FACTORS AFFECTING TRANSIT RIDERSHIP AND THE IMPACT OF INTELLIGENT TRANSIT INFORMATION SYSTEMS (ITIS) – CASE STUDY OF DALLAS AREA RAPID TRANSIT - DART

by

AHMED ISMAIL DAQROUQ

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

December 2018

Acknowledgements

In the name of Allah, Most Gracious, Most Merciful. Praise be to Allah, the Cherisher and Sustainer of the worlds; Most Gracious, Most Merciful; Master of the Day of Judgment. Thee do we worship, and Thine aid we seek. Show us the straight way, the way of those on whom Thou hast bestowed Thy Grace, those whose (portion) is not wrath, and who go not astray (Quran translation: Chapter1, verses 1-7).

I would like to thank some people who supported and guided me through this process. First, I would like to thank my academic advisor, Professor Ardeshir Anjomani. It is with his hard work, vision, invaluable guidance, patience and encouragement that I was able to complete this research. He has taught me how to envision and carry out this research with the best quality. I would like to also thank him for helping me to collect and analyze the data. I would also like to thank my honorable dissertation committee members, Professor Maria Martines-Cosio and Professor Rod Hissong for their guidance, encouragement, and support that help me to gather a significant portion of this research. They helped me not only by providing valuable comments in crafting this study, but also in teaching me in a number of courses that paved the road to success for the completion of this dissertation.

Next, I would like to acknowledge my friend Mr. Abed Abukar the Director of Information Technology at DART for providing the data for the variables of most interest to this research (ITIS). I would also like to thank him for his support and encouragement through the entire process. Lastly, I want to give my family a special thank you for their unconditional love and moral support. This long education journey has been only possible because of my parents' Ismail and Zarifah Daqrouq unimaginable sacrifices. I would also like to acknowledge my wife, Kawthar Daqrouq, for her love, strong support, and encouragement throughout the entire academic journey.

November 14, 2018

Abstract

FACTORS AFFECTING TRANSIT RIDERSHIP AND THE IMPACT OF INTELLIGENT TRANSIT INFORMATION SYSTEMS (ITIS) – CASE STUDY OF DALLAS AREA RAPID TRANSIT - DART

Ahmed Ismail Daqrouq, PhD

The University of Texas at Arlington, 2018

Supervising Professor: Ardeshir Anjomani

Transit ridership is at the heart of transportation policy making and the success of any transit system. Urban planners have been focusing on the need to reduce car dependence and promote more sustainable transportation alternatives. Automobile dependence is a concern for many reasons including congestion in urban areas, pollution, and environmental damages caused by pollution. Switching to more sustainable and environmentally friendly transportation modes such as public transit is likely to be an effective solution to most of these problems. As an alternative to the private car, public transit is an efficient means to move large numbers of people within cities, and transit systems play an important role in combating traffic congestion, reducing carbon emissions, and promoting compact, sustainable urban communities (Taylor et al., 2009). In recent years, the introduction of intelligent transit information systems (ITIS) applications that provide real-time information to transit users created a new hope for increased transit ridership, however, its impact in facilitating increased Transit Usage is not clear yet.

This study explores the factors affecting transit ridership including ITIS and selects the Dallas Area Rapid Transit (DART) as a case in a large metropolitan setting for this research. In order to achieve this purpose, the research examines the factors affecting rail, bus, and transit ridership. In addition, this study attempts to fill some of the gaps that exist in the literature by exploring the impact of intelligent transit information systems (ITIS) on transit ridership, and how its availability has affected transit ridership since 2012. The study adopts a monthly time series perspective (2007 to 2017) to enable the researcher to examine changes in transit ridership over a 10-year period and the incremental exposure to ITIS technology. This enables the research to capture any changes in ridership over this 10-year period, few years before to few years after the implementation of ITIS transit applications, in addition to any seasonal changes.

Most previous studies of transit ridership have not included ITIS as one of the variables thought to influence transit ridership. Therefore, the disparities among the findings of empirical research completed to date point to the necessity for further study. This study addresses these shortcomings by exploring multiple factors measuring population, technology, geography, and socioeconomic characteristics. This is examined through using Time Series / Multiple Regression methods on the dataset to estimate the relationship between the models' variables to answer the research questions related to demand for transit ridership in the DFW area. In this type of research quite frequently, one is interested in interpreting the effect of a percent change of an independent variable on the dependent variable, which we can achieve through a double-log (log-log) model. As such, the elasticity of demand for transit with respect to some of the factors in the model such as percent change in fare, income or the research question variable, ITIS usage, are explored and policy implications out of these elasticities are discussed.

Finally, it has been argued that ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes, and makes transit more competitive with the automobile. Therefore, it behooves us to include also some measure of auto ridership in the models. In order to measure the responsiveness of demand for transit to a relative change in the price related to auto usage, we examine cross-price elasticity of demand for transit and how cross-price elasticity of demand could help us in measuring possible shifts from car to transit as an effect of ITIS usage. We think this research provides a significant contribution to transportation planning literature.

Table of Contents

List of Illustrations

List of Tables

Chapter 1

Introduction

1.1 Background

Transit ridership is at the heart of transportation policy making and the success of any transit system. In the early 21st century and most recently, urban planners have been focusing on the need to promote more sustainable transportation alternatives. In recent years, the energy component of the transportation is becoming more apparent. North America greatly depends on large amounts of cheap energy to keep its economy growing. The price of energy, especially fossil fuels, has been rising in recent years, and the price will likely continue to rise. This will mean that North America must adapt as energy gets more expensive and scarce. One of the areas of adaptations needs to be made in transportation, as transportation consumes large quantities of energy (Greene, 2004). Recent studies estimate that a large percentage of air pollutants is generated by the transportation sector. In 2013, the transport sector accounted for 24% of the CO2 emissions, 75% of which derive from road transport (International Energy Agency, 2013). The transport sector currently accounts for 90% of total oil demand and half of total oil consumption (International Energy Agency, 2013), and the number of cars is expected to double by 2035 when their total number will reach 1.7 billion. This rise is mainly related to the development of emerging economies like China, India and the Middle East. In addition, the expected increase in urbanization is likely to cause serious congestion problems in the next decades in most cities all over the world (Borghesi et al., 2013).

Automobile dependence is a concern for many reasons including congestion in urban areas, pollution, and environmental damages caused by pollution. Other issues are related to human health: air pollution can cause and worsen respiratory diseases, and the increasing car dependence of households is held responsible for obesity and lack of physical exercise, which in turn can cause severe health problems (Borghesi et al., 2013). Switching to more sustainable and environmentally friendly transportation modes, and less congesting, such as public transit, is likely to be an effective solution to most of these problems. For these reasons, the demand for a more sustainable pattern of transportation, reducing automobile dependence and promoting modal switch has been growing in many countries. As an alternative to the private car, public transit is an efficient means to move large numbers of people within cities, and transit systems play an important role in combating traffic congestion, reducing carbon emissions, and promoting compact, sustainable urban communities (Taylor et al., 2008).

1.2 Statement of Purpose and the Significance of Research

This study will explore the factors impacting transit ridership in Dallas Area Rapid Transit (DART), and how can transit ridership be increased to determine if policy and/or actions can be taken to improve ridership in the study area. In order to achieve this purpose, this research will examine the factors affecting rail, bus, and transit ridership. In addition, this research will explore the effect of intelligent transit information systems (ITIS) on transit ridership after the implementation of ITIS applications. These questions are examined in a case study applied to Dallas Area Rapid Transit (DART). The period covered in this research is from 2007 to 2017. The time series perspective undertaken in the research allows us to examine changes in transit ridership over 10 years period in a monthly base and the incremental exposure to ITIS technology.

In addition, this study will attempt to fill some of the gaps that exist in the literature by exploring the impact on transit ridership in the presence of intelligent transit information systems (ITIS), and how the availability of transit information affects transit ridership. Most previous studies of transit ridership have not included ITIS as one of the variables thought to influence transit ridership. Therefore, the disparities among the findings of empirical research completed to date point to the necessity for further study. This study addresses these shortcomings by exploring multiple factors measuring population, technology, geography, and socioeconomic characteristics. This is examined through using Time Series / Multiple Regression methods on the dataset to estimate the relationship between the models' variables to answer the research questions related to demand for transit ridership in the DFW area. In this type of research quite frequently, one is interested in interpreting the effect of a percent change of an independent variable on the dependent variable, which we can achieve through a double-log (log-log) model. As such, the elasticity of demand for transit with respect to some of the factors in the model such as percent change in fare, income or the research question variable, ITIS usage, are explored and policy implications out of these elasticities are discussed.

Finally, it has been argued that ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes, and makes transit more competitive with the automobile. Therefore, it behooves us to include also some measure of auto ridership in the models. In order to measure the responsiveness of demand for transit to a relative change in the price related to auto usage, we examine cross-price elasticity of demand for transit and how cross-price elasticity of demand could help us in measuring possible shifts from car to transit as an effect of ITIS usage. We think this research provides a significant contribution to transportation planning literature. This research provides opportunities to improve transit services because ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes for transit users and non-transit users including the poor and underserved population. From transit users' perspective, the availability of real-time transit information at their fingertips and the time saved by real-time transit information is certainly an economic benefit. Perhaps a deeper social consideration is that social inequity in

American cities, worsened by suburbanization and segregation, may be narrowed to some extent by improving transit service for the disadvantaged and underserved population who are largely captive transit riders. Further, the findings of this research will help North American cities and Dallas Area Rapid Transit specifically to develop strategies that attempt to increase transit ridership for a variety of reasons including: reduce the energy use of transportation in cities, curb congestion, reduce pollution, and provide other social, economic and environmental benefits. In addition, this research will aid policy makers in their decision making regarding further investments in transit ITIS applications.

1.3 Research Questions

The study attempts to answer the following research questions using Dallas Area Rapid Transit as a case study:

1- Does ITIS impact Transit Ridership in Dallas Area Rapid Transit?
2- Does ITIS impact Rail Ridership in Dallas Area Rapid Transit?
3- Does ITIS impact Bus Ridership in Dallas Area Rapid Transit?

In addition, this study will examine the factors that influence transit usage in the presence of intelligent transit information systems (ITIS) and will shed some light on the factors that influence the three types of mass transit in the study area.

Chapter 2

Literature Review

This chapter includes a review of the theories behind the factors that may contribute to or affect changes in transit ridership (dependent variables). It also discusses the rich and well-developed empirical studies regarding the impact of factors affecting transit ridership. For this study, the literature related to the determining factors of transit ridership can be broadly divided into five sections:

1- General transportation, mode choice, and factors impacting transit ridership

2- Connections between rising ridership and use of smart technology

3- Intelligent Transit Information Systems (ITIS) and the impact on transit ridership

4- The impact of ITIS app on transit ridership

5- The potential impact of ITIS app on non-transit users

2.1 Transportation, mode choice, and factors impacting transit ridership

Mode choice refers to the type of transportation mode (walking, driving, bus, and rail) people choose for trips from one point to another (Taylor et al., 2009). Mode choice is the third step in the conventional four-step transportation forecasting model. The steps are trip generation, trip distribution, mode choice, and route assignment. Public transit includes transportation modes such as bus, and commuter rail. The transit ridership literature shows that transit ridership mode depends on a number of economic and social characteristics, such as urban geography, economic activity, and population characteristics (Taylor et al., 2003). In regards to the theories behind the transit mode, discrete choice theory was developed by Daniel McFadden who received the Nobel Prize in 2000 for his pioneering work in developing the theoretical basis for discrete choice. Discrete choice models theoretically or empirically model choices made by people among a finite set of alternatives. The models have been used to examine the choice of which mode of transportation to take to work (car, bus, train) among numerous other alternatives. Discrete choice models specify the probability that an individual chooses an option among a set of alternatives. Transportation planners use discrete choice models to predict demand for planned transportation systems, such as which route a driver will take and whether someone will take personal car or transit. The first applications of discrete choice models were in transportation planning, and much of the most advanced research in discrete choice models is conducted by transportation researchers. As an example, the choice set for a person deciding which mode of transport to take to work includes driving alone, carpooling, taking bus, etc. The choice set is complicated by the fact that a person can use multiple modes for a given trip, such as driving a car to a train station and then taking train to work. In this case, the choice set can include each possible combination of modes. Alternatively, the choice can be defined as the choice of “primary” mode, with the set consisting of car, bus, rail, and other (e.g. walking, bicycles, etc.). Note that the alternative “other” is included in order to make the choice set exhaustive (McFadden, 2000).

Considering the demand theory for transit and the factors affecting the transit demand, amongst all travel modes, how people choose the transit mode? Individuals will have more economic incentives to make the switch away from car dependence and use the transit mode if the total utility or satisfaction of using the transit mode is higher than the total utility of using the automobile. Boarnet and Crane (2001) say that transit service, like other commodities, follows a demand theory of consumption. Individuals are faced with resource constraints and trade-offs among available travel alternatives: personal car, transit, walking, bicycle, etc. The relative attractiveness of those alternatives to individuals depends on relative costs. If the utility of using transit is higher than the costs of driving, a traveler is likely to choose a transit option. If taking a bus or train to work instead of driving a personal car can save a commuter money and travel time, a transit agency is likely to gain a new rider (Armbruster 2010).

First utility increases as travel costs drop, which happens when transit cost/fare or cost of service drop, provided the fares offer a savings over driving and parking, or when more patrons use transit, so fixed costs can be spread over more users. Cost is one of the most important determining factors. It can also be linked to affordability of the user or income. Total economic costs must be the same or less for public transit as for private automobile. Second considering all travel modes and choosing the one that saves the most time. According to the Texas A&M Transportation Institute, the average auto commuter in the United States spends 42 hours per year in traffic. That same study puts the price tag of those delays at $960 per driver. In big cities, the numbers are even worse. Drivers in the 15 largest U.S. metro areas spend an average of 63 hours per year stuck in congestion on the way to work, costing an average of $1,433 per person (Wallace 2017). Third, a mode with higher frequency is desirable as the waiting time reduces and the service frequency increases. Other factors to consider when choosing transportation mode may include accessibility, fuel efficiency/carbon emissions, and integration with other modes, safety, comfort and privacy specifically if they allow relaxation or work en-route. In addition, random events, such as weather, accidents, and road work, may influence mode choice. Considering daily traffic congestion, the travel cost of the car may be lower in the best-case scenario, since it’s the quicker mode, however if the traffic reaches a certain congestion level, then using public transit may become more appealing to some commuters. Nobody likes sitting in traffic and if these drivers had a better choice, they might be willing to use transit. In theory, that alternative is public transit – buses, commuter trains, light rail, street cars and subway systems. At its best, public transportation is as reliable as driving, more efficient, less stressful and cheaper (Wallace 2017). Most American cities fall short of that ideal.

In the U.S., the Interstate Highway Act of 1954 was based on the understanding that the main function of transportation is to provide access to land, and the transportation planner's role is to provide mobility by forecasting future travel demand and determine infrastructures to meet those demands (Dittmar, 1995). There has been more emphasis on the need to promote sustainable and environmentally friendly transportation modes, and less congesting since the Intermodal Surface Transportation Efficiency Act (ISTEA), Transportation Equity Act for the 21st Century (TEA-21), the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU), and the most recent transportation bill, Fixing America's Surface Transportation (FAST) Act (NCTCOG, 2017). In addition, the Transportation Improvement Program (TIP) is a staged, multi-year program of projects proposed for funding by federal, State, and local sources within the Dallas-Fort Worth Metropolitan Area. The 2017-2020 TIP identifies roadway and transit projects programmed for construction within the next four years. The 2017-2020 TIP was developed by the North Central Texas Council of Governments (NCTCOG) in cooperation with local governments, the Texas Department of Transportation (TxDOT), and local transportation agencies. The 2017-2020 TIP was prepared under guidelines set forth in the Code of Federal Regulations (NCTCOG, 2017).

To achieve the standards, set forth by TIP, ISTEA, and SAFETEA-LU referenced above, and as an alternative to the private car, the 2017-2020 TIP for North Central Texas was developed to identify transportation improvement projects recommended by TxDOT and the Regional Transportation Council (RTC) as a result of the comprehensive, cooperative, and continuing regional transportation planning process. This process generates a multi-year listing of roadway and transit projects, and demonstrates that energy, environmental, air quality, cost, and mobility consideration are addressed in regional transportation planning and programming of projects.

