operation in 1996.

DART operates the Trinity Railway Express between Dallas and Fort Worth through inter-local agreement with Trinity Metro (sister city, Fort Worth's transit authority). The agency also operates the Dallas Streetcar and provides funding for the non-profit McKinney Avenue Streetcar (Facts about Dallas, 2018).

According to the American Public Transportation Association, average daily ridership is around 200,000 riders per day. In the 1st quarter of 1998, DART's weekday ridership averaged 211,000 riders per day. Since this time, DART has fluctuated in ridership.

The DART light rail system consists of 93 miles. Before the 1983 election, DART had a plan for 160 miles of rail. DART chose light rail transit as its primary mode of rail transportation in 1984.

Metroraili[2] (Miami)

Metrorail is the rapid transit system of Miami and Miami-Dade County in the U.S. state of Florida. It is operated by Miami-Dade Transit (MDT). MDT is a departmental agency of Miami-Dade County. MDT opened in 1984 and it is Florida's

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[1] www.dart.org
[2] http://www.miamidade.gov/

only rapid transit metro system. There are 23 stations on 24.4 miles of standard track (Miami-Dade County, 2011).

The Metrorail system's ~25-mile dual track connects Miami International Airport (MIA) to Kendall and runs through South Miami, Coral Gables, and downtown Miami—with additional connections to Broward and Palm Beach counties at three locations: Historic Overton Lyric Theatre station – transfer to Brightline, MIA (Orange Line) and the Tri-Rail (Green Line) stations – transfer to Tri-Rail. The Metrorail also covers the Civic Center/Jackson Memorial Hospital area, Brownsville, Liberty City, Hialeah, and Medley in northwest Miami-Dade (Miamidade, 2019).

TRAX[3] (Salt Lake)

Transit Express, or TRAX, is the light rail system in Salt Lake Valley, Utah, serving Salt Lake City and many of its suburbs throughout Salt Lake County. In 2015, Utah Transit Authority (UTA) focused on improving and expanding service and enhancing the rider experience.

As a result of inefficiencies and budget savings, in August 2015, UTA added more than three million dollars in additional services, including expanded bus routes, more nighttime service, and extended TRAX and streetcar operating hours. Also, to enhance safety and security, in 2015, TRAX implemented the installation of safety call boxes on 50 TRAX and Front Runner platforms.

The call boxes operate by a simple button pressed and allow passengers to talk into a hands-free microphone and connect directly with the UTA Transit Police

[3] www.rideuta.com

Department 24 hours a day, seven days a week—saving valuable minutes in case of an emergency (UTA, 2015).

METRO[4] *(Minneapolis)*

Metro is a system of color-coded light rail and bus rapid transit lines owned by the Metropolitan Council that provides service to the Twin Cities region. Metro Transit is the operator of both light rail lines servicing the Minneapolis-Saint Paul region. The Blue Line (2004), was the region's first light rail transit (LRT) corridor.

The Blue Line connects Target Field to Mall of America and links downtown Minneapolis, U.S. Bank Stadium, Minneapolis-St. Paul International Airport and Bloomington's South Loop district. The Green Line, which opened in 2014, reconnects the downtowns of St. Paul and Minneapolis with light-rail trains—decades after streetcars were removed. The project was widely recognized for its construction mitigation techniques and emphasis on equity. Passing through several unique neighborhoods, the corridor provides critical access to a variety of destinations, transit nodes and job centers (METRO, 2016).

BART[5] *(San Francisco)*

Formed in 1957, BART is the United States fifth-busiest heavy rail rapid transportation system operated by the Bay Area Rapid Transit District in San Francisco, CA. Due to the complexity of build and coordination in the Bay Area, the initial system opened during 1972 to 1974 in set stages. Passenger service began in 1972 between MacArthur and Fremont and soon thereafter, the entire system opened in 1974. The new

[4] www.metrotransit.org
[5] www.bart.gov/

BART system was a major step forward in subway technology (BART, 2018). As of late 2019, it is still expanding with an extension to San Jose—the Silicon Valley BART.

According to BART reports, BART serves 48 stations along six routes on 112 miles of rapid transit lines. On average, BART has 423,000 weekdays. BART ridership has rapidly increased since 2010 on par with strong economic growth in the Bay Area. In 2015, the system had 100,000 more passengers each day than it had five years earlier. A major reason for the rapid growth has been high gasoline prices impact on commuters—which led to record levels of ridership during 2012.

Additionally, as stated in the BART 2017 report, stations in the city center areas of San Francisco, Oakland, and Berkeley have the highest ridership whereas suburban stations record lower rider numbers.

MTS[6] (San Diego)

The MTS Trolley (light rail) connects San Diego's east and south county communities with the Downtown region. Light rail service is operated by the San Diego Trolley, Incorporated (SDTI). It is commonly referred to as "The Trolley". According to a recent community impact report by MTS, the trolley ridership has been steadily growing, especially during 2014 and 2015.

Stable growth in ridership can be attributed to higher frequencies in runs and better amenities. Light rail service provided by MTS is among the most utilized systems in terms of patronage in the United States. Generally, approximately 120,000 people rode the Trolley each weekday over the past two years.

[6] www.sdmts.com

In 2015, MTS joined a special task force of five local law enforcement agencies to enhance the safety and security of the transit system. That same year, the MTS average in weekday passengers was 314,127 with 128 trolley cars in operation (MTS, 2016).

The following table compares the aforesaid transit system in each MSA with corresponding ridership data. Each city's transit system is similar in annual ridership and daily boarding numbers, thus, making it easier to utilize said as a holistic methodological framework for light rail ridership study.

Table 2. Light Rail Ridership

System	**Largest City Served**	**Annual Ridership**	**Avg. Daily Weekday Boarding**	**System Length**	**Avg. Daily Boarding per Mile**
BART	San Francisco	49,971,700	159,900	35.7 miles (57.5 km)	4,479
San Diego Trolley	San Diego	37,139,700	115,400	53.5 miles (86.1 km)	2,157
DART	Dallas	28,759,200	95,800	93 miles (150 km)	1,030
METRO Light Rail	Minneapolis-St. Paul	24,955,700	76,600	21.8 miles (35.1 km)	3,514
TRAX (UTA)	Salt Lake City	17,899,600	57,700	46.8 miles (75.3 km)	1,233
Metrorail	Miami	19,282,500	67,800	24.4 miles (39.3 km)	2,779

Source: American Public Transportation Association, 2018

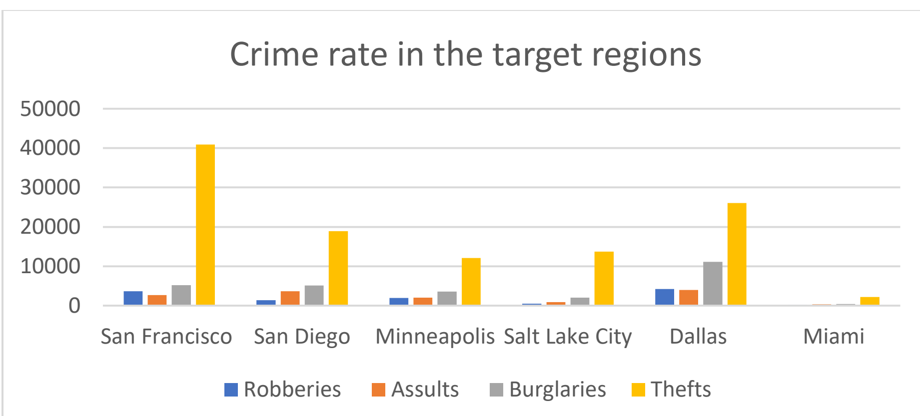
The above-referenced transit systems are among the major networks in the country—both in terms of ridership and rail or route length. Each serve a city with a growing economy and population. Moreover, all are in the center of regional development.

Crime Trend Criteria

The final criteria to be considered for selection of the above-named cities are respective crime trend. The following figures detail the crime rate from 2013 to 2017.

According to statistics tallied from each city's police department, robberies, assaults, burglaries, and theft represent similar ratios of crime rate across the metro areas. The figure below shows that in 2015 (the study year), each city—with respect to density and population—there are similar proportion of selected crime trends.

Therefore, as noted from the crime rate perspective, these case studies have many similarities and thus, selected cities are excellent target samples.



Source: City-data.com

Figure 2. Crime Statistics

Analytical methods

In summary of the theories, this research categorized the influential variables on crime and ridership into two main groups: compositional and ecological. The compositional approach focuses on the effects of sociodemographic characteristics—such as age, ethnicity, class, poverty, and unemployment, etc. The ecological approach identifies urban form and structures—such as density, land use, vegetation, and design, etc.—as influential factors.

There are few scholarly articles studying the relationship between crime and mode choice. Ingalls (1994), in his study "Public Fear of Crime and Its Role in Bus Transit Use," applied methods such as surveys, interviews, and structural equation modelling (SEM) to investigate the factors affecting personal safety perceptions regarding transit use. He discovered that the fear of using public transit mainly came from people's unsafe feeling about their living communities, instead of on transit itself.

Zhang (2016) used a path analysis method to study the crime in more compact land use areas and their impact on public transit use. He concluded that higher population density and more mixed land use may significantly increase crime rate near the bus stops.

Moreover, the level of crime may have a nonlinear effect on ridership considering density around the transit stations. The study indicates that when reported crimes exceed a threshold level, ridership is negatively affected. As a result, very dense residential and commercial development may trigger a rise in crimes.

To examine the impact of crime incidents on ridership, empirical studies applied various methodologies including linear regression models and ordinary least square which are the most common methods used in the ridership studies.

Compared to linear regression, the path analytic method not only follows the usual assumption of ordinary least square regression, but the model could also be specified by a series of paths or structural equations that describe the direct or indirect causal relationships between the variables (Jenatabadi, 2015).

Path analysis enables researchers to break down or decompose correlations among variables into causal and non-causal components. Thus, path analysis helps researchers clarify the complex interrelationships among variables and identify the most significant pathways involved in predicting an outcome.

It can also play an important role in the theoretical or hypothesis testing stage of social research. This method forces researchers to advance detailed and logical theoretical models to explain the outcome of interest and explicitly specify how they think the variables relate to one another within the path diagram (Loehlin, 1987).

Path Analysis

With Path Analysis we could examine the hypothesized links within the model. The AMOS software was used to run structural equation modeling (SEM). The construction of a path model is based on the outcomes of multiple regression analyses. In the path model, "double-headed or single-headed arrows" and squares represent the structural relationships and their directions among the variables (Kline, 2011).

Path analysis models estimate the associations among density, mixed land use, socioeconomic status, vegetation, walkability, crime, and ridership. The path analysis enables us to estimate a model with multiple dependent variables simultaneously and evaluate the goodness of the fit of the entire model, as well as each single equation regression.

Differing from a regular regression model, the path model can distinguish the direct and indirect effects of density, mixed land use and socio-economic status on ridership through crime variables.

During the 1970s, path analysis became popular and numerous papers were published featuring the path analytic method with complex modeling areas including sociology, psychology, economics, political science, ecology, etc.

Compared to single multiple regression models—with specification of one response variable at a time—path analysis estimates as many regression equations as are needed to relate all the proposed theoretical relationships in the model at the same time. Since the early 1980s, path analysis has evolved into a variety of causal or structural equation modeling programs (Lleras, 2005).

A major strength of the path analytic method is that it estimates a system of equations that specify all the possible causal connections among a set of variables. Thus, researchers using non-experimental, quantitative, or correlational data can test whether their hypotheses about the relationships between variables are plausible and supported by the data and represent underlying (causal) processes (Duncan, 1966).

Structural Equation Modeling

SEM has been adopted by several transportation studies. Shiftan et al. (2008) studied the segmentation in transit markets to identify the attributes that increase transit ridership. They used SEM to simultaneously model causal relationships between travelers' attitudes and their socioeconomic characteristics with travel behavior.

Van Acker et al. (2007) used SEM to study the relationship between land use and travel behavior under the assumption that explanatory variables may influence each other, thus the indirect effects on travel behavior must be considered as well (Choo and Mokhtarian, 2007).

Cao et al. (2007) developed a longitudinal SEM for recent movers in eight neighborhoods in Northern California. They found that changes in the built environment have a significant impact on changes in travel behavior after controlling for self-selection.

Zhang (2016) developed a path analysis model to estimate the associations among land use, crime, and ridership. The path analysis has been used to estimate a model with multiple dependent variables simultaneously and evaluate the goodness of the fit of the entire model, as well as that of each single equation regression. Differing from a regular regression model, the adopted path model could distinguish the direct and indirect effects of land use on ridership through crime variables (Zhang, 2016).

SEM is a modeling technique that includes several endogenous and exogenous variables, as well as latent (unobserved) variables specified as linear combinations (weighted averages) of the observed variables. SEM is a series of statistical methods that enable the analysis of the complex relationships between one or more dependent variables and one or more independent variables (Gargoum and El-Basyouny, 2016).