Mobility 2035 was also developed by the North Central Texas Council of Governments (NCTCOG) which represents a blueprint for a Multimodal Transportation System to set forth a Metropolitan Transportation Plan. Some of the major policy objectives are to use Sustainable Development Strategies to: Reduce demand on transportation system, Provide multimodal options, and Emphasis on Environmental Aspects and Quality of Life Issues of Programs and Projects.

In regards to the empirical studies about factors impacting transit ridership, studies of transit ridership include combinations of external and internal factors (Taylor, B., & Fink, C. (2003). External factors are exogenous to the system and its managers, such as population and employment. In DART study area, the population is expected to grow significantly due to the influx of people moving from other States into the DFW area. Employment level is also expected to increase substantially in the DFW area. Population and employment increases are expected to have positive impact on transit ridership and also car ridership. Transit use is expected to be more sensitive than private vehicles to changes in employment levels (Taylor and Fink, 2003). Transit usage declined by approximately 25 percent during the Great Depression of the 1930s. Thus, employment levels are common variables used in transit ridership analysis. (Kain and Liu 1999) use changes in employment as variables in their regression analysis. On the other hand, internal factors are endogenous to the system where transit managers may have some kind of control over, such as service levels, fares, and intelligent transit information technologies employed. Internal factors generally aim to increase efficiency and effectiveness of transit operations. Next section will show some major future transit corridor recommendations in DFW metropolitan area.

A significant body of recent research focuses on the relationships between land use, urban form, and travel behavior. A large attention has been devoted to this topic because policy makers and planners have some control over land use and the deployment of transportation systems, but less control over many of the socio-economic factors (Taylor and Fink, 2003). Further, the New Urbanist movement has impacted many planning scholars and promoted research on the effects of various New Urbanist principles (such as compact, mixed-use developments and interconnected street/sidewalk networks) on travel behavior. Bianco et al. (2000), for example, studied the relationship between parking costs and transit ridership. They considered various strategies, including parking costs, parking regulations, employer paid parking, and transportation demand management (TDM) approaches. They find that the best approach in shifting mode share to transit – a tax on parking spaces – has the lowest political feasibility. Thus, most research on transit use and urban form has focused on other spatial factors such as: residential and employment densities. Others have illustrated that the impact of land use mix and urban design are also important factors. Crane (2000), for example, finds that decentralized residential and occupational locations are difficult to serve with traditional fixed route public transit because transit works best when a large number of people are travelling to and from concentrated nodes of activities. Thus, dense, compact development is more conducive to efficient operations than dispersed and sprawling pattern of urban development.

Other influential factors which were identified by means of literature search on factors that affect ridership levels include: gas prices, education, and socioeconomic characteristics (Taylor et al., 2003). It is believed that factors such as gas price changes over the last decade caused many automobile drivers to switch to transit. An analysis of transit ridership and fuel prices for nine major US cities from 2002 to 2008 found a significant increase in ridership associated with changes in gas prices (Lane, 2010). These studies generally conclude that higher gasoline prices have small but significant effects on transit ridership (Chen et al., 2011; Lane, 2012).

Other research included the Education/Percentage of College Population variable in the study of transit ridership (Dargay, et al. 2002). Most college students live at or around campus, where their activities are usually concentrated. Hence, it is not necessary for many of them to have a car. Therefore, it is important to include this variable in the study of transit ridership analysis. A positive relationship is expected between percentage of college population and transit ridership.

Employment levels, weather conditions, and system fares also matter (Kuby, et al., 2004). In a recent study of the Metropolitan Tulsa Authority, Chiang et al. (2011) reported a statistically significant travel elasticity of fare, which suggests that Tulsa Transit will lose 50,000 passengers if trip fares increase by $1 per day. Studies measuring the impact of fare changes on ridership may focus on different adjustments such as transit pass incentives (Zhou and Schweitzer 2011), or fare increases (Hickey 2005), Other studies explore the effects of fare changes on service coverage (Armbruster 2010), transit supply, employment, and gasoline price (Varley and Chen 2010; Pucher 2002). A study of the impact of fuel price and transit fare on ridership (1996-2009) similarly found that rising gas prices had a more significant effect than decreased transit fares (Chen et al. 2011). General economic theory suggests that the demand for a commodity will decrease if its price increases. Several previous studies, such as Taylor et al. (2009), have examined the influence of transit fare on patronage and found that when the transit fares increase, ridership decreases.

Studies of socioeconomic determinants of transit ridership focus on the travel needs of demographic groups with limited access to automobiles. Research shows that low-income groups are most likely to rely on transit for access to employment and other household's necessities (Alam 2009; Holtzclaw et al. 2002; Polzin et al. 2000). The poor, racial and ethnic minorities, and the elderly constituted 63 percent of the national transit ridership (Pucher and Renne 2003; Renne 2009). Percentage of African American Population- When planning a new route, the transit authorities are required to submit a Title VI report to the Federal Transit Agency (FTA) proving that the rights and benefits of the poor and minorities were given highest-priority consideration in the planning process. Moreover, the report must demonstrate that the proposed route does increase transit accessibility for minorities. Another study used the percentage of African American population to reflect the minority population groups. Literature suggests that a substantial proportion of African American minority population ride transit (Alam 2009). Hence, it is expected that ridership will increase with an increase in the proportion of African American population. Studies of socioeconomic factors also confirm that most of transit riders are low-income, African Americans, Latinos, women, and older adults, who are unable to afford an automobile due to financial constraints (Alam, 2015).

The literature about factors impacting transit ridership is quite mixed. Most previous studies of transit ridership have not included ITIS as one of the variables thought to influence transit ridership. Therefore, the disparities among the findings of empirical research completed to date point to the necessity for further study. This study addresses these shortcomings by testing multiple factors measuring population, technology, geography, and socioeconomic characteristics. This is examined in a case study applied to Dallas Area Rapid Transit (DART).

2.2 Connections between transit ridership and smart technology

It is hypothesized that intelligent transit information systems or ITIS will help transit agencies attract more riders. In order to explain the relationship between rising ridership and the use of smart technology, we need to understand how psychological, sociological and other factors affect travelers' behavior in the presence of ITIS; a satisfactory explanation requires that we are also able to specify the social "cogs and wheels" (Elster 1989) that have brought the relationship into existence. Dutzik & Madsen (2013) point out that Transit apps affect vehicle travel by reducing information barriers, reliability concerns and other hurdles to the use of public transportation. Further, survey research and observations by transit agency officials suggest that real-time transit information is a valuable asset to transit riders and can increase transit ridership by promoting awareness, feedback and collaboration to improve the quality of the services given by the technology. Tang (2010) argues that intelligent transit information systems hold the promise of making transit more attractive to users because of the user benefits. Such systems provide trip makers with information on the status of transit vehicles such as real-time bus or train arrival times, connection availability and real-time origin-destination travel times. Other possible applications are routing, information on payment methods and connection to other modes of transportation. In addition, travelers may perceive that their transit travel experience might improve with transit real-time information systems, leading them to have a positive view about such services, and consequently to increase their use of transit. The relationship of the propensity to increase transit use when given real-time information will therefore be positive. Golob (2000) points out that ITS provides a set of services that support using public transportation and potentially increase transit use. These include providing real-time information about the transit system and schedules, as well as other services that make people feel safer and more confident about using transit. Abdel-Aty and Jovanis (1995) examine a different aspect of service quality impacting transit ridership using transit survey data from Santa Clara and Sacramento, California. They find that most respondents were satisfied with available transit information.

Several other studies find that the penetration of Information and Communication Technologies (ICT) into all aspects of human life has influenced personal activities and related travel behavior (e.g. De Graaff & Rietveld, 2003; Golob, 2000; Golob & Regan, 2001; Mokhtarian et al., 2004; Salomon, 1986, 1998). America's technological and social networking revolution is changing every aspect of American life and transportation is no exception. Mokhtarian et al. (2004) affirm that one of the most major changes has been the emergence of new technology-enabled transportation services, which take advantage of mobile communications technology and social networking tools to provide new transportation choices to Americans. By empowering Americans with additional transportation choices and enhanced ways to navigate these choices, new technology-enabled transportation services could reduce the need for many Americans to own a personal vehicle, thereby resulting in a significant reduction in vehicle travel (Dutzik & Madsen, 2013).

In regards to previous research on passenger needs for real-time transit information and the effects of such information; Dziekan and Kottenho (2007) summarize that there are seven major effects of transit ITIS: reduced perceived wait time, positive psychological effects (e.g., reduced uncertainty, increased ease-of-use and a greater feeling of security), increased Willingness-to-Pay (WTP), adjusted travel behavior (e.g. better use of wait time or more efficient traveling), mode choice effects, higher customer satisfaction and better image of public transportation. Smith (2013) argues that Technology-enabled transportation services have the potential to change transportation behaviors. They can eliminate traditional barriers that prevent travelers from taking public transit or sharing rides. The new services can make it easier for households to own less vehicles - a step that generally leads to reductions in driving. They can also introduce additional transportation choices in places and markets where they are not currently available.

In addition, mobile technology enables riders to use their time riding on trains or waiting for buses more productively. This provides an advantage over driving especially if the use of mobile technology is perceived as being incompatible with the safe operation of a car. Nielsen (2012) adds that a reduction of wait times and associated uncertainties could be one of the primary factors linking these systems to increased transit use (from existing users or non-users of transit). Any system or technology that would reduce perceived wait times and associated uncertainties, whether it is Automatic Vehicle Location (AVL) technology which improves actual on-time service performance or real-time bus and train arrival systems and onboard connection information systems that affects people's perceived wait-times and reduce their anxiety, would be a step in the right direction in increasing transit use (Nielsen, 2012).

Golob and Regan (2001) illustrate that Information technology (Sometimes referred to as communications and information technology, or CIT) is developing quickly, providing unlimited business opportunities for entrepreneurs to develop and sell IT products and services. While most of these products and services are not specifically designed to affect travel behavior, they do, often in subtle and unexpected ways. In addition, cellular telephones and other portable computer and communications devices have redefined our ability to conduct business and dynamically provide real-time information while traveling or at locations away from home or workplace. The wave of technological advances that brought us the Internet, cell phones, and personal digital assistants (PDA’s) is not slowing down (Mokhtarian et al., 2004). The future will bring a next-generation Internet with higher speed, multimedia capability and intelligent agent technology. It will be accessible by both PC’s and smart handheld devices. (Mokhtarian, 2013). These trends offer the possibility of integrating traveler information to daily travel itineraries, points of interest, connectivity within transit modes or to ridesharing opportunities, to detailed weather reports and personal safety information, which could potentially improve the attractiveness of public transportation use. Tang (2010) examines how the attitudinal/psychological factors explain and predict travelers' actual behaviors. These altitudinal factors are investigated using attitudinal models developed from the Theory of Planned Behavior (TPB). Such models are employed in the context of technology adoption and use in the presence of habits, attitudes and behavioral intentions. Golob (2000) argues that the rise of apps in the transportation sector means that riders are increasingly able to make decisions based on the mode of transit that provides the best experience. Uber and Lyft put an emphasis on customer experience with their apps, enabling riders to seamlessly plan trips, pay, share arrival times with others and rate drivers. These apps have eliminated many sources of transportation friction and anxiety for riders. By enabling modern technologies, transit agencies can offer riders an experience comparable to that of ride-sharing services without being restricted to the roads, which are sometimes subject to uncontrollable conditions like traffic or construction detours.

Dutzik and Madsen (2013) add that advances in the Internet and mobile communications technologies have unleashed a wave of modern technology enabled transportation services. New innovations in technology and social networking are beginning to change the transportation landscape in America. New transportation services are providing people with an abundance of new options, helping to overcome barriers to the use of non-driving forms of transportation, and shifting the economics behind individuals' travel choices. Collectively, they have the potential to allow more Americans to reduce their car dependence lifestyles with less driving (Dutzik & Madsen, 2013). Gaylord (2013) points out that the majority of U.S. transit systems now make scheduling information publicly available, enabling developers to produce a variety of new smartphone apps to help riders navigate urban transportation systems. Smartphone-based IT IS tools enable riders to find the best route for a specific trip, track the progress of bus and trains in real time, and pay their fare.

Furthermore, Rainie (2012) states that new apps and tools also enable individuals to plan trips using several modes of transportation, facilitating efficient, seamless, and door-to-door journeys. Zickuhr (2012) illustrates that Information technologies make it easier to ensure seamless connections between various modes of transportation, expanding the number and types of trips that can be completed effectively without a car. Smith (2013) points out that the availability of mobile internet connections has the potential to influence transportation choices in important new ways. Smartphones, for example, provide travelers with access to voice and text communications, information and entertainment en-route, enabling time spent waiting for buses or riding on trains to be used more pleasantly or productively than before. Schwieterman et al. (2012) finds that the ability to stay connected while in travel is an important selling point of public transportation ridership relative to automobile driving, especially considering the increasing alarm of transportation safety officials about the perils of distracted driving.

Giovanni (2013) says that initial findings from recent research suggest that users who perceive public transit as providing an opportunity to multitask may be more likely to choose transit over driving. Mokhtarian et al. (2013) points out in a study of the Wi-Fi inclusion on Amtrak trains in California's Capital Corridor predicted that the service increased the number of trips by 2.7 percent, with the greatest impact on new riders. The ability of mobile Internet technologies to enable productive use of time on public transportation is of critical importance and have the potential to affect how people choose to travel. Gosselin (2011) suggests that providing information about transportation options via the Internet and mobile technologies can give people the same sense of mobility and freedom that comes with owning a car. The researchers concluded that new forms of information access enable choice; they can aid with smart planning and in-the-moment decision-making, reduce users' frustrations, and soften preconceived notions about the downsides of more sustainable transit options when compared with driving (Weigel et al., 2010).

Schwieterman et al. (2013) illustrate that Americans increasingly feel the need to connect via email, social networks and the Internet wherever they go. The increasing importance of mobile connectivity to Americans has the potential to shift traditional conceptions of how individuals value their time- making time spent connected to mobile technologies while waiting for a bus or riding a train more valuable than it might previously have been. The use of mobile technology on public transportation has become very common. An annual observational survey of Chicago-area commuter rail riders found that the percentage using portable electronic devices en route increased from 26 percent in 2010 to 48 percent in 2013 (Schwieterman et al., 2013). More than half of the riders on Amtrak's Acela high-speed rail service in the Northeast use laptops, tablet computers, or other electronic devices at any given time during travel (Schwieterman et al., 2012). Surveys conducted by researchers in Great Britain have found that 80 percent of business travelers riding on trains worked during their journey, with those who worked spending 57 percent of their time working (Department for Transport U.K., 2009). Leggatt

(2013) adds that the ways in which information is disseminated to the traveler has also changed significantly over time - while information dissemination was originally conceived of as occurring via roadside or wayside signs or kiosks or the Internet which could be accessed through personal computers or via in-vehicle navigation systems or vehicle arrival signs at transit stations and stops, the tremendous market penetration of cellular phones, Personal Digital Assistants or other mobile devices in the last 20 years have made real-time travel information ubiquitous and instant, and available through handheld devices. In short, technology-enabled transportation choices can help people target and overcome barriers that might previously have deterred them from taking public transportation, sharing a ride with a friend, biking or walking to their destination.

2.3 Intelligent Transit Information Systems (ITIS)

Considering theories behind ITIS impact on transit ridership, ITIS applications provide real-time information to transit users. It’s nice to have Information about the transit system available to all users. Transit and none transit users will benefit from having knowledge of the whole system with schedules and fare information, especially if the information is current. Perhaps when transit users are presented with better information, like knowing ahead of time about schedules and delays on their route, they adjust their expectations, and they will be willing to use trip planning tools and applications to plan their trips. This might make transit riders feel relaxed and more comfortable about their commutes overall, and because of the technological advances, these apps will evolve to serve the riders even better which may positively influence the transit mode decision, and mitigate the influence of psychological factors that determine personal attachment to automobiles. Moreover, ITIS apps provide information about trip planning, trip navigation, traffic conditions, bus and train arrival times, and mobile ticketing options. These apps also allow commuters to compare travel time and travel cost between different modes and the transit mode making it easier to find the shortest and cheapest travel mode.