There are different methods for estimating the structural equation system, such as the Maximum Likelihood Method, Generalized Least Squares, Weighted Least Squares, and so on. All of them are based on the covariance analysis method, in which the difference between the sample covariance and the model implied covariance matrices is minimized.

However, selecting an appropriate SEM estimation method depends on different assumptions about the probability distribution, the scale properties of the variables, the complexity of the SEM, and the sample size (De Oña et al., 2013).

SEM is a confirmatory, rather than exploratory method, because the modeler is required to construct a model in terms of a system of unidirectional effects of one variable on another (Golob, 2003).

Serving the confirmatory purpose, SEM is a technique where the main aim of the analysis is to test the validity of a certain relationship. When dealing with latent variables, performing the analysis usually includes a combination of confirmatory factor analysis and path analysis (Bollen, 2014).

SEM could be used for regression, simultaneous equations (with and without error-term correlations), path analysis, and variations of factor analysis (Golob, 2003).

The positive and unique feature of SEM is the ability to test network structure. Unlike classical statistical models, which do not represent indirect pathways, it is possible in SEM to determine those important connections. It is this feature of SEM that allows the detection of new unsuspected processes, which is a compelling part of the SEM experience (Eisenhauer, 2015).

However, this implies that model specification must be done prior to the analysis. It is another potential challenge when dealing with unknown relationships between variables.

The other distinctive feature of SEM—compared to Generalized Linear Models—is the model estimation in the SEM framework that involves modelling the covariance matrix of the observed variables as opposed to the observations themselves (Gargoum and El-Basyouny, 2016).

For this research, we could apply SEM as a powerful multivariate technique to have factor analysis and path analysis together because SEM has the advantage in the quantitative study of interactive relationships between variables.

SEM consists of two components—a measurement model describing the relationships between latent and manifest variables and a structural model describing the causal relationships between endogenous and exogenous latent variables (Shen, Xiao, and Wnag, 2016) The independent variable can either be manifest (measurable/observed) or latent (unmeasurable/unobserved).

Moreover, variables in a model can also be either exogenous (not influenced by any other variable in the model) or endogenous (influenced by another variable in the model). When variables in the model are all manifest, SEM simplifies the analysis to a path analysis, in which mediation, moderation, mediated moderation or moderated mediation can all be tested (Hayes, 2013). All variables in the structural model of this research are manifest—for this reason, I apply mediation analysis to study the model.

Mediation Analysis

In the past, a series of regressions were used by researchers to fit and estimate these complex relationships; however, statistical researchers of today have shown the superiority of SEM—greater efficiency coupled with simultaneous estimation of relationships between variables (Lacobucci, 2008).

The mediation model is applied to discover and analyze the underlying relationships of an observed relationship existing between a dependent and an independent variable by including a third explanatory variable, which is normally known as a mediator variable (Jenatabadi, 2015).

Mediation analysis is a statistical method used to understand how a variable x transmits its effects to another variable y. In other words, mediation is used to test whether the effect of x on y is direct only, indirect only (through a mediator variable) or both direct and indirect (Gargoum and El-Basyouny, 2016).

In mediation, we consider an intermediate variable, as the mediator that helps explain how or why an independent variable influences the outcome. In the context of a treatment study, it is often of great interest to identify and study the mechanisms by which an intervention achieves its effect (Gunzler, Chen, Wu, and Zhang, 2013). In this study, the crime is the mediator, socioeconomic and built environment are independent variables, and ridership is the dependent variable.

Baron and Kenny (1986) in their first paper addressing mediation analysis, tested the mediation process using a series of regression equations. However, mediation assumes both causality and a temporal ordering among the three variables under study (i.e. intervention, mediator, and response).

Since variables in a causal relationship can be both causes and effects, the standard regression paradigm is not suitable for modeling such a relationship because of its a priori assignment of each variable as either a cause or an effect.

SEM provides a more appropriate inference framework for mediation analyses and for other types of causal analyses (Gunzler et al., 2013).

To establish a mediation model, the Baron and Kenny approach suggests four steps. First, stablish strong relationship between dependent and independent variables for equation. Second, equation requires a significant relationship between the hypothesized mediator and the independent indicator. Next, a significant mediator variable is required to be related to the dependent variable. However, both mediating and independent variables are predicting the dependent variable in equation. Finally, in the fourth step, the coefficient connecting the dependent variable to the independent one is required, which needs to be greater (in absolute value) than the coefficient connecting the dependent variable to the independent one in the regression analysis in which both the mediating and independent variables, in the unique equation, are predictors of the dependent variable (Baron and Kenny, 1986).

The three regression equations are displayed below:

$Y=\alpha 1+\beta 1X+\varepsilon 1$

$Y=\alpha 2+\beta 2X+\beta MM+\varepsilon 2$

$M=\alpha 3+\beta 3X+\varepsilon 3$

In the above equations, Y is considered as the dependent variable;α1, α2 and α3 are intercepts; and M indicates the mediator; X represents the independent variable; β1 indicates the coefficient related to the dependent and independent variables; β2 shows the coefficient connecting the dependent variable to the independent one, and, ultimately, adjusting them for the mediator; β represents the coefficient linking the mediator indicator to the dependent variable adjusted for the independent one; β3 indicates the coefficient connecting the independent to the mediator variable; and, finally, ε1, ε2, and ε3 indicate the residual terms. Nevertheless, it is noteworthy to mention that the mediation functions can be modified to produce both nonlinear and linear effects, as well as M and X interactions in equation (Jenatabadi, 2015).

Similar to other quantitative analytical methods, SEM has its strengths and weaknesses.

Strength of SEM

When applied correctly, SEM has great flexibility to interplay between theory and data. This function distinguishes SEM in comparing principal components analysis, factor analysis, discriminant analysis, or multiple regressions—because SEM has greater flexibility than a researcher has for the interplay between theory and data (Chin, 1998).

SEM is a multivariate statistical methodology that includes factor and path analysis (Ülengin et al., 2010). SEM's goal is to provide summary of the interrelationships among variables and—like path analysis researchers— test hypothesized relationships between constructs (Lin and Yang, 2009).

The other difference between SEM and other methods is the capacity to estimate and test the relationships among constructs. This advantage is important compared to other general linear models whereby constructs may be represented with only one measure and measurement error is not modeled. Alternatively, SEM allows for the use of multiple measures to represent constructs and addresses the issue of measure-specific error. This difference is important in that it allows researchers to establish the construct validity of factors (Tomarken and Waller, 2005).

In contrast with multivariate regression, SEM allows the user to explicitly test indirect effects between two explanatory variables, where effects between two variables are mediated by another intermediary variable. Additionally, SEM can explicitly incorporate uncertainty due to measurement error or lack of validity of the observed variables (Ülengin et al., 2010).

SEM provides benefits to model relationships among multiple predictor and criterion variables, construct unobservable Latent Variables (LVs), model errors in measurements for observed variables, and statistically test a priori substantive/theoretical and measurement assumptions against empirical data with confirmatory analysis (Chin, 1998).

Comparing to the other major linear-in-parameter statistical methods, SEM has more advantages such as accounting for missing data, and handling of non-normal data (Golob, 2003).

Weakness of SEM

As a weakness of this method, researchers can easily misuse SEM just as researchers are free to conduct different multiple regression models until they find the best mode. They could identify and remove weaknesses in the model and fix them—at which time the final model is a revised one according to their hypothesis. Afterward, the revised model is presented as if it was the originally hypothesized model (Tomarken and Waller, 2005).

A second difference is the interpretation of the SEM model which involves evaluating many results. In SEM, researchers must evaluate multiple test statistics and many fit indices to determine whether the model correctly represents the relationships among constructs and observed variables. To further complicate the issue—some acceptable thresholds in introductory texts published less than a decade ago are now out of date (MacCallum et al., 1993).

Another shortcoming is to consider SEM as a causality method. The model can provide the estimation as it relates to the impact of variables on each. SEM determines the causality relationship between the variables when there are deep background studies, a strong model, and longitudinal data base. Following is detailed explanation of analytical model using SEM.

Explanation of the model through SEM

Transportation and criminology studies cover the mutual causality between built environment and socioeconomic characteristics to crime and ridership. Based on the literature review, to have the best model, there is a need for multiple interrelated equations reflecting the multiple likely directions of causality.

SEM is the selected method because it allows for simultaneous examination of relationships among multiple independent variables and multiple dependent variables and estimates model parameters while accounting for measurement error in latent variables (Kaplan, 2000).

Standard regression analysis implies a statistical relationship based on a conditional expected value, while SEM implies a functional relationship expressed via a conceptual model, path diagram, and mathematical equations.

Following are the analytical steps to assess the structural model. First, correlation analysis studies the correlations between all built environment and socioeconomic factors aligned with the collinearity tests between built environment and crime plus socioeconomic and crime. Afterward, the correlations between crime and ridership should be examined.

1. Multicollinearity Diagnostics: Analyzing the multicollinearity diagnostics between all variables, based on the variance inflation factors (VIF) and tolerance values before the regression analysis.
2. Multivariable Logistic Regression: Analyzing the relationship between built environment and crime, socioeconomic and crime, built environment and ridership, socioeconomic status and ridership, and crime and ridership. The results of multivariable logistic regression will show which variables are significantly related to crime and ridership.

3. SEM Analysis: displaying our hypothesized relationships between built environments, socioeconomic status, crime, and ridership.

In this study, the SEM analysis approach provides model fit information about the consistency of the hypothesized mediational model to examine the causality assumptions. In the structural model, crime is a mediation variable to address the complicated relationship between variables to address the study's hypotheses.

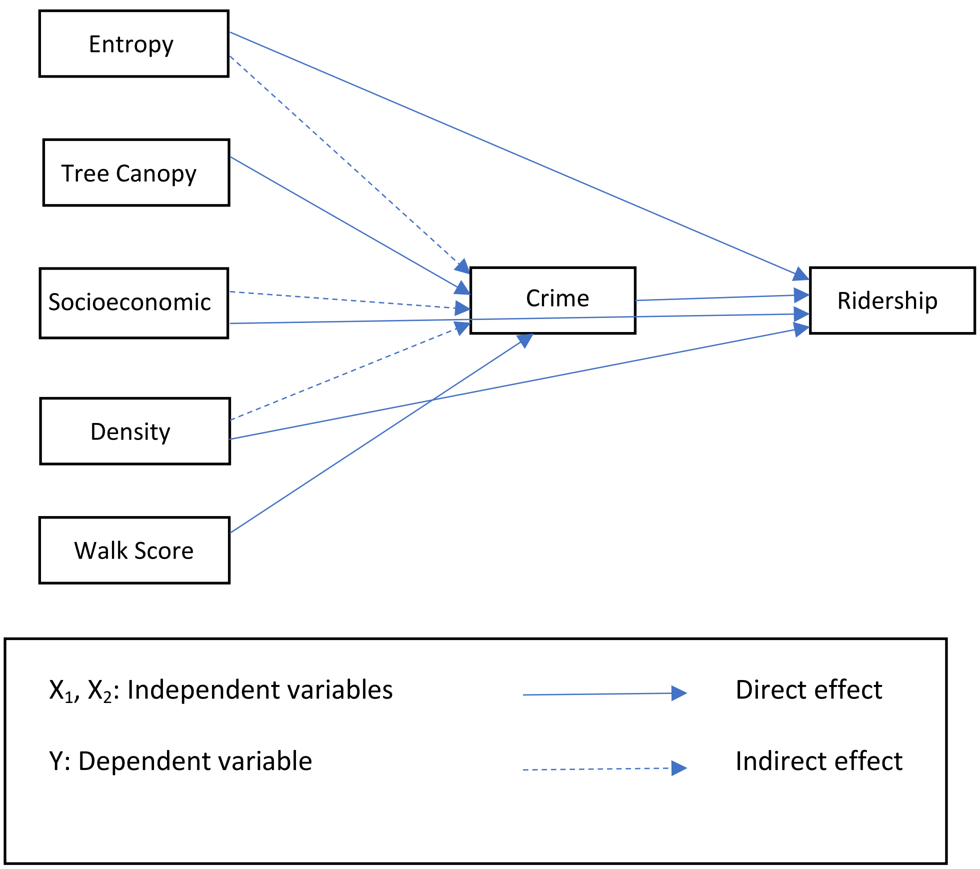


Figure 3. Structural Model

Data Acquisition

This study is a cross-sectional analysis which includes all data and information for 2015. The station level ridership for 2015 has been gathered from each case study's transit authorities.

Crime data is another set of data to be used in the analysis. Time, location, and type of the crime is provided through the police department of each city where the transit stations are located for 2015. The crime data was based on the UCR (Unified Crime Report). The geocoding method in Geographic Information Systems (GIS) analyzes spatially the allocation of each crime incident and its proximity to LRT stations.

Demographic, socioeconomic and built environment data sets are going to be collected from American Community Survey 5-year estimates data for 2015 Census Block Groups intersecting the half-mile around station area. Small location database and transit-oriented development (TOD) database are will be utilized to calculate other factors.

The unit of analysis is a half-mile buffer around the transit stations. Distance to transit is usually measured as an average of the shortest street routes from the residences or workplaces in an area to the nearest rail station or bus stop (Ewing and Cervero, 2001).

Each of the built environment and socioeconomic characteristics is calculated for the area within a half-mile of the transit stop. All built environment and socioeconomic variables are calculated for the half-mile station area in GIS.

Given the proximity of some transit stops to each other, especially in dense urban environments, overlap between station buffers can occur. All variables, however, are re-aggregated to the station buffer even when there is overlap between buffers.

The 0.5-mile distance has become accepted for gauging a transit station's catchment area. This transit catchment areas can make predictions about transit ridership and transit impacts (socioeconomic and on land use); moreover, it is implemented to recommend regulations (e.g., relaxing restrictive zoning). This radius is loosely based on the distance that people are willing to walk to transit (Guerra, Cervero, and Tischler, 2012).

The smallest unit of analysis for most of the data sources is census block group; therefore, GIS techniques help to spatially select the block groups that are in the half-mile buffer around the station.

Variables

There are 248 cases—light rail transit stations—in the data set. For each station, all the variables are gathered based on the literature and background theories—and all variables are calculated according to unit of analysis which is a half-mile buffer around the stations.

The following is the table of variables used in the study.

Table 3. Research Variables

	Variables	**Definition**	**Source**
Dependent Variable	Ridership	2015 annual ridership	Transit Agency
Mediator Variable	Crime	Crime Per Capita	Police Department
Independent Variables	Vegetation	Tree Canopy	National Land Cover Database
	Walkability	Walk Score of each Station	Walkscore.com
	Land Use	Entropy	County GIS
	Density	Population Density	American Community Survey
		Housing Density	American Community Survey
		Intersection Density	Smart Location Data Base
		Road Density	Smart Location Data Base
	Socio-economic	Income Below Poverty Level	American Community Survey
		Non-White Race	American Community Survey
		Non-English Speakers	American Community Survey
		Unemployed	American Community Survey

The table shows the measurement of each variable and the data resources. Next, each variable calculation is explained in detail.

Ridership

Public transit systems carry passengers for travel in many metropolitan areas in the U.S, but in most places, transit is losing market share to private vehicles. There are many factors influencing ridership such as population density, levels of private vehicle ownership, income, and transit system safety (Taylor and Fink, 2003). In this research, the focus is on LRT ridership in 2015 and what factors influence ridership of LRTs.

The ridership data includes annual ridership per station and has been gathered from each light rail agency for 2015 directly through emailcommunication. The following table shows which agencies have ownership or operate the light rail transit for each city. The ridership data refers to annual ridership (2015) of each system per station in the target city.

Crime

Much of the literature has demonstrated a strong link between crime and people's travel behaviors (Zhang, 2016). However, some studies argue that people's transit use is affected not only by transit-related crimes, but also the neighborhood crime-related activities near the station (Delbosc and Currie, 2012).

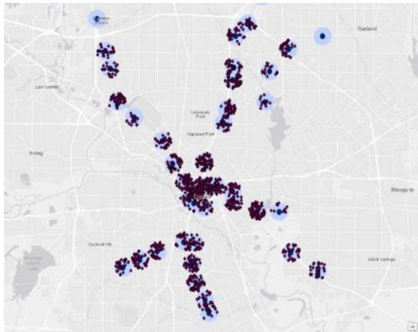
They claim that the fear of using public transit mainly comes from people's unsafe feeling about their living communities, instead of on transit itself. Therefore, the areas served by public transit can easily become high crime areas due to their exposure to the offender population (Yu, 2009).

This research applies three opportunity theories: routine activity, crime pattern, and rational choice theories to study the spatial crime patterns in relationship with environment and its effect on ridership at LRT station level.

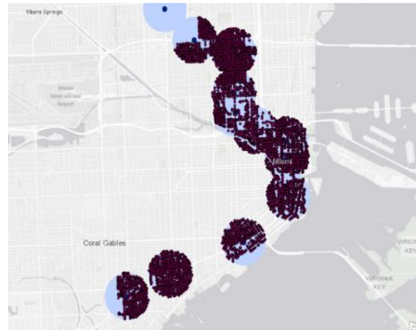
The crime incident reports for 2015 were gathered from the police department of each city. The reports include the address and type of the incidents. Using GIS, all the addresses are geocoded and identified as a point on the GIS map.

Next, the incidents in the half-mile buffer around the stations are counted to get the most accurate data, and then divided by the population of the area to get the per capita crime incidents. It should be noted that homicide and sexual assaults were excluded from the database since they are irrelevant to the ridership study. Following are the geocoded maps of crime incidents around light rail stations in each city.

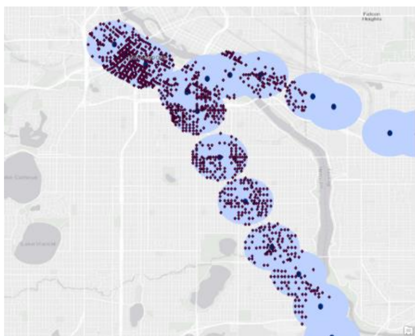
The following images show the geo-location of crime incidents in 2015 in half-mile buffer around each station. The dots represent the crime incidents.



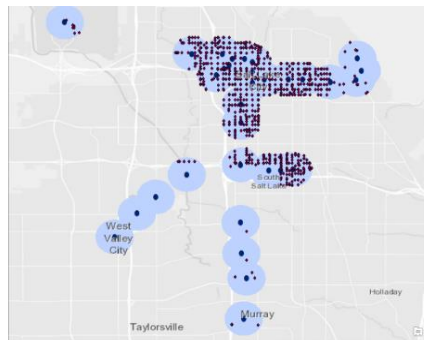
Dallas criminal incidents in half-mile buffer around light rail stations



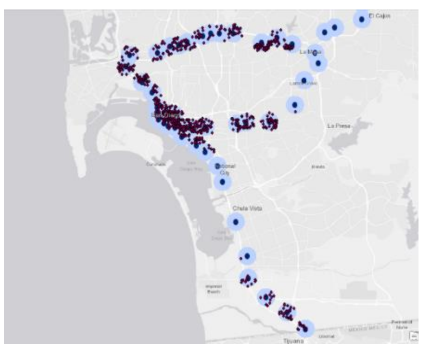
Miami criminal incidents in half-mile buffer around light rail stations



Minneapolis criminal incidents in half-mile buffer around light rail stations



Salt Lake City criminal incidents in half-mile buffer around light rail stations



San Diego criminal incidents in half-mile buffer around light rail stations

San Francisco criminal incidents in half-mile buffer around light rail stations

Figure 4. Crime Distribution around LRT Stations in 2015

Vegetation

To calculate the existed vegetation and plantation around each station, the tree canopy coverage was adopted from National Land Cover Database[7] (NCLD). NLCD 2016 is an ongoing land cover modeling production effort with NLCD scientists providing expertise in research and development, modeling, scripting, scene selection, cloud-masking, land cover mapping, and map production.

NLCD tree canopy cover is a raster geospatial dataset that covers the United States, coastal Alaska, Hawaii, and Puerto Rico. The dataset includes tree canopy estimates percentage for each pixel across all land covers and types and are generated by the United States Forest Service[8] (USFS).

The USFS originates tree canopy cover from multi-spectral Landsat imagery using ground and ancillary information (mrlc, 2019).

After downloading the raster data, the tree canopy square footage in half-mile buffer around each station by the total square footage of the area is calculated. In the database, the closer number to 1 means more vegetation and green coverage, and closer to 0 demonstrate less tree canopy coverage.

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[7] www.mrlc.gov/national-land-cover-database-nlcd-2016
[8] www.fs.usda.gov/

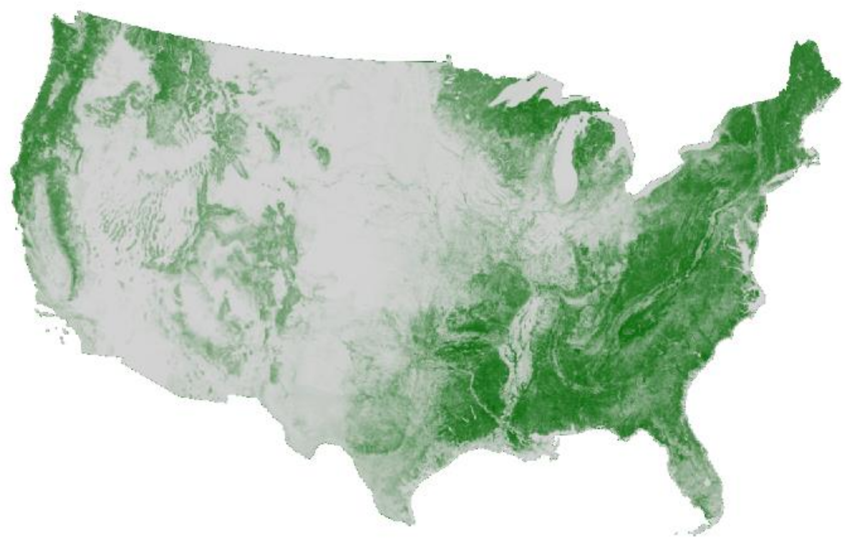

Figure 5. United State Tree Canopy Coverage, 2016

Source: National Land Cover Database

Entropy

According to Loukaitou-Sideris, there are some characteristics such as residential or industrial which determine the volume and characteristics of people in the areas. Some commercial and residential areas where public transits stations are located suffer from high crime rates while others do not.

Therefore, studying the surrounding environments such as businesses and activities in the localities close to transit stations could determine the potential criminal activities around stations (Loukaitou-Sideris et al., 2002).

Mixed-use development is a widely discussed subject of urban sustainability. It helps to manage energy and transportation related problems in urban environments to increase walkability and vital communities. With the purpose of understanding the different functions together, such as residential, commercial, and recreational land uses, it is important to study mixed-use development (Zagorskas, 2016).

Mixed land use is one of the major factors affecting the non-motorized and public transport-based trips—specifically for work purpose. Similar evidence exists from various past studies related to the interaction between land use mix and travel behavior (Bordoli, et al., 2013)

Measuring land-use mix is critical for ridership studies. There are numerous methods of measuring land use such as entropy index, dissimilarity index, distance to walkable destination such as facilities and the number of amenities available within a certain distance (Bahadure and Kotharkar, 2015).

Entropy index quantifies randomness, segregation, and diversity in the dataset. Land-use mix exhibits a pattern of combination and segregation of different land uses. Therefore, entropy index is the most widely accepted and commonly used index by researchers for representing the land-use mix with in geographic area (Cervero, 1988). Cervero derived the entropy Equation as:

$$\text{Entropy Index} = (-1) \times \sum \frac{pj \times \ln(pj)}{\ln(J)}$$

Where, Pj is the proportion of developed land in the Jth land-use type. Since the original land use data from each city contains different categorization and specification of land uses, the land uses were categorized by four main classifications: 1- Utilities and Services, 2- Commercial and industrial, 3- Residential, and 4- Open Space. Entropy index varies between 0 and 1, wherein 0 indicates single use (homogenous) and 1 maximum land-use mix (heterogeneous).

Land use Mix Entropy index (EI) = (-1) $\times$ $\dfrac{[\left(\frac{b1}{a}\right)\times\ln\left(\frac{b1}{a}\right)+\left(\frac{b2}{a}\right)\times\ln\left(\frac{b2}{a}\right)]}{\ln(j)}$

Where, a is the total area in square meter of two land uses, b1 is the commercial land-use area in square meters, b2 is the residential land-use area in square meters, b3 utility services, and b4 open space. J is total number of land uses in the equation.

Walk Score

According to Duncan et al. (2011), Walk Score is a valid indicator of neighborhood walkability in different locations and with different spatial scales. Walk Score data is used by analysts and researchers in the fields of real estate, urban planning, government, public health, and finance.

Walk Score measures the walkability of any address using a patented system. For each station, Walk Score analyzes hundreds of walking routes to nearby amenities. Points are awarded based on the distance to amenities in each category. Amenities within a 5-minute walk (.25 miles) are given maximum points. A decay function is used to give points to more distant amenities, with no points given after a 30-minute walk.

Walk Score also measures pedestrian friendliness by analyzing population density and road metrics such as block length and intersection density. Data sources include Google, Factual, Great Schools, Open Street Map, the U.S. Census, Localize, and places added by the Walk Score user community (walkscore, 2019).

Table 4. Walk Score Categorization

Walk Score	Description
90-100	Walker's Paradise Daily errands do not require a car.
70-89	Very Walkable Most errands can be accomplished on foot.
50-69	Somewhat Walkable Some errands can be accomplished on foot.
25-49	Car-Dependent Most errands require a car.
0-24	Car-Dependent Almost all errands require a car.

Source: Walk score index[9], 2018

Density

There are several environmental factors leading to increase in crime occurrence around transit stations. According to Loukaitou- Sideris (2002), the layout of the street such as alleys, vacant building, and multi-family housing factor is related to the crime incidents around the stations. Street intersections, design, walkability, and density also have impacts on crime in transit stations (Zhang, 2016).