The impact of Intelligent Transit Information Systems technology on ridership has received some attention in the transportation literature in the 1990s. The deployment of automatic vehicle location (AVL) systems to better monitor and control operations was becoming prevalent throughout the U.S. transit industry (Deakin and Sonju, 2011). The focus of most of these deployments was to increase operational efficiency, not to provide customer information. As these deployments matured, transit agencies recognized that data from an AVL system could be used to provide customers with real-time arrival information. At the same time, many transit systems in Europe were demonstrating the benefits of providing such real-time information to their customers. As a result, transit agencies have discovered a growing interest in providing real-time information to customers once they have deployed the AVL technology. Transit agencies of various sizes are beginning to invest in ITIS applications to facilitate real-time information, with the realization that they can have a significant and positive impact on their customers. Also, intelligent transportation systems products that specialize in providing real-time transit information exist on the market today and are being procured and deployed by transit agencies of all sizes (APTA, 2009). In the automobile industry, Waze software is used to provide such information. Like the automobile industry, transit agencies can use ITIS applications to meet the growing need to disseminate safety and security information (e.g., Amber Alerts) to customers in a security-conscious environment (US Department of Transportation, 2010).

In regards to the ITIS empirical studies, according to a study conducted using longitudinal data on route level monthly average weekday ridership in the entire Chicago Transit Authority (CTA) bus system from January 2002 through December 2010, researchers evaluate the ridership impacts of the CTA real-time bus information system. This particular information system is called CTA Bus Tracker and was implemented on different CTA bus routes from August 2006 to May 2009. Benefits realized from deploying real-time bus arrival information systems include improved customer service, increased customer satisfaction and convenience, and improved visibility of transit in the community (CTA, 2009). One of the perceptions among customers is that bus services have improved, and that people traveling late at night now have the reassurance that the next bus is not far away. Given the accuracy with which real-time arrival estimates are now being calculated, more and more existing and potential transit riders are viewing these systems as a necessary part of their travel experiences. Also, the combination of AVL and real-time arrival information systems results in benefits to transit agency staff, including less time required to monitor and control schedule adherence, improved safety and security for operations personnel and riders, less time required to respond to customer inquiries, improved maintenance management, and improved management effectiveness (Zhang et al., 2008).

Most of studies currently done on the topic of intelligent transit information systems have focused on what kind of information is useful and attractive to the potential users. For example, one study by Battelle Memorial Institute and Multisystems, Inc. (2003) on customers' preferences on different types of transit information has tried to identify which type of information is essential or preferred by customers for different trip types. However, no questions were asked on trip makers' travel behavioral changes. Based on this study, for transit pre-trip planning purposes, the highest preferences by respondents were for timetables and that traditional or static forms of information were preferred over real-time information for pre-trip planning. Trip time forecasts were the most preferred kinds of real-time transit pre-trip information. Participants in this study indicated that they would like to have both static and real-time information available at wayside, while at the same time recognizing that the costs are likely to be expensive. Onboard of the transit vehicle, participants expressed the greatest interest in information regarding where to get off the bus and what the current location of the vehicle is.

Other studies have attempted to examine the effectiveness and social benefits of public transit information by measuring traveler's willingness-to-pay for this service. However, most of the studies found that the willingness to pay for transit information is low. Using a focus group, Neuherz et al. (2000) found that public transit users regard travel information as something already covered or paid for by transit fares. Khattak et al. (2003), by analyzing the survey data collected in San Francisco Bay Area in 1997 through a computer-aided telephone interview of individuals who called the region's Traveler Advisory Telephone System (TATS) and were willing to be interviewed, found that public transit users are unwilling to pay as much for travel information as car users. However, other authors have reported more positive results in this regard. By conducting a stated choice experiment on travelers on different inter-city trains in Europe, Molin and Timmermans (2006) found that even though public transit information is highly price sensitive, travelers are still willing to pay for it if the information will provide additional functionality such as real-time information.

As for the evaluation of the effectiveness of ITIS in attracting new riders or otherwise modifying travel behavior, relatively few studies have been undertaken (Turnbull and Pratt, 2003). There is, as yet, no definitive reports of transit ridership increase in response to real-time information dissemination; however, there is research clearly indicating that riders appreciate real-time information, make use of it and are more at ease when it is available (Turnbull and Pratt, 2003). A study done by Mishalani and McCord (2006) has estimated the relationship between perceived and actual waiting times experienced by bus passengers. By analyzing that data collected at bus stops, where no real-time arrival information is provided, the authors found that perceived waiting time was greater than the actual waiting time controlling all other factors. Assuming the perceived waiting time will be the same once the real-time information is provided; the authors concluded that the real-time arrival information will help reduce transit riders' perceived waiting time and uncertainty caused by perceived longer headways.

Among the limited studies done on the potential effects of ITIS applications in attracting more users, especially non-transit users, the study results are quite mixed. A study done by Abdel-Aty (2001) indicated that transit information has the potential in increasing the acceptance of transit as commuter mode for non-transit users. The purpose of this research was to investigate whether traveler information systems would increase the acceptance of transit and determine the types and levels of transit information that are desired by commuters. A computer-aided telephone interview was conducted in this study in two metropolitan areas in Northern California. The survey employed stated preference design to collect data from non-transit users. Using an ordered probit model, the study identified the transit information that commuters seek include operating hours, frequency of service, fare, transfers, seat availability and walking distance to transit station. About 38% of non-transit users indicated that they might consider transit use if appropriate transit information was available to them. About half of them indicated that they were likely to use transit if the preferred information types were provided. However, a study done by Chorus et al. (2006) shows that the impact of transit information on mode choices will be very limited on car-drivers, even if the information provided is actually favorable to transit. In this study, a theoretical regret-based model of information use and effect was employed. Using numerical simulations of the model, the study demonstrates that, even in cases where transit information is acquired, and that message is favorable to transit, its impact on change in mode choices will be limited. Thus the study suggested conservative estimates of the impact of transit information provision on modal shifts.

In another study, Cham et al. (2006) attempted to quantify the return on investment due to the implementation of real-time bus arrival systems. The authors showed that by using fairly conservative assumptions regarding trip volumes that receive real-time bus arrival information, reductions in wait time and reduction in the cost of wait-time uncertainty, that the Portland area's real-time bus and train arrival information system (TriMet Transit Tracker) most likely achieves positive net (social) benefits. The Transit Tracker system provides TriMet riders with a real-time estimate of the expected time until the next transit vehicle arrives at a specific stop (bus) or station (rail). Transit Tracker covers all rail stops and each of TriMet's 7,700 bus stops, although at the time of the study, electronic Transit Tracker information displays had been deployed at only 13 bus stops (4 of which also include voice annunciation and information on the remaining bus stops were available via telephone or the web) and at all TriMet light rail stations (deployed January 2001). This study uses existing TriMet data sources and a benefit-cost methodology to arrive at these conclusions. The authors speculate that it is also possible that better vehicle arrival time information may also generate additional ridership for TriMet, potentially yielding additional benefits to society (e.g., from reduced auto use). However, the existing studies of Transit Tracker use do not provide a reasonable basis for assessing any potential increase in ridership resulting from implementation of the Transit Tracker system. Hence, the potential for increased ridership is not included as a benefit in this brief demonstration. Similarly, while TriMet may also enjoy some cost savings benefits from Transit Tracker's implementation (e.g., a reduction in staff dedicated to customer service phone lines), TriMet has not conducted studies to measure any such potential agency cost savings from Transit Tracker implementation. Therefore such potential agency cost savings benefits were not considered in the demonstration analysis considered in the report.

The results of the literature scan can be summarized as follows: there has been no definitive study on changes in ridership levels due to ITIS applications provision. There are several studies, which have shown that the immediate benefits of these systems accrue due to the fact that riders appreciate the information and use it. The literature indicates that wait times experienced by transit riders is perceived to be burdensome by most transit riders. A reduction of wait times and associated uncertainties could be one of the primary factors linking these systems to increased transit use (from existing users or non-users of transit). Any system or technology that would reduce perceived wait times and associated uncertainties, whether it be AVL technology, which improves actual on-time service performance, or real-time bus and train arrival systems and onboard connection information systems that affects people's perceived wait-times, would be a step in the right direction in increasing transit use (Mishalani and McCord, 2006). Although there are yet no definitive reports of transit use or mode share increase due to ITIS applications dissemination, many studies have found positive psychological effects of real-time information on travelers, such as higher satisfaction level with transit service (Shen et al., 2008), and reduced perceived wait times and anxieties (Dziekan, K., and K. Kottonhoff, 2007). Some studies have even hypothesized that a reduction of perceived wait times and associated uncertainties could be one of the primary factors that consequentially lead to transit ridership increase (The Victoria Transport Policy Institute, 2007).

Previous research on intelligent transit information systems has been summarized in TCRP Report 95 (Turnbull and Pratt, 2003), TCRP Report 48 (Schweiger, 2003), (Abdel-Aty, 2001), and (FTA, 2011). According to these reports, the potential impact of such information systems on transit ridership is an important factor. The availability of real-time information is also impacting travelers' perception of public transit. For example, the ShuttleTrac system implemented at the University of Maryland resulted in increases of two psychological indicators among riders (Zhang et al., 2007). Within this broader literature, the role that ITIS can play in increasing transit ridership levels and to improve customer satisfaction has been receiving increasing interest. However, although transit information has been regarded as one of the most important factors that will increase transit ridership in many studies, there is no convincing evidence in the literature that shows that such information systems can successfully increase transit use, especially from non-transit users. While some studies suggest that ridership effects of such systems are positive, other studies have given more conservative estimates of the impact of ITIS provision on ridership.

Although many studies have considered ITIS real-time transit applications to be one of the most crucial factors that will influence transit ridership (Federal Highway Administration, 2004; Taylor and Fink, 2003; The Victoria Transport Policy Institute, 2007), the current literature does not provide conclusive evidence regarding whether such information systems can successfully increase transit patronage. Most studies completed to date explore ITIS impact on ridership in qualitative and descriptive forms, surveys, and interviews. Descriptive analyses are normally based on qualitative data from surveys and interviews to identify factors affect ridership. However, such studies also may have some methodological and interpretive biases. Such information may be subjective and may also depend on respondents' perceptions and assumptions about internal and external factors related to ridership (TCRP 1995, 1998), thus the data are subject to biases based on limited information (Taylor and Fink, 2003). This study will attempt to quantify the ITIS impact on ridership, and fill the gap in the existing literature by exploring the impact of ITIS transit information systems on transit ridership. Within this broader literature, the role that intelligent transit information systems (ITIS) can play in increasing transit ridership levels and to improve customer satisfaction has been receiving increasing interest. Currently, the transit system is growing and changing rapidly. Given Dallas Area Rapid Transit (DART) has been involved in the planning, programming, and implementation of intelligent transit information programs and projects, it is therefore of interest to find out the impact of ITIS on transit ridership in the DART study area.

2.4 The impact of ITIS applications on transit ridership

In the existing literature related to the relationship between the use of the app and increase ridership, several studies have commented on the role that ITIS app play on public transit ridership. Some studies are based on Stated Preference (SP) or simulated data (Abdel-Aty & Jovanis, 1995; Peng et al. 1999; Abdel-Aty, 2001; Chorus et al., 2006). Abdel-Aty (2001) conducted a SP survey to investigate whether traveler information systems would increase the acceptance of transit and found that such information has the potential in increasing acceptance of transit as commuter mode for non-transit users. A study of Seattle-area bus users who used real-time performance information through a service called OneBusAway found that 90 percent reported that the service reduced the amount of time they spent waiting for the bus, with an actual reduction in wait time averaging 2 minutes. Realtime information was also responsible for a reduction in perceived wait times of about 13 percent (Watkins et al., 2011). More than 30 percent of respondents reported that the service induced them to ride the bus more often (Ferris, 2010). Lewis and Williams (2000) point out that strategies to increase public transit ridership and to improve user satisfaction are an active and ongoing area of research. Customer satisfaction, stemming from service scheduling and reliability, service coverage, information, comfort, cleanliness, and safety and security is another active area of research, which seeks to inform public transportation managers of ways to improve services and attract patronage.

Tang (2010) estimated from using the data from two stated preference surveys that Transit Information Systems applications has a positive effect on the intention to increase transit use in certain groups of travelers and that eventual changes in ridership effect may be small but positive. He also found that in the initial stages of the technology deployment, there is indeed a small positive effect on ridership, in certain routes and areas, controlling for a wide variety of factors that may also affect ridership over time.

Tang et al. (2012) conduct another study of ridership on the Chicago transit system, which introduced a real-time bus location information system from 2006 to 2009. They illustrate that introducing real-time information increased bus ridership by 2 percent. While that impact appears small, it is likely greater today, as convenient smartphone-based tools were only beginning to become available by the end of the study period. A survey of users of the University of Maryland’s campus shuttle service found that real-time data increased ridership by 23 percent (Zhang 2010). Another survey of bus riders on a New York City bus line found that, just six months after providing real-time information, more than half of all riders had used the information, with more than half of those riders consulting the real-time information on every trip. Riders who used the real-time information reported that they felt spending less time waiting for the bus than non-users, even though the amount of waiting time they spent was the same (Rojas, 2013). Boston’s transit agency, the MBTA, has cited the availability of real-time transit information for buses as one of the reasons for this agency to set 15 monthly ridership records in a row from 2011 into 2012. In a June 2012 press release, General Manager Jonathan Davis said “We’re absolutely convinced that the widespread availability of real time bus data is making public transit a more convenient option for commuters. More than 100,000 smartphone users have downloaded ITIS applications that provide arrival time information for more than 180 MBTA bus routes” (Young, 2012).

In addition, researchers from Massachusetts Institute of Technology surveyed riders the day before and the day after the MBTA installed digital train arrival countdown signs in several subway stations in the summer of 2012. Because of the signs, customer satisfaction with the train service increased by 15 percent, and riders’ perceived wait times went down by several minutes (Moskowitz, 2013). By surveying riders in the City of Manitowoc, WI, the research of Peng et al. (1999) gave some insight into the question of whether AVL systems will help to attract more transit riders. About 36% of respondents indicated that they would ride more often if better and timelier transit information were available, but a larger group said they would ride the same amount. It is possible that a greater percentage of respondents would indicate that they would ride more if the AVL system in these areas could be configured to provide real-time arrival information. However, a study done by Chorus et al. (2006) shows that the impact of transit information on mode choices will be limited in affecting car-drivers, even if the information provided is actually favorable to transit. In this study, a theoretical regret-based model of information use and effect was employed. Using numerical simulations of the model, the study demonstrates that even in cases where transit information is acquired, and that message is favorable to transit, its impact on change in mode choices will be limited. Thus, the study suggested conservative estimates of the impact of transit information provision on modal shifts.

Among the studies that were based on actual observed customer responses to real-time transit information, some of the studies did not found evidence showing that transit ridership increased because of the provision of such information (Holdsworth et al., 2007; Zhang et al.,2008; Cham et al., 2006), while many other studies did show such effect after the real-time information was launched (Schweiger, 2003; Infopolis2, 1998; Lehtonen & Kulmala, 2001; Cross, 2003; Rolefson, 2003; Body, 2007). After a Signal Pre-emption/Real-Time Passenger Information System (SR/RTPIS) program was implemented in Auckland, New Zealand, the patronage statistics show an annual increase of 7 percent per year in Auckland (Body, 2007). Similarly, a study for the Phoebus system in Brussels and Angouleme shows that the introduction of real-time information has increased the ridership by 5.8% for the bus lines equipped with this system. And in Liverpool, study shows that the ridership increased by more than 5% on lines equipped with at-stop displays (Schweiger, 2003). Also, the study on Infopolis2 project (Infopolis2, 1998) stated an increase in revenue such as 1.5% due to this system. The results of the literature show that travelers appreciate real-time transit information that is reliable and enables them to make immediate travel decisions, and the provision of the real-time transit information lead to travel time savings to passengers and higher passenger satisfaction with transit system.

2.5 The potential impact of ITIS applications on non-transit users

After reviewing most of the existing literature related to the impact of the apps on non-transit riders, I can conclude that these new ITIS tools/apps reduce negative aspects and cost of using transit through providing information, promoting awareness, feedback and collaboration to improve the quality of the services given by the technology, saving time and other attributes, and make transit more competitive and flexible for individuals to meet their transportation needs. From the ITIS impact reviewed in the existing studies, some studies are based on Stated Preference (SP) or simulated data (Abdel-Aty and Jovanis, 1995; Peng et al. 1999; Abdel-Aty, 2001; Chorus et al., 2006). For example, Abdel-Aty (2001) conducted a SP survey to investigate whether traveler information systems would increase the acceptance of transit and found that such information has the potential in increasing acceptance of transit as commuter mode for non-transit users. A computer-aided telephone interview was conducted in this study in two metropolitan areas in Northern California. The survey employed SP design to collect data from non-transit users. According to the survey results, about 38% of non-transit users indicated that they might consider transit use if appropriate transit information was available to them. About half of them indicated that they were likely to use transit if the preferred information types were provided.

The literature indicates that wait times experienced by transit riders is perceived to be burdensome by most transit riders. A reduction of wait times and associated uncertainties could be one of the primary evidences linking these apps to increased transit use (from existing users or non-users of transit). Nielsen (2012) adds that any system or technology that would reduce perceived wait times and associated uncertainties, whether it is Automatic Vehicle Location (AVL) technology which improves actual on-time service performance or real-time bus and train arrival systems and onboard connection information systems that affects people's perceived wait-times and reduce their anxiety, would be a step in the right direction in increasing transit use (Nielsen 2012). In addition, access to mobile technology also enables riders to use their time riding on trains or waiting for buses more productively. This provides shared transportation with a market advantage over driving since the use of mobile technology is increasingly understood as being incompatible with the safe operation of a car.

Small and Verhoef (2007) affirms that increasing the relative attractiveness of transit travel with ITIS apps and services that provide Wi-Fi in transit, Education about benefits of transit –Monetary savings –Reduced pollution –Less stress –Link to active lifestyles, may cause a subset of commuters to switch from auto to transit. As Small and Verhoef (2007) note, the introduction of Bay Area Rapid Transit (BART) service between Oakland and San Francisco in the early 1970s led to 8,750 automobile trips being diverted to BART. Brechan (2017) argues that the combinations of fare reductions and discounted passes, higher vehicle user fees (such as priced parking or road tolls), improved transit service, transit traveler information and better transit marketing can be particularly effective at increasing transit ridership and reducing automobile use. In addition, this research will allow us to examine how the incremental exposure to technology from 2007 to 2017 may lead to changes in attitudes and behaviors over time as a result of technology adoption and diffusion. In the next chapter, I will discuss the social mechanism, and theoretical approaches and concepts regarding the diffusion and adoption of ITIS technology.

Chapter 3

Theoretical approaches and concepts regarding the diffusion and adoption of ITIS Apps

3.1 Introduction

To explain the social mechanisms that may help non-transit riders become aware of the smart technology and opportunities for riding transit, we need to understand the concepts regarding the diffusion and adoption of ITIS. Elster (1989) states that a satisfactory explanation requires that we are also able to specify the social “cogs and wheels” that have brought the relationship between transit ridership and ITIS apps into existence. In keeping with the age of technology, social networking sites such as Facebook, Twitter, and Myspace can reintroduce transit to non-transit riders and technologically savvy class in many modern cities. More than 50 transit agencies in the United States, including DART have some sort of social media presence. The presence of social media and networking allows transit agencies to advertise, market, and make announcements on their own behalf without the need of a middle man such as a newspaper, commercial, or professional advertising agency (Eirikis, 2010).

A large theoretical literature has developed showing the impact of network effects on the adoption process by consumers. Researchers have used “network effects” to refer to three distinct concepts: direct network externalities, indirect network externalities, and social network effects Rogers (1995). In sociology and communications, “network effects” usually refer to the communication of ideas through social ties. The rapid diffusion of Hotmail email is an example of social network effects. New customers learned about the product from friends through email (Goldfarb, 2004). These models are driven by the importance of personal interaction in learning about an innovative technology and rely on communication of ideas through social ties (Manski (1993). Goolsbee and Klenow (2002), and Bell and Song (2004) examine the impact of network effects on Internet adoption by consumers. Goolsbee and Klenow (2002) use instrumental variables estimation to examine the importance of local spillovers such as learning and network externalities on consumer home PC adoption. They show that these spillovers are connected to Internet usage and argue that this provides evidence of network effects in adoption. Stroeken and Knol (1999) state that the adoption of information technology takes place at the microeconomic level. It is particularly the phases involving the provision of knowledge and confidence-building about the adoption process. Adoption of information technology involves learning about, and becoming aware of, the dynamic environment in relation to the role of information technology.

Diffusion research generally aims to analyze the diffusion of innovations in a social system. In this case, it involves DART Transit sector. Communication with potential adopters is the central theme in the diffusion process as this helps to reduce the uncertainty that exists among travelers with respect to information technology. Stroeken and Knol (1999) argue that homogenization of the group of potential adopters is a necessary requirement for optimizing the effectiveness of communication. The environment and associated communicative connections of this group of potential adopters has thus a profound influence on the adoption degree of an innovation in that social system. Cooper and Zmud (1990) defined IT implementation as “an organizational effort directed toward diffusing appropriate information technology within a user community.” In this research, appropriate transit information technology apps will be diffused within DFW user community to examine the impact of these apps on ridership.

3.2 The Adoption Process

Sheng (1998) created a model to help identify and measure the innovation adoption process as shown in Fig 3-1:

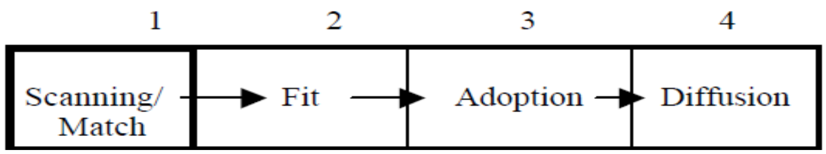

Figure 3-1 Organizational Innovation Adoption Process

(Source: Sheng, 1998)

The four-step process includes:

1. Scanning/Matching: Either an opportunistic approach that scans for new ideas or an approach that scans for innovative solutions for existing problems. In this study, DART will provide Innovative ITIS solutions which aim to reduce negative aspects and cost of using transit through providing information, saving time and other attributes, and make transit use more attractive to existing transit users and non-transit users.
2. Fit: The innovation ITIS solutions are redesigned to fit the user's community needs. Political negotiations are conducted to gain support for the match.
3. Adoption: Initial application use. Identification of a champion. Users are encouraged to regularly use the new ITIS apps.
4. Diffusion: The ITIS application is spread throughout the user community in modified and creative ways through modern apps and social ties which generally attempt to bring an innovation into a new social network and can effectively communicate its benefits to increase overall efficiency or to solve additional problems. New customers and non-transit users will learn about the ITIS apps from friends through social ties, "word of mouth", marketing campaigns, and promotion services which include providing real-time information about transit

arrival and departure times, and other services which make people feel safer and confident about using transit.

Ryan and Gross (1943) used an epidemic model to study the diffusion of hybrid corn to Iowa farmers and find that social networks matter. Coleman et al. (1957) show how network effects shape the pattern of ICT diffusion and identify the role of network effects on the diffusion of new technologies. Stoneman (2002) points out that adoption is the individual-level decision to use a new technology. Diffusion is the aggregation of a number of adoption decisions. Rogers (1995) defines it as “the process by which an innovation is communicated through certain channels over time among the members of a social system.” Epidemic models are commonly used to help forecast the rate of aggregate technology diffusion. Bass (1969) uses an epidemic model to help predict the rate at which a product will diffuse. The central themes of these models -communications and social networks- are also prominent in recent economic research on technology diffusion. For example, Goolsbee and Klenow (2002) have examined how communications and social networks have influenced the diffusion of personal computers, and Bell and Song (2004) have examined use of online grocery services. As noted by Bell and Song (2004), technology spreads through interpersonal contact and information dissemination. Axsen et al. (2009) illustrates that evolving technology can have an impact on the way consumers (travelers) benefit from it and use it -" according to intuition and theories of diffusion, consumer preferences develop along with technological change".

David (1969) assumes that the entire population has perfect information about the technology. Individuals (or firms) adopt the technology when the net benefit of adopting is positive. Rogers (1995) focuses on the role of communications networks in technology diffusion. He details the process through which innovations move from one population to another and discusses the role of five key factors in the individual decision to adopt: relative advantage, complexity, compatibility, trialability, and observability. He emphasizes that these factors are only relevant after informative contact with the innovation, and much of this work focuses on the roles of different communications networks in initiating this contact. This contact is achieved by a “change agent.” The change agent brings an innovation into a new social network and can effectively communicate its benefits. Transit managers aiming to generate technology adoption should think of themselves as change agents (Rogers, 1995). Although formal studies of the role of innovators and change agents have not been conducted in the field of ITIS, it is possible that they will play a substantial role in the diffusion and success of these technologies by commenting on their use and benefits in technology product blogs and "spreading the word" and promotion and collaboration in improving the technology (Droge, 2009).

User studies in this area have examined how social networks and network externalities influence user decisions to adopt new communication technologies (Astebro, 1995; Kraut et al., 1998; Tucker, 2004). Another area of research relates to long-term usage within the user community. This research draws upon the “Technology Acceptance Model (TAM)”, based on the Theory of Reasoned Action from social psychology (Davis, 1989; Davis et al., 1989). The TAM model predicts that perceived usefulness and perceived ease of use are key to predicting long-run usage. Davis (1989) points out that factors that influence behavior, such as user characteristics and system design, do so indirectly through attitudes and subjective norms. Venkatesh and Davis (2000) extend the TAM model to explain perceived usefulness and ease of use in terms of social influence and cognitive instrumental processes. Kim and Malhorta (2005) show that belief updating, self-perception, and habit help explain usage behavior when added to the TAM.

3.3 Theories explaining connection between the ITIS app and transit ridership

In the existing literature related to the connection between marginal drivers taking the leap to using the app and riding transit, different theories have been applied to the analysis of transportation behavior, and the formulation of strategies needed to change that behavior. Some recent development of consumer decision making models include multi-attribute models that are suitable for services or products containing multiple attributes, and attitude models that explain how attitude affect behavior (Abley, 2000). The most influential attitude models are the Fishman decision making model - Theory of Reasoned Action (TRA), and several extended models from TRA, such as Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB). All these three attitude models are also closely related to Adoption Theories.

3.3.1 The Theory of Planned Behavior

The theory of planned behavior TPB, for example, was developed by Dr. Icek Aizen, of the University of Massachusetts. Aizen (1991) states that "according to the theory of planned behavior, human action is guided by three kinds of considerations: beliefs about the likely consequences of the behavior (behavioral beliefs), beliefs about the normative expectations of others (normative beliefs), and beliefs about the presence of factors that may further or hinder performance of the behavior (control beliefs)." (Aizen, 1991). The TPB model of human behavior is shown in Figure 3-2. This model comes from the field of psychology, and shows that human action is guided by three types of considerations:

- Attitude toward the Behavior- An individual's evaluation of an action, such as riding transit. It will be referred to as attitude. In this research ITIS apps provide useful transit information, make transit more attractive to customers, and will ultimately contribute to positive attitude toward the behavior.

- Subjective Norm - An individual's perception of what others will think if he/she performs an action (e.g., what friends and parents will think if he/she rides transit).
- Perceived Behavioral Control or Self-Confidence - An individual's assessment of his/her ability to take an action, such as taking transit. In this case, ITIS apps reduce negative aspects and cost of using transit through providing information, saving time and other attributes, make transit more attractive to customers, and give new drivers more control or self-confidence toward using transit.

Aizen (1991) argues that for each individual, these three types of considerations will have different importance, depending on the behavior or action. For example, young teens, as compared with older adults, may be more affected by the opinions of their peers in a decision to take transit. Attitude, subjective norm, and self-confidence will contribute to an individual's intent to perform an action. Whether an individual holds the intent depends on his/her self-confidence in doing so. The literature scan also shows that the TPB has been applied in multiple European studies of mode choice. Theory of planned behavior has been used extensively to model human social behavior (Daigle et al., 2009). It has been used in the transportation planning field to study psychological factors affecting mode choice and public transportation use (Bamberg, 1995, 1996; Bamberg & Schmidt, 1993, 1998; Heath & Gifford, 2002; Karash et al., 2008). Heath and Gifford (2002) used an empirical strategy motivated by the TPB (with interaction variables) to predict the effectiveness of a universal bus-pass program (U-Pass program, which was offered to students at a considerable price reduction) in increasing the percentage of university students using the bus service and also changes in psychological variables related to bus use. However, there are several limitations of TPB. Some of the limitations are related to the explanatory power of the model, since only three predictors were included in the original TPB. As Ajzen (1991) suggested that TPB is open to expansion, many researchers have proposed additional predictors in the model. Some researchers proposed to include personal and demographic factors in the model. Those factors have been identified as important determinants to form attitudinal factors in Huang (1993)'s consumer behavior model and Pearmain (1991)'s travel behavior model. Further, several studies (Bruijn et al., 2008; Bruijn et al., 2009; Mullan & Wong, 2009) found that reasoned use and habit lead to resistance to change in behavior and suggested expanding TPB to include habitual factors. Moreover, according to other research related to the TPB, appropriate interventions can break habits by changing underlying psychological factors related to these habits and lead to behavior change (Heath and Gifford, 2002), thus the interaction between interventions and habit should also be considered in the model if appropriate.

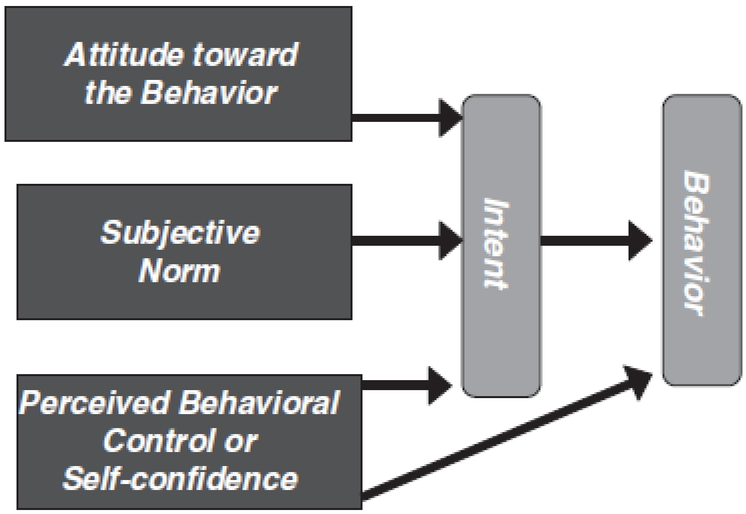

Figure 3-2 The theory of planned behavior

(Source: Aizen, 1991)

3.3.2 Innovation Diffusion Theory

Kelly (2012) argues that Technology is a potentiator source of possibilities and options, allowing savings of time and costs to organizations. Its technique nature and method are strongly associated to knowledge that when applied to practice can provide competitive advantage for companies in the eco-nomic scenario. Arthur (2011) argues that Technological innovation is the main engine of economic development. According to Stal (2007), innovation is the development of a new method, device or machine that, on the market, could change the way in which things happen. This change has to be transformative in bringing improvements (Tigre, 2006) such as improving transit services to users by reducing the uncertainty associated with using transit and bringing improvements to the quality of transit service. According to the Oslo Manual (OECD, 2010), “innovation is clearly part of a business strategy based on transforming ideas into value. Generally, improved goods, services or processes" and can be configured as product, process, marketing and organizational innovation. Rogers (1983) proposed the innovation diffusion theory, consisting of five stages, which occur over time, given the influence of the social system and the communication channels, as shown in Fig. 3.3

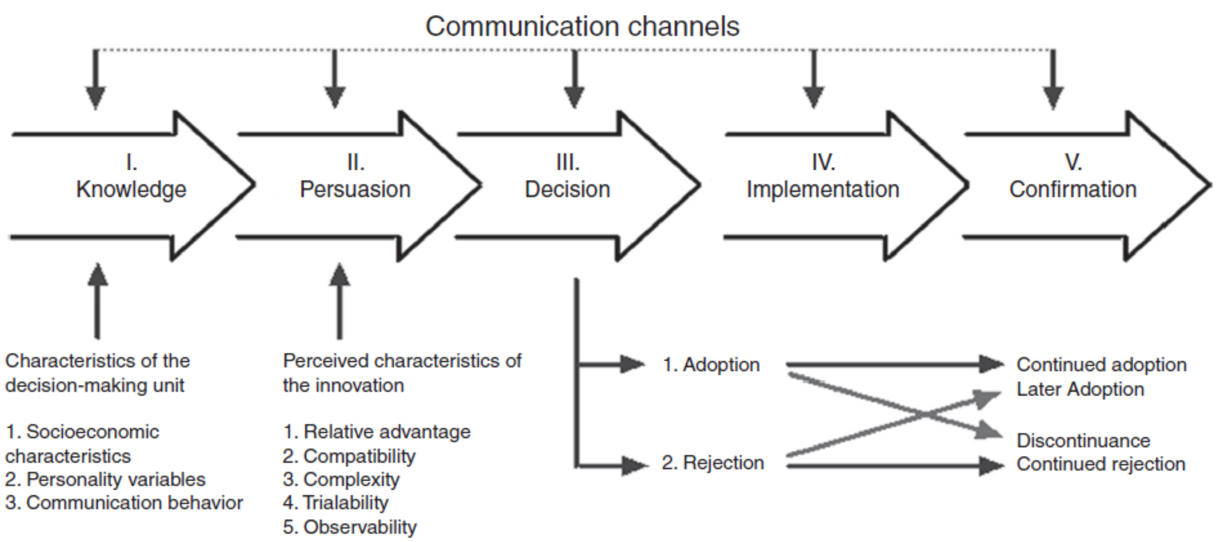

Figure 3-3 Decision process innovation

(Source: Rogers, 1983)

The innovation decision process is the search for information made by a sequential activity in which the subject is motivated to reduce uncertainty about the advantages and disadvantages of a particular innovation. This process consists of five phases: previous conditions for adoption, knowledge about innovation or technology, persuasion of the possible adopter by deepening the knowledge about technology and searching for more information about the same; decision to adopt or reject the technology; implementation, that is the moment in which the technology is put into use; and finally the stage of confirmation in which the adopter evaluates and decides the maintenance of the adoption or rejection of it after it has been put into use (Rogers, 1983).