To calculate density, there are two different resources to extract data. The first one is Smart Location Database. The Smart Location Database is a data product and service provided by the U.S. EPA Smart Growth Program.

The Environmental Protection Agency's (EPA) released Smart Location Database[10] (SLD) to address the growing demand for data. The SLD includes several

[9] www.walkscore.com/
[10] www.epa.gov/smartgrowth/smart-location-mapping

demographics, employments, and built environment variables for every Census Block Group (CBG) in the United States (epa.gov, 2013). For this study, "Total Road Network Density" and "Intersection Density" were retrieved from SLD.

Road Density = $\frac{\text{Total lane Miles of Roads}}{\text{land (acre)}}$

Intersection Density = $\frac{Number\ of\ Intersections}{Land\ (acre)}$

Housing Density = $\frac{\text{Total Housing}}{\text{land (acre)}}$

Population Density = $\frac{\text{Total Population}}{\text{land (acre)}}$

Moreover, Housing and Population Density were retrieved from American Community Survey on the Census Bureau's database. Housing density and population density were calculated by dividing the total housing units and total population by half-mile buffer around the station area.

Socioeconomic Status

Referring to the most relevant study, Loukaitou-Sideris (2002) claims low-income neighborhoods around stations are significantly more exposed to crime activities. However, the relationship between crime and a neighborhood's income level is a controversial matter among scholars.

According to social disorganization theory (Shaw and McKay, 1942), residential characteristics such as poverty, family stability, residential mobility, ethnicity, immigration status, percent of renters in the areas, youths, and unemployment rates have direct association with crime risks (Wang and Minor, 2002; Andersen, 2006).

It could be concluded that socioeconomic characteristics play an important role in transit ridership and possibility of crime incidents in an area. In this study the broad term of socioeconomic status refers to unemployment, having income below poverty level, non-English speakers, and non-white people. Like density, the Factor Reduction Analysis is used to reduce many variables into fewer numbers of factors.

Factor Reduction Analysis for socioeconomic and density

Considering the limitation in studied cases of the research, the lower variables to test in the model, increases the validity of the analysis. Therefore, for socioeconomic and density the factor analysis was adopted to omit the high correlated variables and reduce the number of factors in the Structural Equation Model.

Factor Reduction Analysis technique extracts maximum common variance from all variables and puts them into a common score.

Dimension reduction through factor analysis method runs with SPSS software. Technically the method is Principal Component with a slight difference to Factor Analysis. They both achieve the same goals and that is why these names are used interchangeably. However, this method of factor extraction was used as it fits better with research design and methodology

Socioeconomic

There are different variables measuring socioeconomic status such as people with no employment or below the poverty income level.

The first step is to see if there are variables or factors that could load together and represent the same construct. The correlation table shows all the factors are correlated and the determinant value is greater than .001.

Multicollinearity and singularity were also checked. Therefore, correlations with greater than 0.9 scores were removed from the analysis. For socioeconomic status—after omitting the unfitted variables—the variables that remain in equation for low socioeconomic status construct are non-employed, Non-English speakers, Non-White race, and income below poverty rate.

Table 5. Correlation Matrix (Socioeconomic)

		Unemployed	**Non-English Speaker**	**Non-white**	**Income below Poverty**
Correlation	Unemployed	1.000	.931	.851	.855
	Non-English Speaker	.931	1.000	.788	.816
	Non-White	.851	.788	1.000	.709
	Income below poverty	.855	.816	.709	1.000

a. Determinant = .010

In addition to coefficient and significant, the KMO and Bartlett's Test of Sphericity was run. For the extraction, the Eigenvalues greater than 1 show how many factors to extract. Because of the correlation between the variables for the rotation, Direct Oblimin is the standard method applied in social science for correlated factors.

Table 6. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.819**
Bartlett's Test of Sphericity	Approx. Chi-Square	1134.312
	df	6
	Sig.	.000

The Kaiser-Meyer-Olkin Measure of Sampling Adequacy should be more than 0.5 to be acceptable, and here it is .819 which is notably greater than 0.5. The Bartlett's test of sphericity is significant, and here the P value is significant at level of .001 as well.

Table 7. Total Variance Explained

Com-ponent	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.479	86.979	86.979	3.479	86.979	86.979
2	.293	7.325	94.304			
3	.173	4.314	98.618			
4	.055	1.382	100.000			

Extraction Method: Principal Component Analysis.

The total variance table shows that the cumulative initial Eigenvalue for the first factor almost explains the 87% of the variance. The scree plot also confirms that it is above the Eigenvalue.

Figure 6. Socioeconomic Scree Plot

Density

As there are many factors to estimate density, The Factor Reduction Analysis (FRA) was implemented. This technique extracts maximum common variance from all variables and puts them into a common score.

First, the covariation of between the variables should be checked to load together and represent the density construct. The correlation table shows all the factors are correlated and the determinant value is greater than .001. Finally, we checked for high density factors and find population density, housing density, intersection density, and street network density in the analysis.

Table 8. Correlation Matrix

		Housing Density	Population Density	Road Density	Intersection Density
Correlation	Housing Density	1.000	.940	.550	.478
	Population Density	.940	1.000	.474	.424
	Road Density	.550	.474	1.000	.857
	Intersection Density	.478	.424	.857	1.000

a. Determinant = .021

Regrading to KMO and Bartlett’s test, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy is .616 which is acceptable, and the P value shows the model is significant.

Table 9. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.616
Bartlett's Test of Sphericity	Approx. Chi-Square	944.289
	Df	6
	Sig.	.000

Table 10. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.864	71.588	71.588	2.864	71.588	71.588
2	.939	23.473	95.062			
3	.142	3.557	98.619			
4	.055	1.381	100.000			

In addition, the total variance table shows the cumulative initial Eigenvalue for the first factor and explains the 71.5% of the variance—the Scree Plot also confirms above the Eigenvalue.

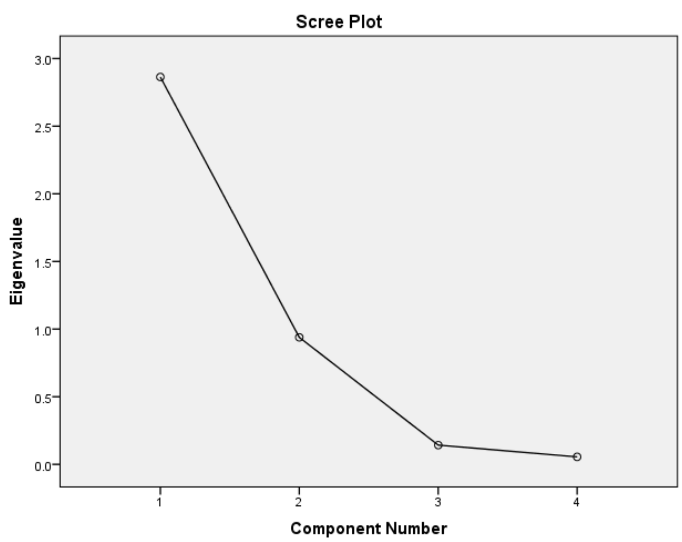

Figure 7. Density Scree Plot

Adjusting the Unit of Analysis

Creating the proper database consists of various techniques and methods. The socioeconomic demographics and built environment data which were gathered from different sources should be adjusted to our research unit of analysis.

The unit of analysis for this study is the half-mile buffer around the stations; however, blocks groups are the smallest unit of census geography available for this study. The inefficient way to calculate the data within the half-mile buffer around the station is to spatially select the target area. However, there is a better method to aggregate data in a half-mile buffer—weighting by block group population centroid (Martin, 1989).

Adjusting block groups in the half-mile buffer around the stations allows me to only choose the block groups that fall into the half-mile buffer area. Mostly, in downtown areas or high-density locations we have overlaps between the buffer zones of the stations—the overlaps block groups were eliminated from the data base to prevent the duplicate numbers in the data analysis.

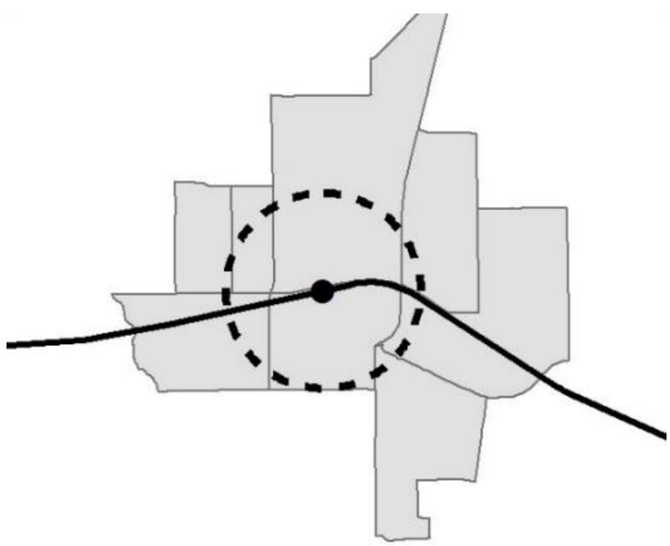

Figure 8. Station Buffer and Block Group boundary Overlaps

Population centroid of a block group refers to a geographical point with the highest population in the defined area. The block group centroids have X and Y location coordination and they are used to calculate a weight for the highlighted block group. Therefore, the block groups with their centroid point located in the half-mile buffer zone are going to get aggregated in the half-mile buffer around the stations as the unit of analysis.

To clean up and prepare the crime data, said data was gathered from reports of 2015—from each city's police department's UCR coded database—and the geocoding process with GIS software was adopted. The collected crime data contains the specific address of the crime incidents. With geocoded addresses, the locations of the crimes and recognized distribution patterns on the map were identified. This can be done by analysis tools available with ArcGIS. To be more specific, geocoding is the process of assigning an XY coordinate to the description of a place by transferring the descriptive location-specific elements to those in the reference data. The geocoding process is defined as the steps involved in translating an address entry, searching for the address in the reference data, and locating them as feature points on the map (Zandbergen, 2008).

Next, with spatial analysis methods in GIS, only crime incidents that happened around the half-mile buffer of stations were selected and aggregated to keep the consistency throughout other data sources. This research eliminates the homicide- and rape-related crime incidents.

Additionally, before running the SEM analysis, it is important to check for the skewness in the variables. Therefore, the normality for both ridership as a dependent variable and crime per capita as the mediator were checked.

To check the normality, the histogram graph in SPSS software demonstrates the frequency of both ridership and crime per capita.

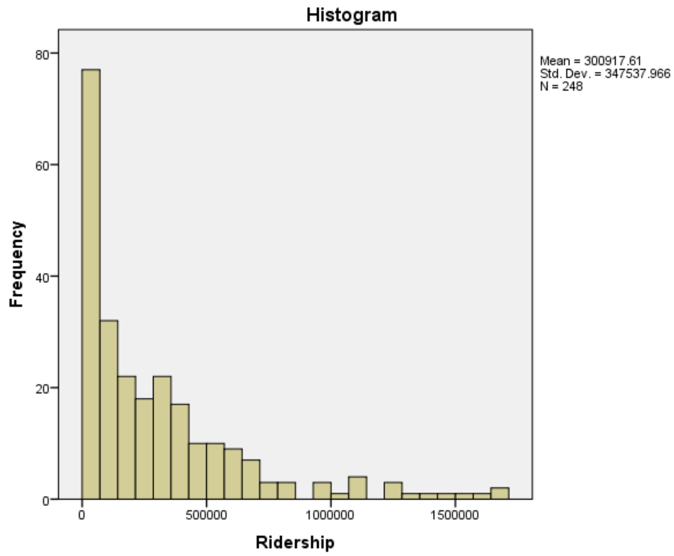

Figure 9. Ridership Frequency Histogram

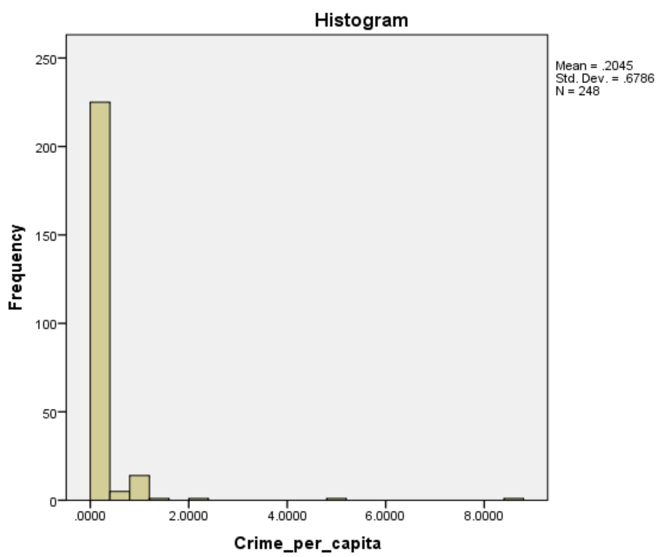

Figure 10. Crime Frequency Histogram

Because the skewness is positive and there are no negative and zero value, log10 transform was used to normalize the data.