3.3.3 The information processing theory

Miller (1956) developed the information processing theory. This theory is an approach to the cognitive development of a human being, which deals with the study and the analysis of the sequence of events that occur in a person's mind while receiving some new piece of information such as transit information received via one of the ITIS apps. Huang (2001)'s used this theory to study consumer preference to analyze the relationship between perception, attitude and behavior intentions. Huang proposed a theoretic model of these psychological and behavior factors (Figure 3-4) and tested this model empirically using the data of a Georgia consumer survey on consumers' risk perception, attitude and behavior intentions toward pesticide use. The research results suggested that consumers' perception significantly affects their attitudes towards pesticide use, which in turn influence consumers' perception and behavior's intentions. However, the relationship between consumer perception and behavior' intention is not significant (Tang, 2010).

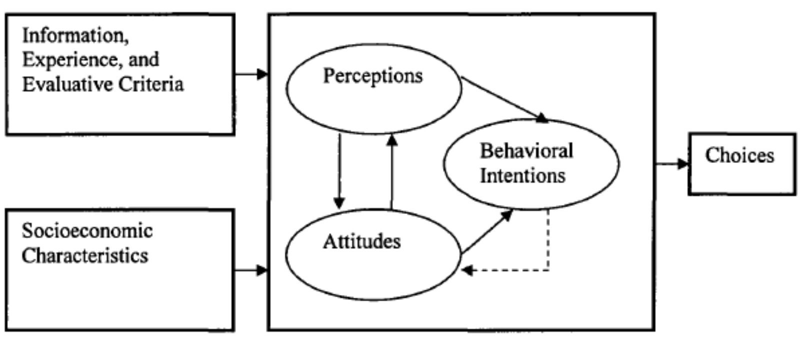

Figure 3-4 Information processing theory

(Source: Huang, 2001)

3.3.4 Adoption theories

Pederson (2005) illustrates that studies of Information and Communication Technology (ICT) adoption takes one of three possible approaches, a diffusion approach, an adoption approach or a domestication approach (Pedersen, 2005). Diffusion researchers typically describe the aggregate adoption process in an industry, community and society in general, as an S-shaped function of time that may be used to categorize adopters of various kinds (Rogers, 1995). This approach has been used in studying the diffusion of numerous transportation technologies. Rogers (1962) identified five categories of adopters in his Diffusion of Innovations Theory: innovators, early adopters, early majority, late majority, and laggards. Innovators are the first pioneers to adopt an innovation. Innovators are willing to take risks, youngest in age, have the highest social class, have great financial lucidity, very social and have closest contact to scientific sources and interaction with other innovators. They are well-informed risk-takers who are willing to try an unproven product. Early adopters are the second fastest category of individuals who adopt an innovation, and who, based on the positive response of innovators, begin to purchase and use products. Early adopters are younger in age, have a higher social status, have more financial lucidity, advanced education, and are more socially forward than late adopters (Rogers 1962). Adoption researchers typically describe and explain the adoption decision of individual end-users applying different individual and social theories of decision making (Pedersen, 2005).

The domestication research typically studies the adoption and use of technology in everyday life (Silverstone and Hirsch, 1992). The focus of domestication research is on the societal consequences of the domestication of technology; that is the process in which the use of technology becomes integrated into our everyday life.

3.3.5 Theory of Reasoned Action

Theory of Reasoned Action (TRA) was originally proposed by Fishbein and Ajzen (1975). In the Theory of Reasoned Action (TRA), attitude is defined as a person's overall evaluation of an object and comprised of salient beliefs the person held about an object, the strength of the beliefs and the evaluation of each beliefs (Fishbein, 1967). Ajzen and Fishbein (1980) argued that the best predictor of whether a person will perform a certain behavior is that person's behavioral intention. Every decision made by an individual depends on the person's intention to perform or not to perform the act. Furthermore, one's behavioral intentions are determined by two factors: one's attitude toward the act, and a social normative factor. One's attitude toward the act means an individual's evaluation of the act instead of the object. The social normative factor represents one's judgment about the expectations of others and one's motivation to comply with those expectations (Ajzen & Fishbein, 1980). According to the theory of reasoned action, if people evaluate the suggested behavior as positive (attitude), and if they think their significant others want them to perform the behavior (subjective norm), this results in a higher intention (motivation) and they are more likely to perform the action.

3.3.6 Technology Acceptance Model (TAM)

The Technology Acceptance Model is considered an Extension of Theory of Reasoned Action. The Technology Acceptance Model (TAM) originally proposed by Davis (1989) is one of the most influential extensions of Ajzen and Fishbein's theory of reasoned action in the literature. The technology acceptance model uses two technology acceptance measures - ease of use, and usefulness to replace TRA's attitude measures. The roles of these two acceptance measures in predicting behavior have been suggested as prominent by earlier studies (Tornatzky & Klein, 1982; Stewart, 1986). In TAM, it is assumed that when someone forms an intention to act, they will be free to act without limitation (Bagozzi et al., 1992; Davis et al., 1989).

3.3.7 Perceived Behavioral Control and Self Efficacy

Perceived behavioral control tries to measure the respondent's confidence in executing given behavior. The perceived behavioral control concept came from the self-efficacy (Fishbein and Cappella, 2006; Ajzen, 2002). The concept of self-efficacy is rooted in Bandura (1977)'s social cognitive theory. It refers to the conviction that one can successfully perform a behavior in order to produce certain outcome. The concept of self-efficacy is used as perceived behavioral control in TPB model. It indicates the perception of the ease or difficulty in executing particular behavior. Such perception is related to beliefs about the presence of factors that may facilitate or impede performance of the behavior.

3.3.8 Pearman's Travel Behavior Theory/ Model

Pearman et al. (1991) presented a model depicting the decision-making process underlying travel behavior (See Figure 3-5) that is closely related to Ajzen and Fishbein's theory of decision making - a model that originates from the field of psychology. In this model, there are two sets of variables, one are observable variables that "serve to promote and constrain market behavior", and the second are non-observable variables that "reflect consumer's understanding of their options and influence their decisions to pursue particular strategies" (Pearmain et al., 1991), which are also internal mental elements.

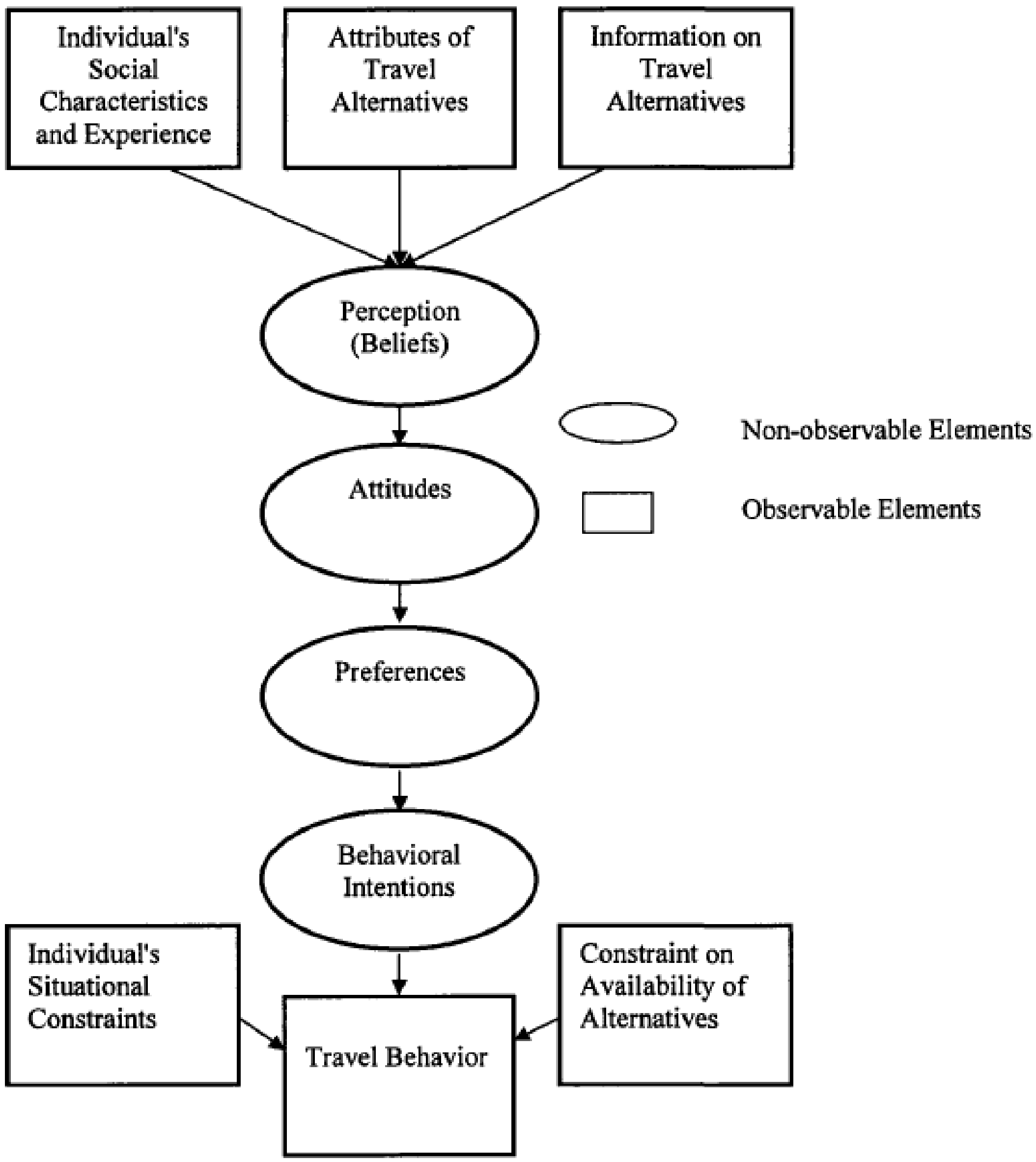

Figure 3-5 Components of travel behavior

(Source: Pearmain et al. 1991)

Chapter 4

The elasticity of demand for transit

4.1 Introduction

Demand elasticity refers to how sensitive the demand for a good is to changes in other economic variables, such as the prices and consumer income (Hamilton, 2008). Demand elasticity is calculated by taking the percent change in quantity of a good demanded and dividing it by a percent change in another economic variable. For example, if the elasticity of transit ridership with respect to transit fares is –0.5, this means that each 1.0% increase in transit fares causes a 0.5% reduction in ridership, so a 10% fare increase will cause ridership to decline by about 5% (Hamilton, 2008).

Quite frequently one may be interested in interpreting the effect of a percent change of an independent variable (e.g. price or income) on the dependent variable (e.g. demand for transit). In this case, the elasticity of ***y*** (e.g. demand for transit) with respect to ***x*** (e.g. price or income) could be defined as the percent change in ***y*** divided by the percentage change by ***x.***

Elasticity of demand for transit = percent change in transit ridership / percentage change by income.

As an example, for $Ej = 2.0$ we can say that about the mean of the variable, a *1%* increase in xj will lead to a *2%* increase in y. In general, a high elasticity value indicates that a good is price-sensitive, that is, a relatively slight change in price causes a relatively substantial change in consumption. A low elasticity value means that prices have relatively insignificant effect on consumption (Hensher, 2008). Economists use several terms to classify the relative magnitude of elasticity values. Unit elasticity refers to an elasticity with an absolute value of 1.0, meaning that price changes cause a proportional change in consumption. Elasticity values less than 1.0 in absolute value are called inelastic, meaning that prices cause less than proportional changes in consumption. Elasticity values greater than 1.0 in absolute value are called elastic, meaning that prices cause more than proportional changes in consumption. For example, both a 0.5 and –0.5 values are considered inelastic, because their absolute values are less than 1.0, while both 1.5 and –1.5 values are considered elastic, because their absolute values are greater than 1.0. (Litman, 2004).

According to Williams (1999), the elasticity indicates the sensitivity of demand to changes in *X*:

- If the elasticity is positive, then an increase in *X* results in an increase in demand.
- If the elasticity is negative, then an increase in *X* results in a decrease in demand.
- The larger the absolute value of the elasticity, the more sensitive the demand is to *X*.
- We say that demand is "elastic" with respect to *X* if the absolute value of the elasticity is greater than 1.0. This occurs when demand changes by more than 1% if *X* changes by 1%.
- We say that demand is "inelastic" with respect to *X* if the absolute value of the elasticity is less than 1.0. This occurs when demand changes by less than 1% if *X* changes by 1%.

4.2 The elasticity of demand for transit with respect to some of the factors in the model

In this section I will discuss the elasticity of demand for transit with respect to some of the factors in the model such as percent change in fare, income or ITIS. I will illustrate my expectations for the signs of elasticities or their relative magnitude and sensitivity of transit to changes in these variables considering the literature, and I will also explore policy implications out of these elasticities.

4.2.1 Fare Elasticities

There is extensive literature on the impacts of transit fare on transit ridership (Mattson, 2008). Many of the studies found transit fare to be an important factor to affect transit ridership (Kain and Liu, 1995; Liu, 1993; Kohn, 2000; Taylor and Fink, 2003). However, there are also studies showing the relationship between transit ridership and transit fare to be quite inelastic (Mattson, 2008). For example, Paulley et al. (2006) finds that travelers living in area with lower population density are more likely to switch to car use once transit fare increases.

In addition, Hamilton (2008) investigates the impact of fare on transit ridership and finds that while it generally is recognized that a fare increase would result in some ridership decrease, the magnitude of such decrease is difficult to measure and can vary greatly among transit systems. A ten percent increase in bus fares would result in approximately a four percent decrease in ridership. This shows that today's transit users react more severely to fare changes than found by Simpson and Curtain. The Simpson and Curtin formula states that ridership will decline by one-third percent for each one percent increase in fare (Curtin, 1968). Additionally, the study shows that transit riders in small cities are more responsive to fare increases than those in large cities (Curtin, 1968). The fare elasticity is approximately - 0.36 for systems in urbanized areas with population of 1 million or more. The elasticity is -0.43 in urbanized areas with less than 1 million population. Although the data for peak vs. off-peak services are available for only six transit systems, the study shows that the difference between the fare elasticity levels is very clear: The average peak-hour elasticity is -0.23 while the off-peak hour elasticity is -0.42, indicating that peak-hour commuters are much less responsive to fare changes than transit passengers travelling during off-peak hours (Hamilton, 2008). More (2002) states that Transit Systems which raise fares are expected to find that mass transit industry, like most other goods and services, faces a downward sloping demand curve with respect to price. The downward sloping demand curve means that as fares increase, ridership will decrease. The passenger reaction to fare change can be quantified by measuring the percent change in ridership occurring with a one percent change in fare. The resultant number is known in economics as the fare elasticity of demand or simply, fare elasticity (Moore, 2002).

After a detailed review of international studies, Goodwin (1992) produced the average elasticity values summarized in Table 4-1. He noted that price impacts tend to increase over time as consumers have more options (related to increases in real incomes, automobile ownership, and now telecommunications that can substitute for physical travel). Nelson, et al (2006) found similar values in their analysis of Washington DC transit demand. Nijkamp and Pepping (1998) found elasticities in the –0.4 to –0.6 range in a meta-analysis of European transit elasticity studies. Table 4-1 summarizes international transportation elasticities.

Table 4-1 Transportation Elasticities

	Short run	Long run
Bus demand and fare cost	-0.28	-0.55
Railway demand and fare cost	-0.65	-1.08
Petrol consumption and petrol price	-0.27	-0.71
Traffic levels and petrol price	-0.16	-0.33

(Source: Goodwin, 1992)

Dargay and Hanly (1999) studied the effects of UK transit bus fare changes over several years to derive the elasticity values summarized in Table 4-2. They used a dynamic econometric model (separate short- and long-run effects) of per capita bus patronage, per capita income, bus fares and service levels. They found that demand is slightly more sensitive to rising fares (-0.4 in the short run and –0.7 in the long run) than to falling fares (-0.3 in the short run and –0.6 in the long run), and that demand tends to be more price sensitive at higher fare levels. They found that the cross-elasticity of bus patronage to automobile operating costs is negligible in the short run but increases to 0.3 to 0.4 over the long run, and the long run elasticity of car ownership with respect to transit fares is 0.4, while the elasticity of car use with respect to transit fares is 0.3. This table shows elasticity values from a major UK study.

Table 4-2 Bus Fare Elasticities

Elasticity Type	Short run	Long run
Non-Urban	-0.2 to -0.3	-0.8 to -1.0
Urban	-0.2 to -0.3	-0.4 to -0.6

(SourceDargay and Hanly, 1999)

Further, Oram and Stark (1996) illustrate that commuter transit pass programs, in which employers provide discounted transit passes, may significantly increase ridership. Subsidize transit passes can encourage occasional riders to increase transit use or prevent ridership losses if implemented when fares are increasing. Many campus UPass programs, which provide free or discounted transit fares to students and staff, have been quite successful, often doubling or tripling the portion of trips made by transit, because college students tend to be relatively price sensitive (Brown et al., 2001). Holmgren (2007) used meta-regression to explain the wide variation in elasticity estimates obtained in previous demand studies. He calculated short-run U.S. elasticities with respect to fare price (−0.59), level of service (1.05), income (-0.62), price of petrol (0.4) and car ownership (−1.48). The analysis indicates that commonly-used elasticity estimates treat transit service quality as an exogenous variable, which reduces analysis accuracy, and recommends that demand models include car ownership, price of petrol, own price, income and some measure of service among the explanatory variables, and that the service variable be treated as endogenous. Luk and Hepburn (1993) summarize travel demand elasticities developed for use in Australia, based on a review of various national and international studies. These standardized values are used for various transport planning applications throughout the country, modified as appropriate to reflect specific conditions. Table 4-3 shows elasticity values adopted by the Australian Road Research Board.

Table 4-3 Australian Travel Demand Elasticities

Elasticity Type	Short run
Bus demand and fare	-0.29
Rail demand and fare	-0.35
Mode shift to transit and petrol price	+0.07
Mode shift to car and rail fare increase	+0.09
Travel level and petrol price	-0.10

(Source: Luk & Hepburn 1993)

In addition, fare elasticities have several policy implications. Knowledge of fare elasticity is extremely important for transit managers for five primary reasons:

1- It provides information on the expected ridership and farebox revenue resulting from a proposed change.

2- Ridership and revenue estimation after a fare increase as an integral part of the transit route scheduling and budgeting processes.

3- There may be serious social and political consequences of increasing bus or transit fares. Therefore, good fare policy and planning requires “what if” analysis of passenger behavior.

4- There exists a theoretical point of unitary fare elasticity beyond which increasing fares will result in decreasing fare revenues and thereby negate any possible revenue generation through fare policies.

4.2.2 Income Elasticities

In economics, income elasticity of demand measures the responsiveness of the quantity demanded for a good or service (e.g. Transit ridership) to a change in the income of the people demanding the good. It is calculated as the ratio of the percentage change in quantity demanded to the percentage change in income (Perloff, 2008). As for income elasticities, previous studies have shown that income level is negatively related to transit use (Gomez-Ibanez, 1996); various authors have found widely diverging results for the income elasticity of demand for busing routes. Holmgren (2007) found using a meta-analysis that estimates on the income elasticity of demand for public buses were ambiguous and highly dependent on the demand specifications included. He found that while some studies had found negative income elasticities of demand, some had also found positive results, and that the overall average was 0.17. Several authors have investigated the demand for public transportation on a route by route basis. Schmenner (1975) pursued a methodology of restricting his area of study to populations within two city blocks of bus routes in three Connecticut cities. The study found that in bus transit with the log of revenue per mile or revenue per hour as the dependent variable, the sign on the log of family income was positive when all three cities in his study were pooled. When performed on a city by city basis, the sign on family income fluctuated, seeming to indicate that city-specific factors were key drivers behind this result. Further, he claimed that previous studies had suggested that demand for busing was price inelastic.

In addition, Glaeser and Rappaport (2006) found that the fixed time-cost of subways is less than that for bus transit, and that subways had on the whole a “much lower” time-cost per mile. They also found that when surveying all modes of public transit with 2000 census tract data in Boston, Chicago, New York, and Philadelphia that there was a positive correlation between the log of income and public transit usage for fixed distances outside of the Central Business District. When changing the urban mix to Houston, Atlanta, Pheonix, and Los Angeles, the authors found that the correlation was negative. Differing levels of urban residential and employment concentrations seem to produce different patterns of transit usage according to this study. While the first set of cities was specifically selected to include subway transit, the study did not attempt to find separate results on income for rail and bus transit (Asquith, 2011). Moreover, Dargay et al. (2002) compared transit elasticities in the UK and France between 1975 and 1995 through a log-log model. The study indicates that transit ridership declines with income and with higher fares and increases with increased transit service kilometers. These researchers found that transit elasticities have increased during this period. Table 4-4 summarizes the findings. This table shows mean elasticity values based on 1975 to 1995 data.

Table 4-4 Transit Elasticities

	England (Log-Log)	France (Log-Log)
Income		
Short Run	-0.67	-0.05
Long Run	-0.90	-0.09
Fare		
Short Run	-0.51	-0.32
Long Run	-0.69	-0.61
Transit VKM		
Short Run	0.57	0.29
Long Run	0.77	0.57

(Source: Dargay, et al. 2002)

Income elasticities have several policy implications. Knowledge of income elasticity is extremely important for transit managers and urban planners. Choosing which groups of consumers to target with expansions or upgrades to rail transit is a critical policy-making question with many millions of dollars at stake. Further, from a public policy point of view, if it is known that rail-transit is not an inferior good would perhaps lead policy makers to choose other forms of public subsidies to increase mobility among the poor (Asquith, 2011). Research has also shown that rail transit ridership is greatest in more densely populated, lower-income areas (Gordon & Willson, 1985).

4.2.3 Gas Prices Elasticities

The price of gasoline affects the total cost of travel incurred by consumers. Based on standard economic intuition, alternative travel options will become more attractive at different gas prices. The hypothesis would be that an increase in gas prices increases the public transit ridership and a decrease in gas prices decreases public transit ridership. Han and Lee (2009) found long-run elasticities of 0.25 for subway passenger trips and 0.32 for subway passenger kilometers with respect to fuel prices in

Seoul, Korea between 2000 and 2008. Iseki and Ali (2014) used panel data of transit ridership and gasoline prices for ten selected U.S. urbanized areas over the period of 2002 to 2011 to analyze the effect of gasoline prices on ridership of the four transit modes—bus, light rail, heavy rail, and commuter rail. Their analysis improves upon past studies on the subject, this study accounts for endogeneity between the supply of services and ridership, and controls for a comprehensive list of factors that may potentially influence transit ridership. The analysis found varying effects, depending on transit modes and other conditions. Compelling evidence was found for positive short-term effects only for bus and the aggregate: a 0.61-0.62% ridership increase in response to a 10% increase in current gasoline prices (elasticity of 0.061 to 0.062). The long-term effects of gasoline prices, on the other hand, was significant for all modes and indicated a total ridership increase ranging from 0.84% for bus to 1.16% for light rail, with commuter rail, heavy rail, and the aggregate transit in response to a 10% increase in gasoline prices. The effects at the higher gasoline price level of over $3 per gallon were found to be more substantial, with a ridership increase of 1.67% for bus, 2.05% for commuter rail, and 1.80% for the aggregate for the same level of gasoline price changes. Light rail shows even a higher rate of increase of 9.34% for gasoline prices over $4. In addition, a positive threshold boost effect at the $3 mark of gasoline prices was found for commuter and heavy rails, resulting in a substantially higher rate of ridership increase (Iseki & Ali, 2014).

The Congressional Budget Office used highway traffic count data to conclude that fuel price increases can cause modal shifts (CBO, 2008). They find that a 20% gasoline price increase reduces traffic volumes on highways with parallel rail transit service by 0.7% on weekdays and 0.2% on weekends, with comparable increases in transit ridership, but find no traffic reductions on highways that lack parallel rail service.

Currie and Phung (2008) found that in Australia, the cross elasticity of transit ridership with respect to fuel prices are 0.22, with higher values for high quality transit (Rail/BRT) and for longer distance travel, and lower values for basic bus service and shorter-distance trips. Lane (2008) analyzed the relationships between fluctuations in gas prices and transit ridership in nine U.S. cities between June 2001 and September 2006. He found a statistically strong positive relationship, particularly in cities with rail transit systems. He developed a model which predicts how much transit demand would increase given an increase in fuel prices, as summarized in Table 4-5. This table indicates the percentage increases in fuel prices and transit ridership that can be expected from $4.00, $5.00 and $6.00 fuel prices in various U.S. cities.

Table 4-5 Fuel Price Impacts on Transit Ridership

City	$4.00		$5.00		$6.00	
	Fuel	Transit	Fuel	Transit	Fuel	Transit
Los Angeles	20.65%	6.21%	43.13%	14.36%	65.99%	23.97%
Chicago	22.26%	8.72%	45.03%	18.94%	68.21%	30.27%
Boston	29.11%	6.53%	53.15%	14.49%	77.63%	23.44%
San Francisco	23.82%	3.76%	46.65%	9.68%	70.36%	17.07%
Miami	26.65%	10.88%	50.24%	23.70%	74.25%	37.93%
Seattle	29.25%	10.31%	53.35%	22.66%	77.85%	36.50%
Houston	36.65%	12.21%	62.01%	26.15%	87.90%	41.31%
Denver	29.20%	17.91%	53.26%	35.70%	77.75%	53.50%
Cleveland	36.82%	18.61%	62.31%	36.83%	88.24%	54.91%

(Source: Lane, 2008)

Currie and Phung (2007) calculated the aggregate cross-elasticity of US transit demand with respect to fuel price (e) to be 0.12, indicating that transit demand increases 1.2% for every 10% gas price increase. US light rail is particularly sensitive to gas prices, with values for (e) measured at 0.27 to 0.38. Bus ridership is only slightly sensitive to gas prices (e= 0.04) and heavy rail is higher (0.17) which is consistent with most international evidence. A longitudinal model suggests some acceleration in transit mode sensitivity. APTA (2011) used data from previous studies and recent experience by U.S. transit agencies to evaluate how transit ridership would grow in response to increased fuel prices. Regular gasoline prices increased 35% from $3.053 per gallon on 31 December 2007 to a peak of $4.114 on 7 July 2008, then declined 61% to $1.613 on 27 December 2008. Transit ridership increased during this period, with a 3.42% increase during the first quarter, 5.19%, and 6.52% during the third quarter, indicating a lag between fuel price and transit ridership changes. Based on this research they developed a model that predicts how annual transit ridership is expected to increased using low, average, and high elasticity values. Mattson (2008) analyzed fuel price increase impacts on transit ridership in U.S. cities. He found longer-run elasticities of transit ridership with respect to fuel price are 0.12 for large cities, 0.13 for medium-large cities, 0.16 for medium-small cities, and 0.08 for small cities. For large and medium-large cities, the response is quick, mostly occurring within one or two months after the price change, while for medium and small cities, the effects take five to seven months. The quicker response in larger cities may be explained by the fact that large city residents are generally more accustomed to public transport and so are quicker to shift mode than in smaller cities where transit use is uncommon. The elasticity is lowest for the smallest cities, meaning that people in small urban or rural areas are less likely to switch to transit. Medium-small cities have the highest response (Mattson, 2008).

Haire and Machemehl (2007) analyzed ridership in five U.S. cities and found statistically significant correlation between ridership and fuel prices, suggesting that rising fuel prices increased transit use in historically auto-oriented American cities. They estimate that, on average, a one percent fuel price rise increases transit demand approximately 0.24 percent, or approximately 0.09 percent ridership gain for each additional cent of fuel price. Maley and Weinberger (2009) found that in Philadelphia, fuel price increases had a larger effect on regional rail ridership (0.27 to 0.38 elasticities) than on local bus ridership (0.15 to 0.23 elasticities), probably due to a larger portion of rail riders being discretionary transit users who have the option of driving, and so are more likely to do so when fuel prices decline. Blanchard (2009) used regional gasoline prices, transit ridership and supply data from 218 US cities from 2002 to 2008 to estimate the cross elasticity of demand for four transit modes with respect to gasoline price. The results indicate that the cross-price elasticity of transit demand with respect to gasoline price ranges from -0.012 to 0.213 for commuter rail, -0.377 to 0.137 for heavy rail, -0.103 to 0.507 for light rail, and 0.047 to 0.121 for bus. The values vary significantly between cities, but are not highly correlated with urban population size, and the cross-price elasticity increased over this time period for commuter rail, light rail, and motorbus transit. Jung et al. (2016) used a data set of debit and credit card transactions in Korea to examine the effect of gasoline prices on individual choices between private vehicle and public transit travel. The study found significant heterogeneity, with some people being much more price sensitive than others. Brand (2009) found that the 20% 2007 to 2008 U.S. fuel price increase caused a 3.5% VMT reduction, indicating a short-run price elasticity ranging from -0.12 to -0.17. Accounting for base trends (between 1983 and 2004 VMT increased about 2.9% annually and gasoline consumption increased about 1.2% annually, reflecting population, income and GDP growth) the short-run VMT fuel price elasticity ranged from -0.21 to -0.30. During this period, transit ridership increased about 4%. This increase was widespread, with 86% of transit agencies reporting ridership increases. Comparing the transit ridership increase to VMT decline indicates that only about 5% of the reduced vehicle travel shifted to transit, although this shift was much greater in major cities with high quality public transit services. For example, in New York

City traffic declined 6.3% through the Lincoln and Holland Tunnels, and more than 7% on four major bridges.

Because of rising gas prices, APTA (2011) showed that public transit systems across the country are reporting significant increases in ridership. Eighty-six percent of public transit systems report increased public transportation ridership over the past year with increases ranging from 2 percent to 30 percent. Most agencies report ridership increases during both peak and off-peak hours (62 percent) with two out of ten observing an increase primarily during peak hours. Among the small number of systems reporting a decrease in ridership, well over half have increased transit fares, cut service or both (8 out of 13). Public transportation agencies are taking a wide range of actions in response to increased ridership. Four out of ten (42 percent) have increased service on existing routes. Many of those adding service on existing route have also expanded into other areas, with three in ten (29 percent) reporting they have expanded service into new geographic areas. Although many agencies have responded with specific changes, almost four in ten (38 percent) have made no changes to service and as a result, are experiencing increased crowding on existing routes. Many agencies are not able to take action to respond to increasing ridership and, in some cases, are even cutting service.