Summary

This chapter opened with defining the methodology, research questions and hypotheses. It went through the details of research goals and concentration referring to previous studies. Following was, an explanation of the characteristics of the target areas such as demographics, LRT ridership and crime statistics factors. The next step was defining the analytical method, explaining path analysis, structural equation modeling, and mediation analysis. Moreover, the definition of each variable and data gathering and data cleaning process was covered. The final step explained adjusting the unit of analysis to a half-mile buffer around the stations to achieve the same level of data for all variables.

The next chapter details empirical analysis and modeling.

Chapter Five

Introduction

Ridership success could be measured by a variety of variables such as socioeconomic status, built environment, land use, and density. As mentioned in the literature review, there are many studies referring to the impact of socioeconomic status on ridership (Tyler et.al, 2009; Kim and Kim, 2016; Gomez-Ibanez, 1996).

Moreover, influence of built environmental factors such as density, road network, walkability, and accessibility on ridership have been mentioned in several scholars' works (Cervero and Kockelman, 1997; Cervero, 1993; Ryan and Frank, 2009) Land use factor is one of the most important factors to study in relationship with ridership, especially in an urban context (Loukaitou-Sideris et al (2001).

A neglected factor in many studies is crime (Zhang, 2016). Crime is one of the crucial factors related to transit ridership. Based on the previous studies and theories, crime has an impact on ridership. In this study crime has a mediation role between other factors and ridership.

Empirical Analysis

In this study, built environment factors are represented by household density, population density, road network density, and intersection density. The process of calculation of each factor, and the final density factor, has been described in previous chapter as similar to how socioeconomic factors have been defined by median income, poverty level, race, and spoken language. The land use factor or entropy and vegetation are also included in the research variables. Most important to this research was that the crime factor was implemented as a mediated factor to see how the ridership model could work.

The variables included in the model are grouped into following categories:

- Entropy
- Density: population density, housing density, road network density, and intersection density
- Socioeconomic: median income, poverty level, language spoken, and race
- Tree canopy
- Walk score
- Crime per capita
- Annual ridership per each station

In my study, the number of cases (stations) is relatively small (248 stations) and therefore, variables are categorized into smaller groups because the general rule in SEM analysis is to have 15 cases per each variable (Stevens, 2012).

SEM is a powerful and flexible extension of the general linear model and has several assumptions—to produce reliable results these assumptions should be met or at least approximated. According to Stevens (2012), a good general rule for sample size is 15 cases per predictor in a standard ordinary least squares multiple regression analysis.

Since SEM is closely related to multiple regression in some respects, 15 cases per measured variable in SEM is not unreasonable. In this study there are 248 cases (stations) and 7 predictors which is acceptable.

Analyzing crime effect on ridership requires having the whole picture model, including all the variables in the equation. Therefore, instead of linear regression, SEM is used to reflect the best interaction of exogenous and indigenous variables.

The factors are determined to be good and normal and thus, the SEM Analysis by AMOS software was run. AMOS gives a graphical interface that allows one to draw out the model, make specifications and run the analysis. In path analysis there is a set of measured variables to estimate both direct and indirect effects. There are two types of variables in path analysis—exogenous are variables in the model that do not have any predictors associated with them and endogenous variables that are unidirectional. In this model, ridership and crime are endogenous and entropy, tree canopy, socioeconomic status, density, and Walk Score are exogenous.

The SEM model is completely relying on the pervious findings and theories. Therefore, according to the background studies and theories, the following Mediating Model was proposed. This model demonstrates crime per capita's influence on ridership and plays as a mediator in the relationship between the Independent variable and ridership as independent variable.

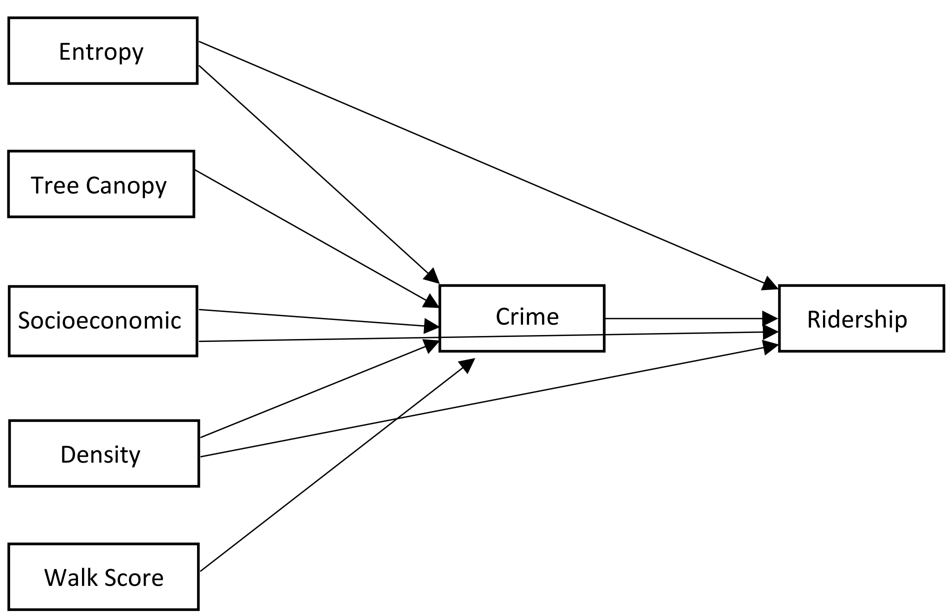

Figure 11. Path Analysis model with Crime Mediation

Model Fit Summary

The purpose of statistical techniques is to develop a well-defined model. Herein the predicted and observed data values to assess goodness of fit through the statistical measures are as follows.

The most important factor is the chi-square significance test. In SEM path analysis the p-value should not be statistically significant with high chi-square value (Hox and Bechger, 2007).

The p-value of the Chi-square tests is 0.323 which shows the good fit model. Also, the degrees of freedom associated with the test should be more than 1 to be acceptable in this study, it is 4. Therefore, the low ratio of chi-square to degrees of freedom and the p-value greater than .05 are showing the model's goodness of fit.

Due to small sample dataset (N=248) and the likelihood ratio chi-square test is sensitive to sample size, other tests to check the model fit were examined. The Tucker-Lewis Index (TLI), the Normed Fit Index (NFI, the Parsimony-NFI (PNFI), and the Comparative Fit Index (CFI) indices are typically scales between 0 to 1. The closer to 1 indicates the between goodness of fit (Kaplan, 2008). The rule of thumb said that greater than .9 or .95 values would be more indicative of a good fitting statistical model.

According to Kaplan (2000), the mentioned indices are so restrictive that to get the approximate fit of the model, it is preferable to consider Root Mean Square Error of Approximation (RMSEA). RMSEA measure the approximate fit of a model. RMSEA value less or equal to 0.05 indicates the close or better fit (Browne and Mels, 1990). Here in the default model, the RMSA is 0.026 and indicates goodness of fit.

The following table presents the goodness of fit model indices in the studied model.

Table 11. Goodness of Fit Indices

Indicators	Value	Accepted Cutoff Values
Chi-square	4.671	-
Degrees of freedom	4	-
Probability level	0.323	> 0.05
Comparative Fit Index (CFI)	0.999	> 0.90
Normed Fit Index (NFI)	0.991	> 0.95
Non-Normed Fit Index (NNFI) (or the Tucker-Lewis Index: TLI)	0.993	> 0.90
Root Mean Square Error of Approximation (RMSEA)	0.026	< 0.05

Assessment of normality

As mentioned earlier, AMOS software is used to run the model. In the analysis configuration, maximum likelihood estimation of the model, indirect direct and total effects, normality, and outliers are studied. After running the analysis, first, the assessment of normality should be checked. Skewness statistics and kurtosis statistics are essential critical values for testing. The key point is to make sure that skewness falls inside of positive or negative 1.96 to accept the null at the 0.05 level.

Table 12. Assessment of Normality

Variable	skew	c.r.	kurtosis	c.r.
Walk Score	-.555	-3.566	-.693	-2.227
Density	1.011	6.502	.281	.904
Socioeconomic	1.482	9.526	3.221	10.353
Tree Canopy	-1.229	-7.902	2.904	9.334
Entropy	-.589	-3.785	.062	.199
Crime	-.217	-1.392	-.168	-.540
Ridership	-.859	-5.520	-.295	-.947
Multivariate			18.294	12.833

As my sample size is relatively small, it is acceptable to observe significant kurtosis and non-normality in the data per each variable.

Bootstrapping

A strong assumption is clean measures would be somewhat compensatory for sample size and the number of variables per factor influences improving fit statistics (Iacobucci, 2010). Anderson and Gerbing (1984) found that with "three or more indicators per factor, a sample size of 100 will usually be sufficient and a sample size of 150 will usually be sufficient for a convergent and proper analysis."

Bootstrap could work as a solution to increase the sample size. These methods empirically generate sampling distributions via resampling without replacement from the original data. Using bootstrap samples, researchers can estimate accurate significance levels and appropriate standard errors for various model parameters including direct and indirect effects. Bootstrap methods represent a second choice when fitting covariance structures to non-normal data (Bollen & Stine 1993).

It also works as a method to correct for non-normality in the database. However, there are some assumptions to meet before bootstrapping in AMOS.

First, the input database should be complete for sample data non-normality test and using any of its bootstrap features. In other words, you should solve the missing data problem before you use AMOS's non-normality diagnostic and bootstrap features.

Second, your sample size should be large enough to ensure the reliability of the parameter estimates. Nevitt and Hancock (1998) suggest a minimum sample size of 200 for SEMs.

Maximum Likelihood Estimates

The maximum likelihood technique has been used for estimating linear structural equation models and has confirmatory maximum likelihood in factor analysis (Jöreskog, 1970). Here in this study, the maximum likelihood estimates the relationships between the variables.

The following table includes all the parameters of regression weights such as Unstandardized Estimate (Estimate), Standard Error (SE), Critical Values (CR), and P value. Each unstandardized regression coefficient represents the amount of change in the dependent or mediating variable for each one-unit change in the variable predicting it.

Table 13. Regression Weights

Variables			Estimate	S.E.	C.R.	P value
Crime	<---	Entropy	-.125	.281	-.446	.656
Crime	<---	Tree Canopy	.661	.429	1.541	.123
Crime	<---	Socioeconomic	-.010	.095	-.109	.913
Crime	<---	Density	.331	.102	3.227	**.001
Crime	<---	Walk Score	.002	.003	.665	.506
Ridership	<---	Crime	.476	.056	8.470	***
Ridership	<---	Entropy	.519	.249	2.084	*.037
Ridership	<---	Socioeconomic	-.137	.081	-1.676	.094
Ridership	<---	Density	.001	.085	.010	.992

Note: Unstandardized Estimate (Estimate); Standard Error (S.E.); Critical Value (C.R.)
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Reviewing the unstandardized regression weights on the path coefficients shows that crime has positive strong significant regression weights on ridership with p-value less than 0.001. In other words, the level of crime incidents—measured by crime per capita around the stations—is a significant predictor of ridership. This means ridership per station in 2015 increases by 0.476 units for each unit of increase in crime.

Density has significant positive impact on crime with p-value <0.01. It can be concluded that adding one unit of density in half-mile buffer around the stations will increase the crime per capita in the same area by 0.331 unit.

The model also indicates that mixed land use areas around light rail transit stations have positive and significant impact on ridership at p-value < 0.05. Considering unstandardized estimates one unit increase of entropy in half-mile buffer around the stations result in transit system ridership growth by 0.519 units.

Additionally, there is not much difference between the standardized and unstandardized coefficients in this example—perhaps because the units are derived from survey measurement items. By contrast, variables with very different measurement scales inputted to same model can result in sharp discrepancies between the standardized and unstandardized regression coefficient output.

Covariance

To see the covariance relationship, we have the covariance table which has p-values associated with those—essentially testing whether the covariance is significantly different from zero. If it is not significantly different, there should be correlation values among exogenous variables. Covariance model contains the familiar Estimate, S.E. (standard error), and C.R. (Critical Ratio: the estimate divided by its standard error)—quantities that are computed assuming normal distribution of the observed variables.

Table 14. Covariance

			Estimate	**S.E.**	**C.R.**	**P**
Entropy	<-->	Socioeconomic	-.056	.013	-4.413	***
Density	<-->	Walk Score	11.519	1.680	6.858	***
Tree Canopy	<-->	Walk Score	.317	.163	1.945	*.052
Socioeconomic	<-->	Walk Score	6.926	1.568	4.417	***
Socioeconomic	<-->	Density	.814	.081	10.029	***
Tree Canopy	<-->	Socioeconomic	-.011	.004	-2.537	*.011
Entropy	<-->	Density	-.065	.013	-4.973	***
Entropy	<-->	Walk Score	-.979	.300	-3.262	**.001

Note: Unstandardized Estimate (Estimate); Standard Error (S.E.); Critical Value (C.R.)
*** p<0.001, ** p<0.01, * p<0.05

As it is shown in the table, every covariance between the variables is significant at the p-value < 0.05. As expected, referring to the literature, these variables have a covaried relationship between each other. It is worth highlighting that Walk Score has strong positive covariance with density, tree canopy, and socioeconomic status. It can be concluded that the more pedestrian friendly environments—around transit stations—have a positive significant relationship with higher density, more green space and socioeconomic status of people who live in half-mile buffer around the light rail stations. Also, entropy has negative covariance with socioeconomic status and density; that is to say, the more mixed land use areas have covaried with low socioeconomic status and according to the literature review, residential areas have more density; therefore, high mixed land use has negative covariance with density.

The following figure demonstrates the studied path analysis model with all regression weights and covariances.

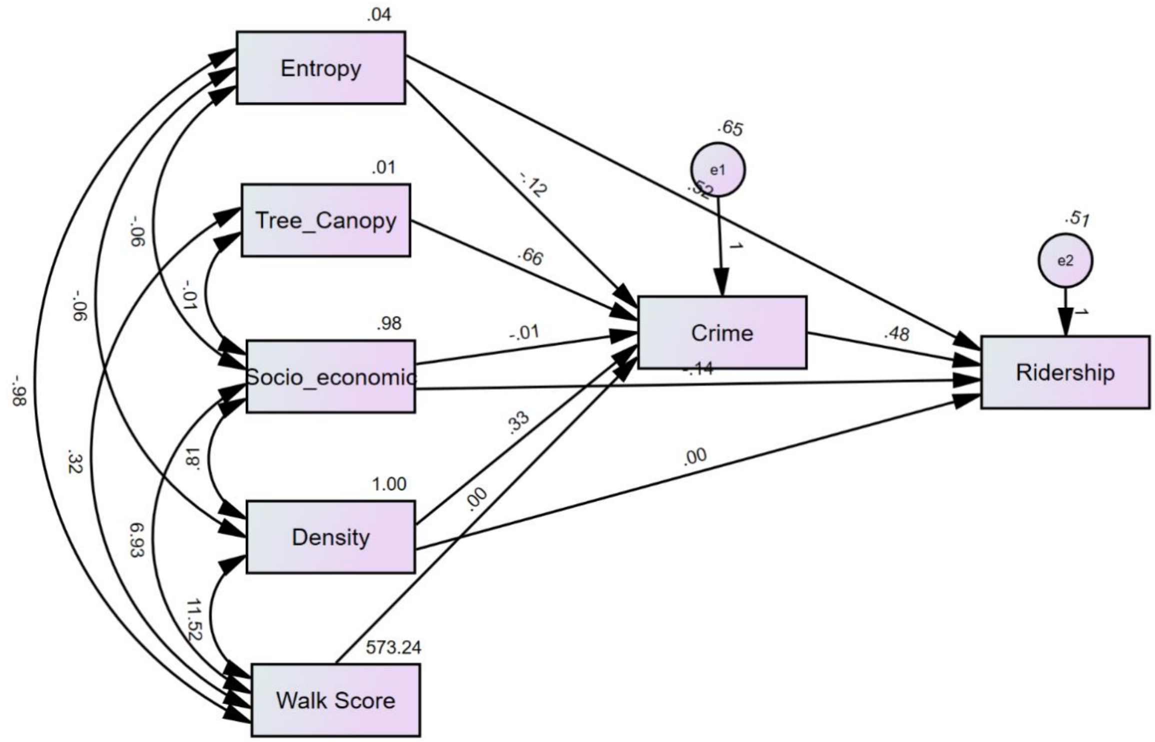

Figure 12. Unstandardized Regression Weights on Paths

Squared Multiple Correlations

Another important table to consider is Squared Multiple Correlations. The squared multiple correlation of Crime is 0.169—which indicates that the variables that are directly predicting crime accounted for about 16.9% of the variation in the crime variable and about 24.3% of variance of ridership was accounted by the predictors.

	Estimate
Crime	.169
Ridership	.243

Table 15. Squared Multiple Correlations

Indirect, Direct, and Total Effects

SEM models distinguish three types of effects: direct, indirect, and total effects. According to Bollen (1989), Direct effects refer to the influence of one variable on another variable in absence of mediator variable in the path model. However, the indirect effects refer to the influence of one variable to another mediated by at least one intervening variable (Bollen, 1989) and the sum of the direct and indirect effects are called total effect.

In the studied path model, crime acts as a mediator factor for the variables affecting ridership. The theoretical model explains the ways in which different factors — density, entropy, and socioeconomic status—have both direct and indirect effects on ridership.

The direct effect shows co-efficiency of each factor on crime and ridership. The indirect explains the impact of independent factors on dependent variable considering the mediator variable and the total effect is the overall effect of each independent variable on the dependent variable.

The following table shows the effects of each factor on dependent variable (ridership) and mediator variable (crime) in the default model.

Table 16. Direct, indirect, and total effect

		Socioeconomic status	Density	Entropy	Tree canopy	Walk score	Crime
Direct	Crime	-0.012	0.375	-0.027	0.091	0.045	0.000
Indirect		0.000	0.000	0.000	0.000	0.000	0.000
Total		-.012	0.375	-0.027	0.091	0.045	…
Direct	Ridership	-0.164	0.001	0.122	0.000	0.000	0.511
Indirect		-0.006	0.191	-0.014	0.047	0.023	0.000
Total		-0.17	0.192	0.108	0.047	0.023	0.511

The direct effect represents the amount of change of the dependent variable (Ridership) and mediator variable (Crime) due to a change of 1 unit of independent variables (Socioeconomic status, Density, Tree Canopy, Entropy, and Crime)

This may indicate that low socioeconomic status supports less valuable property compared to richer neighborhoods. Burglary, theft, and larceny crimes occur in more affluent areas (Metz and Burdina, 2018).

Han and Bhattacharya (2013) claim that socioeconomic variables are not very significant and they are not systematic predictors of either property or violent crime.

Furthermore, the results showed that lesser entropy has negative relationship with crime per capita. In the other words, station neighborhoods with less mixed land use have more crime. However, density, tree canopy and walk score have positive relationships with crime.

Regarding the variables relationship and total effect on ridership, it is noticeable that socioeconomic status has a negative relationship with ridership. This means the lower socioeconomic status is around the stations, the higher ridership we have for the public transit. This relationship explains the fact that captive riders use public transit as it is the most affordable mode choice for their commute. However, the total effect of other variables is positive.

The next step is to check the significances of these relationships and effects. In path analysis with mediation factor, the two-tailed significance test could be used to determine the significance of the paths and effects among the variables. The values assigned for each path is considered as p-value.

The following table shows the results of the two-tailed significance test.

Table 17. Direct, indirect, and total two-tailed Significance test

		Socioeconomic	Density	Entropy	Tree canopy	Walk score	Crime
Direct	Crime	0.956	.002**	.626	.184	0.511	…
Indirect		…	…	…	…	…	…
Total		0.956	.002**	.626	.184	0.511	…
Direct	Ridership	0.142	0.989	0.043**	…	…	.0.002**
Indirect		0.956	0.003**	0.608	0.177	0.482	…
Total		0.126	0.113	0.116	0.177	0.482	0.002**

**= P<0.005

The table shows that there is positive significant direct effect from Crime to Ridership as the p-value is less 0.05. Moreover, Entropy has positive significant direct effect on Ridership as the p-value is less 0.05. Density, also, has positive significant direct effect on Crime as the p-value is less 0.05.

It could be concluded that density has the biggest significant positive impact on crime. Among other variables, crime has the biggest positive direct impact on ridership as total effect with 0.511 points. Entropy also has significant positive impact on ridership. The only significant indirect path is between density impacts on ridership through crime with 0.191 points.

Following is an explanation of mediation relationship between variables in support of conclusion and respective path analysis.

Mediation

The mediation shows the significant and insignificant direct and indirect effects and how these effects results in mediation, no mediation, or partially mediation effect.

Table 18. Mediation Confirmation

Hypothesis	Results
Entropy ⟶ Crime ⟶ Ridership	No Mediation
Socioeconomic ⟶ Crime ⟶ Ridership	No Mediation
Density ⟶ Crime ⟶ Ridership	Full Mediation
Crime ⟶ Ridership	Direct impact
Tree canopy ⟶ Crime	---
Walk Score ⟶ Crime	---

The table shows that there is a full mediation from Density to Crime and to ridership because the indirect effect is significant through the crime and all the other mediations in the model are insignificant. It also could be concluded that there is positive significant effect of entropy on ridership.

The research result indicates that crime has a positive significant effect on ridership. As Cozens and Love (2015) mentioned in their study, the relationship between crime and ridership is complex. The result complies with previous findings of Ferrell in 2008. As he mentioned in the study (2012), the influence of neighborhood crime activities on mode choice varied by the crime type, the mode of travel, and the city type.

Also, Zhang (2016) surmised that the positive association probably reflects that a rise in ridership is associated with an increase of crimes due to high activity, and the negative association reflects a decline of community security and fall in ridership.

In this research the positive impact indicates the high demand of transit use by captive riders. The positive association possibly reflects a rise in ridership is associated with an increase of crimes due to a concurrent relationship

Also, the result indicates that entropy has direct positive significant impact on ridership. This aligns with Cervero (2002) and Spillar and Rutherford (1998)—mixed land use of residential, commercial, and office in proximity of transit stations brings more transit ridership.

In addition, residential and employment densities have long been thought to be critical determinants of transit use. Many studies have been conducted to investigate the impact of density on ridership (Gomez-Ibanez, 1996; Cervero, 1993; Spillar and Rutherford, 1998; Pushkarev and Zupan, 1977; Cervero and Kockelman, 1997).

Moreover, the criminology perspective asserts that density plays an important role on occurrence of criminal activities (Loukaitou-Sideris, 1999; Harris, 1971). This study aligns with Clarke, Belanger, and Eastman (1996) investigation of 206 New York subway stations which found that in higher density areas there will be more crime incidents.

The contribution of this study is to highlight the role of density in ridership evaluation considering crime as mediator factor.

Comparison between Regions

After analyzing the relationship and the impact of density and socioeconomic variables on crime and ridership, it is important to check factors affecting crime among all the regions. The previous analysis showed that walk score and tree canopy have important impact on crime. In this section, the ANOVA test is used to examine if there is any significant difference between studied regions regarding walkability and vegetation. The research question is:

Is there any significant difference in tree canopy and walk score in half-mile buffer around the stations in different regions in the sample of data?

To answer this question the following are hypotheses to examine.

Null Hypothesis 1: There is no difference between vegetation coverage in half-mile buffer around LRT stations in different regions of the sample data.

Alternative Hypothesis 1: There is difference between vegetation coverage in half-mile buffer around LRT stations in different regions of the sample data.

Null Hypothesis 2: There is no difference between walk score in half-mile buffer around LRT stations in different regions of the sample data.

Alternative Hypothesis 2: There is difference between walk score in half-mile buffer around LRT stations in different regions of the sample data.

Based on the study of each region, there are differences regarding the walking score and vegetation as each region has different car dominancy or different climate.

ANOVA Statistics = (Between- groups variance) / (Within- groups variance)

First, the data should meet the assumption to be analyzed be the ANOVA. The assumptions are:

The data in all groups being compared is normally distributed and can be checked by looking at histograms

To meet the first assumption, the data distribution histogram is checked for the normality of the walk score and tree canopy variables.

Table 19. ANOVA Descriptive Analysis

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Tree Canopy	Dallas	50	.850	.124	.017	.815	.886	.4000	1.000
	Miami	22	.799	.141	.030	.736	.862	.5000	1.000
	Minneapolis	32	.889	.085	.015	.858	.920	.6667	1.000
	San Diego	52	.840	.127	.017	.805	.876	.3333	1.000
	San Francisco	44	.868	.117	.017	.832	.903	.4744	1.000
	Salt Lake City	48	.856	.122	.017	.821	.892	.3333	1.000
	Total	248	.853	.121	.007	.838	.868	.3333	1.000
Walk Score	Dallas	49	57.96	19.565	2.795	52.34	63.58	22	97
	Miami	22	71.09	20.695	4.412	61.92	80.27	14	99
	Minneapolis	32	73.31	23.828	4.212	64.72	81.90	13	96
	San Diego	52	67.29	21.802	3.023	61.22	73.36	11	100
	San Francisco	44	80.30	20.936	3.156	73.93	86.66	23	100
	Salt Lake City	48	55.04	25.122	3.626	47.75	62.34	5	94
	Total	247	66.49	23.681	1.507	63.53	69.46	5	100

Descriptive statics table shows:

For tree Canopy:

Dallas (M=0.85, SD=0.124, n=50), Miami (M=0.84, SD=0.141, n=22), Minneapolis (M=0.86, SD=0.085, n=32), San Diego (M=0.85, SD=0.127, n=52), San Francisco (M=0.85, SD=0.117, n=44), Salt Lake City (M=0.85, SD=0.122, n=48)

For Walk Score:

Dallas (M=57.96, SD=19.56, n=50), Miami (M=71.09, SD=20.69, n=22), Minneapolis (M=73.31, SD=23.82, n=32), San Diego (M=67.29, SD=21.8, n=52), San Francisco (M=80.30, SD=293, n=44), Salt Lake City (M=55.04, SD=25.12 n=48)

The homogeneity of variance tests if the variances are same for each group. To check the variance, we run the Levene test. If the Levene test is not significant at the level of 0.05 or lower, then it could be concluded that we have not violated the assumption of homogeneity of the variance in the ANOVA analysis.