Gas prices elasticities have many policy implications. Hansen (2016) showed that gas prices indeed affect transit ridership in all forms, with elasticity values ranging between 0.0581-0.147. Thus, there is a quantifiable effect that is of value to both policy makers and public transit operators to better effectively manage fleet and respond to consumer demands when gas prices increase. Transit agencies should prepare for a potential increase in ridership during peak periods that can be generated by substantial gasoline price increases over $3 per gallon for bus and commuter rail modes, and over $4 per gallon for light rail, in order to accommodate higher transit travel needs of the public through pricing strategies, general financing, capacity management, and operations planning of transit services (Iseki & Ali, 2014). In addition, a substantial spike in gas prices may cause many riders to switch from auto-travel to public transportation and reduce road congestions.

4.2.4 ITIS Elasticities

It has been argued that ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes, and makes transit more attractive to customers. As a result, the elasticity of demand for transit ridership with respect to ITIS is positive. I expect an increase in ITIS app usage increases the demand for transit ridership. As for ITIS elasticities, some previous studies were conducted based on Stated Preference (SP) or simulated data (Abdel-Aty & Jovanis, 1995; Peng et al., 1999; Abdel-Aty, 2001; Chorus et al., 2006). For example, Abdel-Aty (2001) conducted a SP survey to investigate whether traveler information systems would increase the acceptance of transit and found that such information has the potential in increasing acceptance of transit as commuter mode for non-transit users. A computer-aided telephone interview was conducted in this study in two metropolitan areas in Northern California. The survey employed SP design to collect data from non-transit users. According to the survey results, about 38% of non-transit users indicated that they might consider transit use if appropriate transit information was available to them. About half of them indicated that they were likely to use transit if the preferred information types were provided. Turnbull and Pratt (2003) point out that improved marketing, schedule information, easy-to-remember departure times, and more convenient transfers can also increase transit use, particularly in areas where service is less frequent.

TRB's Transit Cooperative Research Program (TCRP) Report 95 conducts a study on Transit Information and Promotion, examines travelers' responses to mass-marketed and targeted information and promotions, customer information services, and real-time transit information dissemination. This report is part of TCRP's Traveler Response to Transportation System Changes Handbook series. Based on this report, transit information is one of the key factors that will influence transit ridership; however, although many studies have been conducted to examine the effects of information of drivers' behaviors (Avineri & Prashker, 2006; Shiftan et al. 2007; Abdel-Aty et al. 1997; Abdel-Aty & Abdalla, 2004; Chen and Jovanis, 2003; Schofer et al., 1993; Wardman et al., 1997; Heathington, 1969; Yumoto et al.1979; Boyce, 1988; Al-Deek et al.1988; Mobility 2000, 1990; Kirson et al. 1991; Sparmann, 1991), studies exploring the potential impact of such systems on transit riders are relatively few (Turnbull & Pratt, 2003; TCRP, 2003; Abdel Aty , 2001; Fries et al., 2009). Additionally, the analysis results on whether such system will increase transit patronage is quite mixed (Balcombe et al., 2004).

ITIS elasticities have several policy implications. Knowledge of ITIS elasticities will help North American cities and Dallas Area Rapid Transit specifically to develop strategies that attempt to increase transit ridership for a variety of reasons including: reduce the energy use of transportation in cities, curb congestion, reduce pollution, and provide other social, economic and environmental benefits. It will aid policy makers in their decision making regarding further investments in transit ITIS applications. In addition, the use of these data by transit operators, transportation planners, and transit marketers presents significant opportunities for both short-term and long-term gains in transit use. Transit properties that leverage objective customer information from these systems may be able to be more proactive in serving transit customers (Under TCRP Project B-29, "Transit Market Research: Leveraging ITS and Transit ITS Data,". It will also enable service providers to target services towards those areas (or customers) that are most likely to increase transit use because of these services, design improved ITIS, and develop transit promoting programs. In addition, the underlying reasons for deploying this kind of applications include both economic and social considerations. Transit agencies expect these systems to boost the ridership, and hence revenues, by attracting more passengers. From transit users' perspective, the availability of real-time transit information at their fingertips and the time saved by real-time transit information is certainly an economic benefit. Besides, transit agencies may boost their public images by making such visible efforts to improve their service. Perhaps a deeper social consideration is that social inequity in American cities, worsened by suburbanization and segregation, may be narrowed to some extent by improving transit service for the disadvantaged population who are largely captive transit riders. This analysis will help DART's transit managers increase their operational efficiency and provide better real-time customer information to retain existing customers and perhaps attract new customers.

4.2.5 Employment Elasticities

Several studies have found employment level to be a significant factor to affect transit ridership (Taylor & Fink, 2003). A change in employment level will change transit use due to the change of demand (Mattson, 2008). During Great Depression of 1930s, transit ridership had decreased by 25% nationwide (APTA, 2001). Chung (1997) also found that employment had greater impacts than fare on CTA transit ridership from year 1976 to 1995. Fehr and Peers (2004) illustrate that employment is closely related to variables such as income and the economic level in general, which have a powerful influence on all segments of the transit market. Since demand for mass transit is dependent upon the level of travel inducing activities, ridership should be strongly and positively related to the general economic level. Therefore, as employment decreases then ridership should also decrease (Goodwin,1992). Previous studies have shown that employment elasticities range from +0.50 to +0.70. (Cain, 2007). One researcher reported an employment elasticity of 1.086, meaning that a 1.086 percent increase in ridership occurs for each one percent increase in jobs (Fehr & Peers, 2004). Asquith (2011) finds that the nature of employment could be a key determinant of how residents choose to commute. Neighborhoods with large numbers of unemployed workers are likely to also have large numbers of underemployed or part time workers who would be less likely to travel to the type of white-collar jobs that cluster in the CBD.

4.2.6 Weather Elasticity

Khattak and Palma (1997) explored how adverse weather conditions might affect traveler's behavior by conducting a survey with Brussels commuters. The survey results show that more than one-quarter of the respondents reported that adverse weather was either very important or important in changing their mode choice. Guo et al. (2007) used the Chicago Transit Authority in Illinois as a case study to investigate the impact of five weather elements (temperature, rain, snow, wind, and fog) on daily bus and rail ridership, and showed that weather condition impacts transit ridership: Good weather increase transit use, while bad weather decrease such usage.

4.3 Cross price elasticity of demand for transit

Cross-elasticities refer to the percentage change in the consumption of a good resulting from a price change in another related good. For example, automobile travel is a substitute for transit travel, so an increase in the price of driving tends to increase demand for transit. Cross price elasticity of demand could help in measuring possible shifts from competing good as an effect of its price increase. To help analyze cross-elasticities it is useful to estimate mode substitution factors, such as the change in automobile trips resulting from a change in transit trips. These factors vary depending on circumstances (Litman, 2004). For example, when bus ridership increases due to reduced fares, typically most of the added trips will substitute for an automobile trip. Conversely, when a disincentive such as parking fees or road tolls causes automobile trips to decline, generally 20-60% shift to transit, depending on conditions. Pratt (1999) provides information on the mode shifts that result from various incentives, such as transit service improvements and parking pricing (Litman, 2004).

For the competing mode, the local gasoline price is important. Although there are other alternate modes, such as walking, and bicycling, whose costs are not related to gasoline prices, the automobile is by far transit’s major competitor. Concerning prior research Mokhtarian, et al. (2013), studied an aggregation of four cases in earlier studies and produced a bus demand to auto operating costs cross elasticity of +0.74. This is consistent since the cross elasticity between a good or service and its substitute should always be positive. That is, as the price of the good or service increases (e.g. auto travel), the demand for the substitute (e.g. transit travel) should also increase and vice versa. Small and Verhoef (2007) note that the introduction of Bay Area Rapid Transit (BART) service between Oakland and San Francisco in the early 1970s led to 8,750 automobile trips being diverted to BART. Anderson (2014) uses a regression discontinuity design based on a 2003 labor dispute within the Los Angeles transit system, and finds that average highway delay increases by 47% when transit service ceases operation. The effects of mass transit have recently been examined in various contexts. Bauernschuster et al. (2017) use a similar research design to Anderson (2014) and find that transit strikes in Germany resulted in an 11-13% increase in total hours spent in cars during these strikes, and a commensurate increase in accident and emission externalities. Using a regression discontinuity framework, Yang et al. (2008) find that subway openings in Beijing in the last decade led to an average reduction in travel delays of approximately 15% across Beijing, following a near doubling of the rail network in the city.

Hensher (1997) developed a model of cross-elasticities between various forms of transit and car use, illustrated in Table 4-6. This type of analysis can be used to predict the effects that transit fare changes will have on vehicle traffic, and the effect that road tolls or parking fees will have on transit ridership. Such models tend to be sensitive to specific demographic and geographic conditions and so must be calibrated for each area. Table 4-6 indicates how various changes in transit fares and car operating costs affects transit and car travel demand. For example, a 10% increase in single fare train tickets will cause a 2.18 reduction in the sale of those fares, and a 0.57% increase in single fare bus tickets. This is based on a survey of residents of Newcastle, a small Australian city.

Table 4-6 Direct and Cross-Share Elasticities

	Train Single Fare	Train Ten Fare	Train Pass	Bus Single Fare	Bus Ten Fare	Bus Pass	Car
Train, single fare	-0.218	0.001	0.001	0.057	0.005	0.005	0.196
Train, ten fare	0.001	-0.093	0.001	0.001	0.001	0.006	0.092
Train, pass	0.001	0.001	-0.196	0.001	0.012	0.001	0.335
Bus, single fare	0.067	0.001	0.001	-0.357	0.001	0.001	0.116
Bus, ten fare	0.020	0.004	0.002	0.001	-0.160	0.001	0.121
Bus, pass	0.007	0.036	0.001	0.001	0.001	-0.098	0.020
Car	0.053	0.042	0.003	0.066	0.016	0.003	-0.197

(Source: Hensher, 1997)

The Congressional Budget Office used highway traffic count data to conclude that fuel price increases can cause modal shifts (CBO 2008). They find that a 20% gasoline price increase reduces traffic volumes on highways with parallel rail transit service by 0.7% on weekdays and 0.2% on weekends, with comparable increases in transit ridership, but find no traffic reductions on highways that lack parallel rail service. Currie and Phung (2008) found that in Australia, the cross elasticity of transit ridership with respect to fuel prices are 0.22, with higher values for high quality transit (Rail/BRT) and for longer-distance travel, and lower values for basic bus service and shorter-distance trips. TRACE (1999) provides detailed elasticity and cross elasticity estimates for several types of travel (car-trips, car-kilometers, transit travel, walking/cycling, commuting, business, etc.) and conditions, based on numerous European studies. Comprehensive sets of elasticity values such as these can be used to model the travel impacts of various combinations of price changes, such as a reduction in transit fares combined with an increase in fuel taxes or parking fees. It estimates that a 10% rise in fuel prices increases transit ridership 1.6% in the short run and 1.2% over the long run, depending on regional vehicle ownership. This declining elasticity value is unique to fuel because fuel price increases cause motorists to purchase more fuel-efficient vehicles (Littman, 2004). Table 4-7 summarizes elasticities of trips and kilometers with respect to fuel prices in areas with high vehicle ownership (more than 450 vehicles per 1,000 population). This table shows the estimated elasticities and cross-elasticities of urban travel in response to a change in fuel price or other vehicle operating costs.

Table 4-7 : Elasticities and Fuel Price

Term/Purpose	Car Driver	Car Passenger	Public Transport
Trips			
Commuting	-0.11	+0.19	+0.20
Business	-0.04	+0.21	+0.24
Education	-0.18	+0.00	+0.01
Other	-0.25	+0.15	+0.15
Total	-0.19	+0.16	+0.13
Kilometers			
Commuting	-0.20	+0.20	+0.22
Business	-0.22	+0.05	+0.05
Education	-0.32	+0.00	+0.00
Other	-0.44	+0.15	+0.18
Total	-0.29	+0.15	+0.14

(Source: TRACE, 1999)

Table 4-8 indicates how parking prices affect travel by automobile and public transit.

Table 4-8 Parking Price Elasticities

Term/Purpose	Car Driver	Car Passenger	Public Transport
Trips			
Commuting	-0.08	+0.02	+0.02
Business	-0.02	+0.01	+0.01
Education	-0.10	+0.00	+0.00
Other	-0.30	+0.04	+0.04
Total	-0.16	+0.03	+0.02
Kilometers			
Commuting	-0.04	+0.01	+0.01
Business	-0.03	+0.01	+0.00
Education	-0.02	+0.00	+0.00
Other	-0.15	+0.03	+0.02
Total	-0.07	+0.02	+0.01

(Sources: TRACE 1999)

Frank, et al. (2008) evaluate the effects of relative travel time on mode choice. They find that, walking and biking will be used for shorter trips, such as travel to local stores and mid-day tours from worksites if services are nearby, and rates of transit use are more sensitive to changes in travel time than fare levels, with wait time much more ‘‘costly’’ than in-vehicle time. Their analysis suggests that a considerable growth in transit ridership could be achieved through more competitive travel times on transit. Hensher and King (2001) point out that parking prices and road tolls tend to have a greater impact on transit ridership than other vehicle costs such as fuel, typically by a factor of 1.5 to 2.0, because they are paid directly on a per-trip basis. Table 4-9 shows how parking prices affects travel in a relatively automobile-oriented urban region. This table shows elasticities and cross-elasticities for changes in parking prices at various Central

Business District (CBD) locations. For example, a 10% increase in prices at preferred CBD parking locations will cause a 5.41% reduction in demand there, a 3.63% increase in Park & Ride trips, a 2.91 increase in Public Transit trips and a 4.69 reduction in total CBD trips.

Table 4-9 Parking Elasticities

	Preferred CBD	Less Preferred CBD	CBD Finge
Car Trip, Preferred CBD	-0.541	0.205	+0.035
Car Trip, Less Preferred CBD	+0.837	+0.015	+0.043
Car Trip, CBD Fringe	+0.965	+0.0286	-0.476
Park & Ride	+0.363	+0.136	+0.029
Ride Public Transit	+0.291	+0.104	+0.023
Forego CBD Trip	+0.469	+0.150	+0.029

(Source: Hensher and King, 2001)

Currie and Justin Phung (2007) calculated the aggregate cross-elasticity of US transit demand with respect to fuel price (e) to be 0.12, indicating that transit demand increases 1.2% for every 10% gas price increase. US light rail is particularly sensitive to gas prices, with values for (e) measured at 0.27 to 0.38. Bus ridership is only slightly sensitive to gas prices (e= 0.04) and heavy rail is higher (0.17) which is consistent with most international evidence. A longitudinal model suggests some acceleration in transit mode sensitivity. Litman (2017) finds Cross-elasticities between transit and automobile travel are relatively low in the short run (0.05) but increase over the long run (probably to 0.3 and perhaps as high as 0.4). Price elasticities have many applications in transportation planning. They can be used to predict the ridership and revenue effects of changes in transit fares; they are used in modeling to predict how changes in transit service will affect vehicle traffic volumes and pollution emissions; and they can help examine the impacts and benefits of mobility management strategies such as new transit services, road tolls and parking fees (Wallis, 2004).

4.3.1 Measuring shifts from car to transit as an effect of ITIS

Cross price elasticity measures responsiveness of demand for good X i.e. transit ridership following a change in the price of a substitute good Y i.e. auto ridership. Substitutes are products in competitive demand. With substitutes, an increase in the price of one good (ceteris paribus) will lead to an increase in demand for a rival product. For example, a decrease in the price of transit will lead to a decrease in demand for auto travel. The value of cross price elasticity for transit and auto travel is always positive. Cross price elasticity of demand could help in measuring possible shifts from competing good as an effect of its price increase. The stronger the relationship between two products, the higher is the co-efficient of cross-price elasticity of demand. Close substitutes have a strongly positive cross price elasticity of demand i.e. a small change in relative price causes a big switch in consumer demand (Litman, 2004).

In this study, we expect ITIS apps to reduce the price and cost of using transit through providing information, saving time, and making transit easier to use, cheaper and more competitive with the automobile. Therefore, it behooves us to include also some measure of auto ridership in the models such as "average monthly weekday traffic counts in DART area". This may include the counts registered at Automatic Traffic Recorder (ATR) stations maintained by TxDOT. This ATR variable will help us in measuring the responsiveness of demand for transit ridership as an effect of ITIS considering the price of auto ridership, controlling for all other important explanatory variables. We expect a decrease in the price of transit as an effect of ITIS will lead to a decrease in demand for auto ridership which is considered a substitute product. As such, the cross price elasticity of demand for transit with respect to a percent change in the research question variable, ITIS usage, is examined. This will help us examine possible shifts from auto to transit in the presence of ITIS.