Table 20. Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
Tree Canopy	.873	5	242	.500
Walk Score	1.454	5	241	.206

The assumption of homogeneity of variance was tested and found tenable using Levene’s test.

Tree canopy Levene’s test = 0.87, p = 0.5 and Walk score Levene’s test = 1.45, p = 0.2.

The next step is to check for the significance of ANOVA test. If the ANOVA significance value is less or equal to 0.05, then it shows that there is a significant difference among the means of dependent variable in the 6 regions.

Table 21. ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Tree Canopy	Between Groups	.125	5	.025	1.712	.132
	Within Groups	3.531	242	.015		
	Total	3.656	247			
Walk Score	Between Groups	20231.381	5	4046.276	8.284	.000
	Within Groups	117718.360	241	488.458		
	Total	137949.741	246			

The ANOVA test for tree canopy is not statistically significant. There was not a significant effect of independent variable (tree canopy) on dependent factor (regions) at the $p < 0.05$ level for the three conditions [$F (5, 242) = 1.71$, $P=0.132$].

However, the ANOVA test for Walk Score is statistically significant. There was a significant effect of independent variable (Walk score) on dependent factor (regions) at the $p < 0.05$ level for the three conditions [$F (5, 241) = 8.284$, $P=0.00$].

The next step is to evaluate the multiple comparisons by Post Hock test. The Post Hock test demonstrates exactly where the difference among the regions occurred.

Post Hock tests

Now that the ANOVA test indicates that there is a difference between regions regarding walkability, the Post Hock test is needed to show where these differences are.

The following table is the result of Post Hock test which compared the regions by the mean difference.

Table 22. Multiple Comparisons

Dependent Variable: Walk Score							
	(I) City	(J) City	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Dallas	Miami	-13.931	5.680	.143	-30.25	2.39
		Minneapolis	-16.153*	5.026	.018	-30.59	-1.71
		San Diego	-10.128	4.397	.197	-22.76	2.50
		San Francisco	-23.135*	4.589	.000	-36.32	-9.95
		Salt Lake City	2.118	4.486	.997	-10.77	15.01
	Miami	Minneapolis	-2.222	6.149	.999	-19.89	15.44
		San Diego	3.802	5.647	.985	-12.42	20.02
		San Francisco	-9.205	5.797	.607	-25.86	7.45
		Salt Lake City	16.049	5.716	.060	-.37	32.47
	Minneapolis	San Diego	6.024	4.988	.833	-8.31	20.35
		San Francisco	-6.983	5.158	.754	-21.80	7.83
		Salt Lake City	18.271*	5.067	.005	3.72	32.83
	San Diego	San Francisco	-13.007	4.548	.052	-26.07	.06
		Salt Lake City	12.247	4.444	.068	-.52	25.01
	San Francisco	Salt Lake City	25.254*	4.634	.000	11.94	38.57

Post hoc comparisons using Tukey Honest Significance Test (HSD) indicated that the mean score for Dallas (M=57.96, SD=19.56, n=50) compared to Minneapolis and San Francisco is significant at level $p < 0.05$; also, Salt Lake City (M=55.04, SD=25.12, n=48) and has significant difference in mean score with Minneapolis and San Francisco at level of $p < 0.05$.

Summarizing, a “one-way ANOVA” was conducted to compare the walkability in half-mile buffer around the stations in different regions (Dallas, Miami, Minneapolis, San Diego, San Francisco, and Salt Lake City). The results showed that there was significant difference between different regions with regards to walkability at the $p < 0.05$ level [$F(5, 241) = 8.284$, $P=0.00$]. Tukey HSD post hoc test indicated that the mean score for the Dallas walkability (M=57.96, SD=19.56, n=50) was significantly different than the San Francisco (M=80.30, SD=293, n=44) and Minneapolis (M=73.31, SD=23.82, n=32). Also, Salt Lake City (M=55.04, SD=25.12 n=48) has significant difference in mean score with Minneapolis and San Francisco at level of $p < 0.05$.

Collectively, these results indicated that Salt Lake City has the lowest walk score among other regions and Dallas is the next region with lowest walk score compared to San Francisco and Minneapolis. Apparently, Miami and San Diego do not have any significant difference in mean score with other regions.

Summary

This chapter provided the results of the Path model with crime as mediation factor developed via SEM in the AMOS software. The first section described the model fit results, covariance relationship, indirect and direct, and total effects followed by the mediation analysis. The second part compared the regions with regards to vegetation and walkability by ANOVA with SPSS software.

The next chapter discusses the conclusions of the present research, explaining the impact of crime on ridership. Additionally, it provides the recommendation to policies encouraging TOD design based on CPTED. The last chapter finishes with research limitation and recommendation for further studies.

The last chapter details conclusions and implications.

Chapter Six

Conclusion

Fear of crime may be the most important factor discouraging ridership (Wachs, 1993). It may also apply to rail transit systems. Crime at or in the vicinity of rail transit stations could discourage travelers from using transit (Loukaitou-Sideris et al., 2002).

There may be a discrepancy between reported crime and perceived crime or safety. The perceived crime level, rather than simple crime statistics, may significantly influence individuals. However, the number of reported crimes at stations is found to be significantly associated with socioeconomic characteristics of the surrounding neighborhoods (Loukaitou-Sideris et al., 2002).

Factors influencing travel behavior have been extensively studied in recent decades. It is believed that socioeconomic and built environment characteristics are important in promoting ridership, walkability, and biking (Cervero and Murakami, 2010).

Since crime plays an important role in preventing non-driving travel mode choice (Loukaitou-Sideris, 2006), the association between neighborhood crime and travel behaviors attracts much greater attention lately.

Crime tends to occur in diverse situations and under varied circumstances (Brantingham and Brantingham, 1993) and can be directly tied to the social and physical surroundings of LRT stations. Criminology studies discovered that fear of crime or environmental safety is a crucial factor in people's modal choice of walking or public transit (Ingalls et al., 1994; Kim et al., 2007).

To address the mentioned concern from transportation planning point of view, this study first runs geo-locating technique in GIS software to analyze the spatial distribution of crime in half-mile-buffer around stations in six metropolitan statistical areas (Dallas, Miami, Salt Lake City, Minneapolis, San Diego, and San Francisco).

This empirical study applied Path analysis using Structural Equation Modeling by AMOS software for modeling of LRT ridership and crime per capita as mediator factor. Furthermore, station neighborhood characteristics such as socioeconomic status, built environment factors, and land use attributes are implemented in the analysis considering half-mile buffer around transit stations as unit of analysis.

This exploratory research applies theories of transit crime and ridership to the local context of LRT stations. Based on statistical analysis and model results, planners can understand the characteristics of an area that are most related, and potentially contribute to criminal activity around the LRT stations. Also, they could identify crime as one of the main factors resulting in LRT ridership reduction.

The study found that Crime has positive impact on ridership. As Cozens and Love (2015) mentioned in their study, the relationship between crime and ridership is complex. The result complies with previous findings of Ferrell in 2008. In a study in 2012 he mentioned that the influence of neighborhood crime activities on mode choice varied by the crime type, the mode of travel, and the city type.

Also, the positive association reflects that a rise in ridership is associated with an increase of crimes due to high activity, and the negative association reflects a decline of community security and fall in ridership (Zhang 2016). In this research the positive impact indicates the high demand of transit use by captive riders. The positive association possibly reflects a rise in ridership is associated with an increase of crime due to a concurrent relationship.

In the other words, most of the light rail transit users in this study would use the transit despite criminal activities. This finding signifies a critical importance of this study to focus on providing safe environments around transit stations to attract both captive and choice riders and create safer communities.

Also, it indicates that entropy has direct positive significant impact on ridership. Aligned with Cervero (2002), Spillar and Rutherford (1998), mixed land use of residential, commercial, and office in proximity of transit stations brings more transit ridership.

The most important outcome of the research is the full mediation impact of density on ridership through crime. It shows that density has indirect positive impact with ridership and direct positive influence on crime and a full mediation between density, crime, and ridership.

Residential and employment densities have long been thought to be critical determinants of transit use. The impact of density on ridership has been studied in many researches (Gomez-Ibanez, 1996; Cervero, 1993; Spillar and Rutherford, 1998; Pushkarev and Zupan, 1977; Cervero and Kockelman,1997).

In addition, from the perspective of criminology, density plays an important role on occurrence of criminal activities (Loukaitou-Sideris, 1999; Harris, 1971). This study aligned with Clarke, Belanger, and Eastman (1996) investigation of 206 New York subway stations which found that in higher density areas there will be more crime incidents.

The additional analytical section paid attention to the comparison between regions regarding the walkability and vegetation around the LRT stations. The results indicated that Salt Lake City has the lowest walk score among other regions and Dallas is the next region with lowest walk score compared to San Francisco and Minneapolis. Apparently, Miami and San Diego do not have any significant difference in mean score with other regions.

The contribution of this study is to highlight the role of crime on ridership. Although TOD policies encourage density around the stations, density could bring threat to the area by attracting criminal activities. To modify the impact of density on crime attraction around the stations, or designing out the crime, there are Crime Prevention Through Environmental Design Guidelines to follow; however, the most important step is creating a sense of community through an all-inclusive approach to physical, social and economic development.

Planning and Design Implications

The findings of this study could be applied in transportation planning and designing public space such as transit stations and their neighborhoods. It is important to note that transit-oriented development (TOD) planning mostly emphasizes development efficiency and density, thus, it is possible to discounts two important aspects of sustainability: environment quality and social equity (Lin and Gau, 2006).

Colquhoun (2004) in “Design out Crime” book proposed practical guidelines to prevent criminal activities and create safe communities. These guidelines are defined by Defensible Space, Crime prevention through environmental design (CPTED), and Situational Crime Prevention/2nd Generation CPTED School of thoughts.

Following are the summary of practices to design out crime:

Restrict access points by controlling and limiting the presence of unlawful persons. Develop defensible space through physical environment by manipulating personal behavior to reduce crime. Consider Situational Crime Prevention—both management and design interventions—by reducing the opportunities for crime. Develop social and economic strategies in conjunction with physical development which together are crucial for sustainable communities.

The second generation CPTED (Greg Saville and Gerry Cleveland, 1977) identified the design of the built environment as the first step to create healthy, safe, and sustainable communities. The most important factor is creating a sense of community through an all-inclusive approach to physical, social, and economic development.

To create a sense of community, they must cultivate skills in neighborhoods at a small, local scale based on ecological principles, values of a healthy community, respecting personal choice and privacy, creating common places and events of social interaction, and celebrating diversity. It also means that they have the capacity to resolve their community's own problems with agreed upon terms.

To capture the interaction between the physical characteristics and people in planning concept, there are several alternative design solutions to apply against crime possibilities and built environment around the transit stations. Following are some steps for a comprehensive planning for crime prevention through design.

- Site survey: Analysis of physical features, levels, ground conditions, tree canopy, and other vegetation.
- Background study: Studying the transit station location and how it relates to the existing local neighborhood plans and planning policies.
- Traffic study: Status of roads around street, the connectivity of the streets, and traffic volume.
- Walkability: Studying major pedestrian paths, especially from stations to shops, play areas, city centers, open space, facilities and vice versa.
- Visibility: Visibility of transit stations from surrounding streets, buildings, or other locations.

- Urban design analysis: Structural and architectural character of the buildings surrounding transit station including heights of the buildings, landmark buildings, open spaces, public areas, and important landscape features.
- Materials analysis: Building materials such as glass and transparent doors and windows, walls and roofs of buildings, and murals.
- Community survey: Conducting a survey to identify the hopes and fears of the public transit commuter and the community within the transit station.

This cannot happen in one day; however, by implementing CPTED solutions in both the physical and social aspects, there is great potential to enhance the quality of life for society and the communities around transit stations.

Policy Implications

There are rules and regulations related to policing the public area which are in broad scope of security and criminal activities. These regulations are mainly conducted by police forces and police departments. However, there are not specific regulations and policies regarding the safety in transit stations.

American Public Transportation Association (APTA) published a few standards regarding safety in transportation facilities. Following are the existing recommendations and standards addressing security from multiple perspectives.

- Crime Prevention through Environmental Design (CPTED) for Transit Facilities

APTA SS-SIS-RP-007-10

This Recommended Practice is to ensure that security measures are employed based on the CPTED concepts. First, it intends to incorporate security procedures prior to designing, building, or remodeling transit facilities and the areas surrounding the facilities.

Second, identify all the stakeholders in the process application of CPTED concept. Third, identify the transit security Recommended Practice requirements that cannot be met and the reason(s) and describe the alternate measures to provide security (APTA, 2010).

- Gates to Control Access to Revenue and Nonrevenue Transit Facilities

APTA SS-SIS-RP-005-10

This recommended practice provides direction for the installation of gates to control access to transit facility areas under the authority of a transit agency. A gate is also a part of access control systems. Gates are the moveable element of a fencing system and the weakest point. Gates available to the transportation industry are ranging from high security to cost-effective chain link. Gate material and design should be integrated with other security standards, including CPTED, to provide protection along with other security solutions (APTA, 2010).

- Fencing Systems to Control Access to Transit Facilities

APTA SS-SIS-RP-003-10

This Recommended Practice is focused on installation of fencing systems to control accessibility of transit facilities under the jurisdiction of a transit agency. A fencing system is an element of access control systems. It defines boundaries, channels access, provides visual barriers, and can prevent and delay invasion and trespassing. Fencing systems should be cohesive with other security standards and best practices, such as lighting and barriers. This Recommended Practice is intended to guarantee security considerations are implemented during the design and building process (APTA, 2009).

- Security Lighting for Non-revenue Transit Facilities and Passenger Facilities

APTA SS-SIS-RP-002-10

APTA SS-SIS-RP-001-10

These documents established recommended practices for lighting systems to enhance the security of people, operations, and important infrastructures. Nonrevenue facilities include right-of-ways, equipment storage, maintenance yards, and other areas restricted to passenger access. Security lighting is one of the most cost-effective security measures for any organization to improve its security. Effective security lighting discourages criminal behavior and may enhance safety. It also creates a sense of security and openness for employees and staff at transit nonrevenue facilities. Throughout this recommended practice, Occupational Safety and Health Administration (OSHA) safety lighting standards and security industry lighting best practices were applied (APTA, 2009).

The National Crime Prevention Council (2003) provides guidelines especially for transit facilities. Following are several adopted policy recommendations for LRT stations safety guideline:

- Commuters using other modes of transit such as bus or taxi to reach LRT stations should be clearly visible from streets and buildings as far as possible. Any obstacle that blocks the view (such as walls, large bushes, or power boxes) should be removed or modified.
- Design special landscape to ensure full visibility and plant low height vegetation to create a peaceful and relaxing environment.
- It is important to avoid isolation areas near bus shelters or transit stations such as a large parking lots or vacant land. Also, it important to have security measures around alleys or buildings set far back from the street.
- The station shelters and stands should be designed to eliminate any hiding space. Utilizing sitting rails instead of benches will prevent people sleeping

there. Lighting is another important factor to consider in designing transit platforms to protect passengers and transit operators.

Regarding security implementations in transit facilities, the “Voice of God” project was a huge success in Sacramento. The Sacramento Regional Transit District (SacRT) in 2017 used a public address (P.A.) system as a security enhancement tool. If a passenger violates even a basic station rule, a SacRT security staff uses the P.A. system to talk with the violator. The main point is that SacRT security staff could be miles away, remotely monitoring surveillance cameras from the Security Operations Center in downtown Sacramento. It has sent a clear message that light rail stations are under constant surveillance by the agency. When security personnel identify a problem, they issue a simple and direct statement such as to communicate with the violator, and if that person does not acquiesce a security staff of the transit agency will be dispatched to the station to issue a citation (Minns, 2019).

Research Advantages and Limitations

In contrast with multivariate regression, SEM allows the user to explicitly test indirect effects between two explanatory variables, where effects between two variables are mediated by another intermediary variable. Additionally, SEM can explicitly incorporate uncertainty due to measurement error or lack of validity of the observed variables (Ülengin et al., 2010)

SEM equipped a researcher with the benefits to model relationships among multiple predictor and variables and statistically test a theoretical based model with confirmatory analysis (Chin, 1998). SEM has more advantages compared to most other linear-in-parameter statistical methods such as accounting for missing data and handling of non-normal data (Golob, 2003).

This method, just like other analytical methods, has limitations. Following are the study limitations referring to the data gathering and data analysis.

In this research there were difficulties of gathering information from different transit agencies and police departments for ridership and crime data. Also, the aggregated data, different units of analysis, lack of current and accurate data were among the problems of data gathering.

The issue of sample size is one issue that has no consensus. Therefore, researchers may find conflicting information on what sample size is adequate for SEM. Assuming no problems with data (e.g., missing data or non-normal distributions), recommend a minimum sample size of 200 for any SEM (Tomarken and Waller, 2005). Although, in this research the mentioned threshold has been met; however, more cases (transit stations) could help achieve more accurate data.

Multicollinearity was another problematic factor. Multicollinearity happens when measured variables are very highly related. In this research, built environment factors had multicollinearity. The best solution to solve the multicollinearity or bivariate correlation is to remove the redundant variables (Tomarken and Waller, 2005). Therefore, few variables were removed to achieve the better results.

Cross sectional analysis compared to longitudinal analysis has limitations especially when studying the impact and causality between the variables. Limited access to data sources resulted in choosing cross-sectional analysis.

The SEM analysis helped to evaluate the effects of factors on each other. In the case of data availability longitudinal analysis gives a better perspective on the casual relationships.

Recommendation for future studies

Further studies could focus on just one station as a case study and gather detailed information about the characteristics of the station platform and neighborhoods around it. It could be followed by a focus group study to get the best insight from the residents of the neighborhoods and the public transit passengers.

Moreover, a longitudinal study for time series could be more accurate to examine the causal relationship between the variables.

Lastly, having mixed quantitative and qualitative analysis could also add value to a study.

Appendix A

Mediation Modeling Through Path Analysis

Model fitness results:

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	31	4.671	4	.323	1.168
Saturated model	35	.000	0		
Independence model	14	516.466	21	.000	24.594

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.991	.953	.999	.993	.999
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.190	.189	.190
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCPef	LO 90	HI 90
Default model	.671	.000	10.410

Saturated model	.000	.000	.000
Independence model	495.466	425.135	573.215

FMIN

Model	**FMIN**	**F0**	**LO 90**	**HI 90**
Default model	.019	.003	.000	.042
Saturated model	.000	.000	.000	.000
Independence model	2.091	2.006	1.721	2.321

RMSEA

Model	**RMSEA**	**LO 90**	**HI 90**	**PCLOSE**
Default model	.026	.000	.103	.599
Independence model	.309	.286	.332	.000

Total, direct, and indirect effects:

Total Effect

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	.002	.331	-.010	.661	-.125	.000
Ridership	.001	.158	-.142	.315	.459	.476

Standardized Total Effects

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**

Crime	.045	.375	-.012	.091	-.027	.000
Ridership	.023	.192	-.170	.047	.108	.511

Direct Effect

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	.002	.331	-.010	.661	-.125	.000
Ridership	.000	.001	-.137	.000	.519	.476

Standardized Direct Effect

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	.045	.375	-.012	.091	-.027	.000
Ridership	.000	.001	-.164	.000	.122	.511

Indirect Effects

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	.000	.000	.000	.000	.000	.000
Ridership	.001	.158	-.005	.315	-.060	.000

Standardized Indirect Effect

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	.000	.000	.000	.000	.000	.000
Ridership	.023	.191	-.006	.047	-.014	.000

Variances

	Estimate	Lower	Upper	P
Entropy	.038	.032	.043	.002
Tree_Canopy	.015	.012	.018	.001
Socio_economic	.978	.792	1.238	.001
Density	.996	.848	1.164	.001
WalkScore	573.238	506.128	644.492	.001
e1	.646	.563	.770	.000
e2	.510	.457	.595	.000

Total Effects - Two Tailed Significance (BC)

	WalkScore	Density	Socio_economic	Tree_Canopy	Entropy	Crime
Crime	.511	.002	.960	.186	.629	...
Ridership	.489	.106	.138	.171	.116	.003

Standardized Total Effects - Two Tailed Significance (BC)

	WalkScore	Density	Socio_economic	Tree_Canopy	Entropy	Crime
Crime	.511	.002	.956	.184	.626	...
Ridership	.482	.113	.126	.177	.116	.002

Direct Effects - Two Tailed Significance (BC)

	WalkScore	Density	Socio_economic	Tree_Canopy	Entropy	Crime
Crime	.511	.002	.960	.186	.629	...
Ridership	...	.989	.145	...	.041	.003

Standardized Direct Effects - Two Tailed Significance (BC)

	WalkScore	Density	Socio_economic	Tree_Canopy	Entropy	Crime

Crime	.511	.002	.956	.184	.626	...
Ridership	...	.989	.142	...	.043	.002

Indirect Effects - Two Tailed Significance (BC)

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	...	...	...	...	...	...
Ridership	.489	.003	.952	.171	.615	...

Standardized Indirect Effects - Two Tailed Significance (BC)

	WalkScore	**Density**	**Socio_economic**	**Tree_Canopy**	**Entropy**	**Crime**
Crime	...	...	...	...	...	...
Ridership	.482	.003	.956	.177	.608	...

Appendix B

ANOVA Test

Multiple Comparisons							
Tukey HSD							
Dependent Variable	(I) City	(J) City	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tree Canopy	Dallas	Miami	.0512958	.0309034	.560	-.037480	.140072
		Minneapolis	-.0389166	.0273454	.713	-.117472	.039638
		San Diego	.0101581	.0239249	.998	-.058571	.078887
		San Francisco	-.0172605	.0249683	.983	-.088987	.054466
		Utah	-.0059875	.0244087	1.000	-.076106	.064131
	Miami	Dallas	-.0512958	.0309034	.560	-.140072	.037480
		Minneapolis	-.0902124	.0334540	.080	-.186316	.005891
		San Diego	-.0411377	.0307213	.763	-.129391	.047115
		San Francisco	-.0685563	.0315407	.254	-.159163	.022051
		Utah	-.0572833	.0310995	.441	-.146623	.032056
	Minneapolis	Dallas	.0389166	.0273454	.713	-.039638	.117472
		Miami	.0902124	.0334540	.080	-.005891	.186316
		San Diego	.0490748	.0271394	.462	-.028888	.127038
		San Francisco	.0216561	.0280635	.972	-.058962	.102274
		Utah	.0329292	.0275668	.839	-.046262	.112120
	San Diego	Dallas	-.0101581	.0239249	.998	-.078887	.058571
		Miami	.0411377	.0307213	.763	-.047115	.129391
		Minneapolis	-.0490748	.0271394	.462	-.127038	.028888
		San Francisco	-.0274186	.0247426	.878	-.098497	.043659
		Utah	-.0161456	.0241777	.985	-.085601	.053310
	San Francisco	Dallas	.0172605	.0249683	.983	-.054466	.088987
		Miami	.0685563	.0315407	.254	-.022051	.159163
		Minneapolis	-.0216561	.0280635	.972	-.102274	.058962
		San Diego	.0274186	.0247426	.878	-.043659	.098497
		Utah	.0112730	.0252106	.998	-.061150	.083696
	Utah	Dallas	.0059875	.0244087	1.000	-.064131	.076106
		Miami	.0572833	.0310995	.441	-.032056	.146623
		Minneapolis	-.0329292	.0275668	.839	-.112120	.046262
		San Diego	.0161456	.0241777	.985	-.053310	.085601

		San Francisco	-.0112730	.0252106	.998	-.083696	.061150
Walk Score	Dallas	Miami	-13.132	5.672	.192	-29.43	3.16
		Minneapolis	-15.353*	5.023	.030	-29.78	-.92
		San Diego	-9.329	4.400	.280	-21.97	3.31
		San Francisco	-22.336*	4.590	.000	-35.52	-9.15
		Utah	2.918	4.488	.987	-9.98	15.81
	Miami	Dallas	13.132	5.672	.192	-3.16	29.43
		Minneapolis	-2.222	6.121	.999	-19.81	15.36
		San Diego	3.802	5.621	.984	-12.35	19.95
		San Francisco	-9.205	5.771	.603	-25.78	7.37
		Utah	16.049	5.690	.058	-.30	32.40
	Minneapolis	Dallas	15.353*	5.023	.030	.92	29.78
		Miami	2.222	6.121	.999	-15.36	19.81
		San Diego	6.024	4.966	.830	-8.24	20.29
		San Francisco	-6.983	5.135	.751	-21.73	7.77
		Utah	18.271*	5.044	.005	3.78	32.76
	San Diego	Dallas	9.329	4.400	.280	-3.31	21.97
		Miami	-3.802	5.621	.984	-19.95	12.35
		Minneapolis	-6.024	4.966	.830	-20.29	8.24
		San Francisco	-13.007*	4.527	.050	-26.01	.00
		Utah	12.247	4.424	.066	-.46	24.96
	San Francisco	Dallas	22.336*	4.590	.000	9.15	35.52
		Miami	9.205	5.771	.603	-7.37	25.78
		Minneapolis	6.983	5.135	.751	-7.77	21.73
		San Diego	13.007*	4.527	.050	.00	26.01
		Utah	25.254*	4.613	.000	12.00	38.51
	Utah	Dallas	-2.918	4.488	.987	-15.81	9.98
		Miami	-16.049	5.690	.058	-32.40	.30
		Minneapolis	-18.271*	5.044	.005	-32.76	-3.78
		San Diego	-12.247	4.424	.066	-24.96	.46
		San Francisco	-25.254*	4.613	.000	-38.51	-12.00

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