In addition, ITIS apps increase transit quality by reducing negative aspects of using transit through reducing uncertainties associated with transit use and saving access and wait time. An increase in transit quality as an effect of ITIS apps primarily reduces the price of using transit and makes transit more attractive to customers. A reduction in the access and wait times associated with public transit use, has been demonstrated to have a much more significant effect on modal choice than changes in monetary costs (Wardman, 2004). This reduction in the generalized cost of transit travel may lead to a downward shift in the auto demand curve following an increase in transit quality if the cross-elasticity between modes is positive. In general, Transit and auto are substitutes. Therefore, an increase in transit attractiveness and quality as an effect of ITIS may cause some commuters to substitute transit travel for trips previously taken by automobile, thereby decreasing auto travel.

Other studies have examined the effect of public transit supply on the demand for auto travel. For example, Beaudoin et al. (2015) estimate the effect of past public transit investment on the demand for automobile transportation by applying an instrumental variable approach that accounts for the potential endogeneity of public transit investment, and that distinguishes between the substitution effect and the equilibrium effect, to a panel dataset of 96 urban areas across the U.S. over the years 1991-2011. The results show that, owing to the countervailing effects of substitution and induced demand, the effects of increases in public transit supply on auto travel depend on the time horizon. In the short run, when accounting for the substitution effect only, they find that on average a 10% increase in transit capacity leads to a 0.7% reduction in auto travel. However, transit has no effect on auto travel in the medium run, as latent and induced demand offset the substitution effect. In the long run, when accounting for both substitution and induced demand, they find that on average a 10% increase in transit capacity is associated with a 0.4% increase in auto travel. They also find that public transit supply does not have a significant effect on auto travel when traffic congestion is below a threshold level. Additionally, they find that there is substantial heterogeneity across urban areas, with public transit having significantly different effects on auto travel demand in smaller, less densely populated regions with less-developed public transit networks than in larger, more densely populated regions with more extensive public transit networks.

Beaudoin et al. (2015) find that there is substantial heterogeneity across urban areas. When accounting for the substitution effect only, the magnitude of the elasticity of auto travel with respect to transit capacity varies from approximately -0.008 in smaller, less densely populated regions with less-developed public transit networks; to approximately -0.215 in larger, more densely populated regions with more extensive public transit networks. When accounting for both the substitution effect and the induced demand effect in the long run, the elasticity of auto travel with respect to transit capacity varies from approximately 0.005 in smaller, less densely populated regions with less-developed public transit networks; to approximately 0.129 in larger, more densely populated regions with more extensive public transit networks. The Federal Highway Administration (2012) suggests that the elasticity of auto travel with respect to transit fares ranges from 0.03 to 0.1 in the short run. While there is a general belief that commuters are more responsive to changes in the time components of transit travel, there does not appear to be a widely used estimate of the elasticity of auto travel with respect to transit capacity. McFadden (1974) uses a disaggregate discrete choice approach and estimates that the elasticity of auto travel with respect to waiting and travel time for bus and rail ranges from 0.02 to 0.15.

Chapter 5

Case Study: Dallas Area Rapid Transit (DART)

5.1 Introduction

Dallas Area Rapid Transit (DART) is a regional transit agency authorized under Chapter 452 of the Texas Transportation Code and was created by voters and funded with a one-cent local sales tax on August 13, 1983. The service area consists of 13 cities: Addison, Carrollton, Cockrell Hill, Dallas, Farmers Branch, Garland, Glenn Heights, Highland Park, Irving, Plano, Richardson, Rowlett, and University Park. As of March 2017, DART serves Dallas and 12 surrounding cities with more than 140 bus or shuttle routes, eight On-Call zones, 93 miles of light rail transit (DART Rail), and paratransit service for persons who are mobility impaired. The DART Rail System is considered the longest light rail network in the United States. DART extensive network of Light Rail, Trinity Railway Express commuter rail, bus routes and paratransit services move more than 220,000 passengers per day across our 700-square-mile service area. The DART Rail System provides fast, convenient service to work, shopping and entertainment destinations in Dallas, Carrollton, Farmers Branch, Garland, Irving, Plano, Richardson and Rowlett. Plus, the TRE commuter rail line links DART customers to Irving and downtown Fort worth (See fig. 5-1 and 5-2).

5.2 Study Area

This study covers transit ridership in Dallas Area Rapid Transit (DART) operation area which is located in four counties in Dallas-Fort Worth (DFW) Metropolitan; these counties are Collin, Dallas, Denton, and Tarrant. The period covered in this research is from 2007 to 2017. The time series perspective undertaken in the research allows us to examine changes in transit ridership over 10 years period in a monthly base and the incremental exposure to ITIS technology.

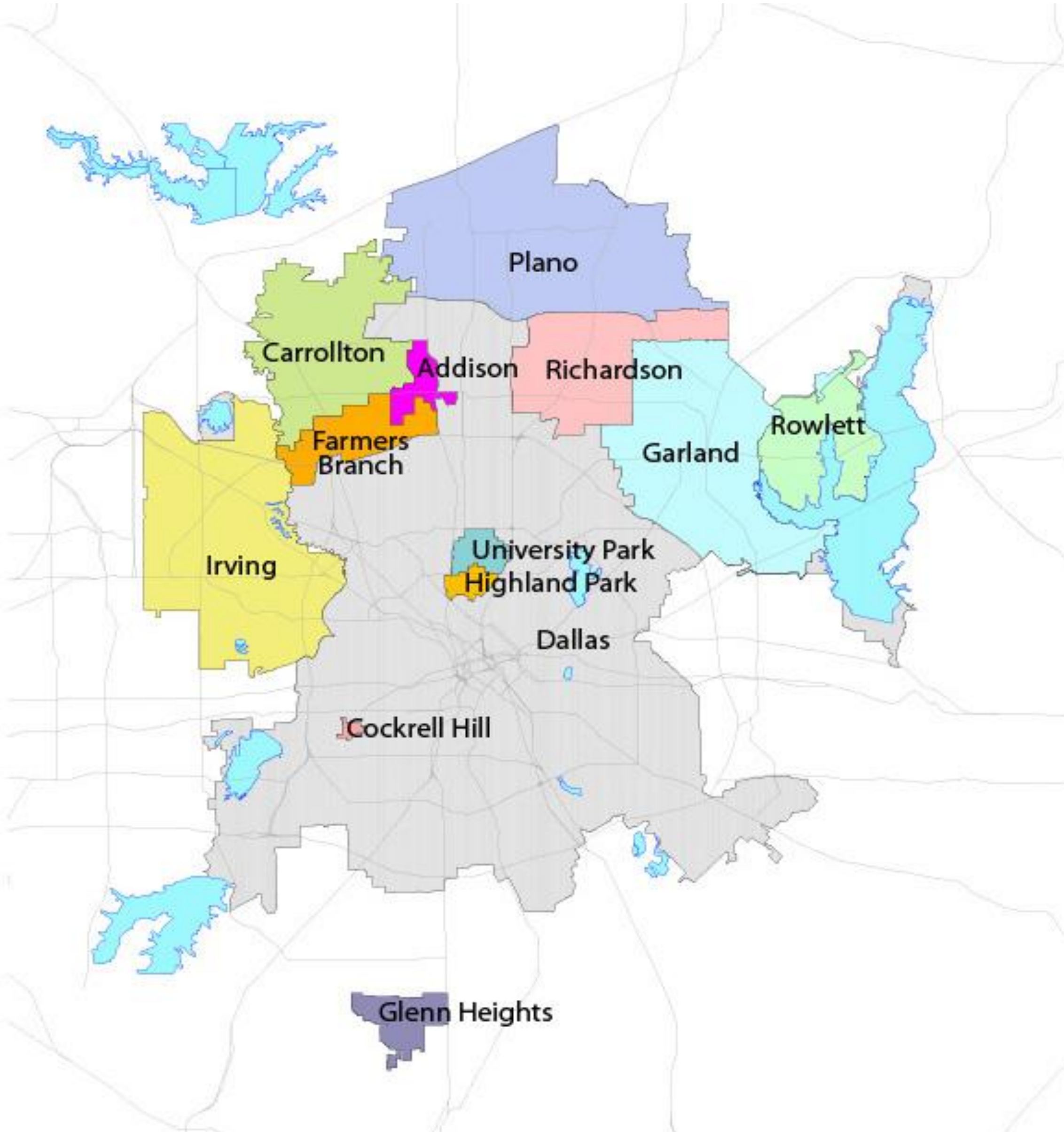

Figure 5-1 DART Service Area

(Source: DART.org, DART Reference Book March 2017)

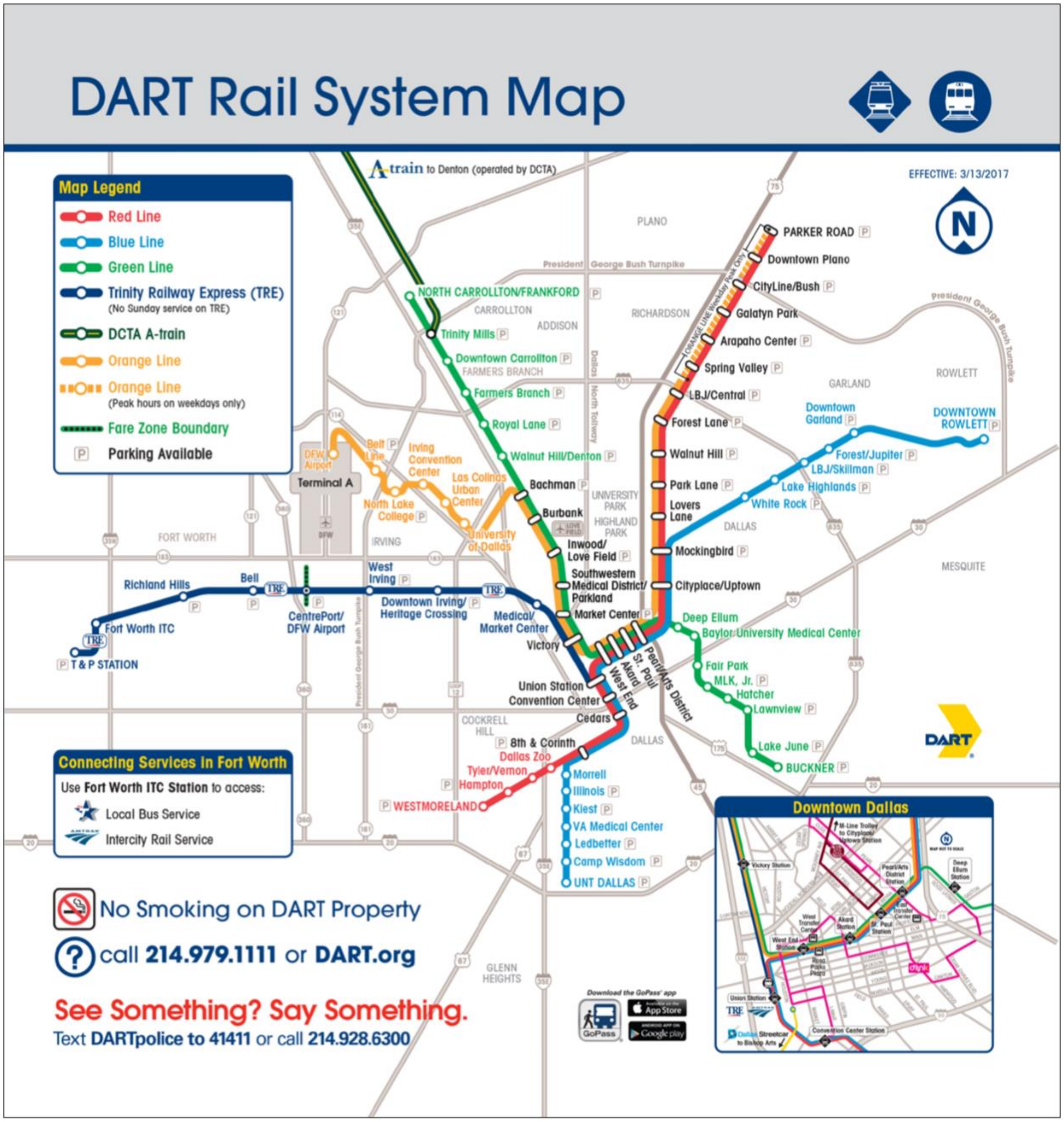

Figure 5-2 DART Rail System Map

(Source: DART.org, DART Reference Book March 2017)

5.3 DFW Metropolitan Area

DART is considered part of the Dallas-Fort Worth Metropolitan (DFW) Area in which congestion levels and road conditions are getting worse. Automobile dependence is a concern for many reasons including congestion in urban areas, pollution, and environmental damages caused by pollution. The level of congestion / delay is expected to increase substantially in DFW area between the year of 2017 and 2040 (See fig. 5-3 and 5-4)

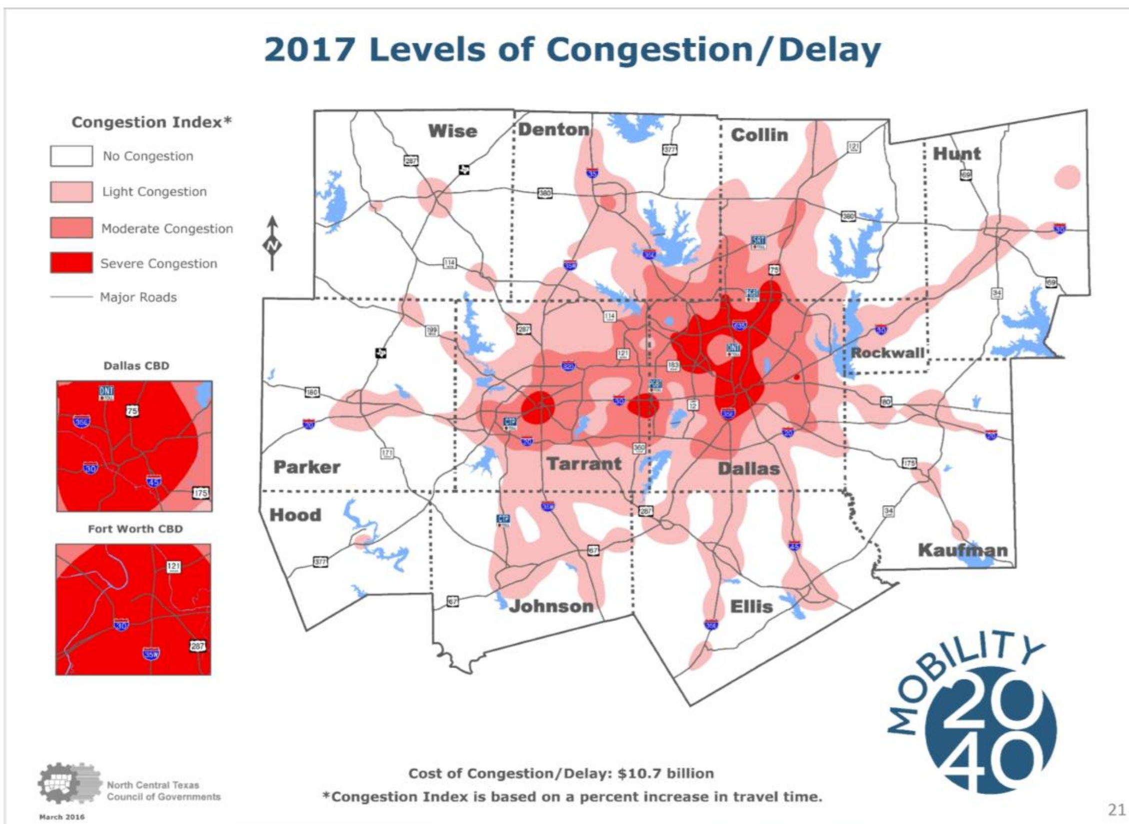

Figure 5-3 2017 Levels of Congestion/ Delay

(Source: Mobility 2040 Presentation, NCTCOG)

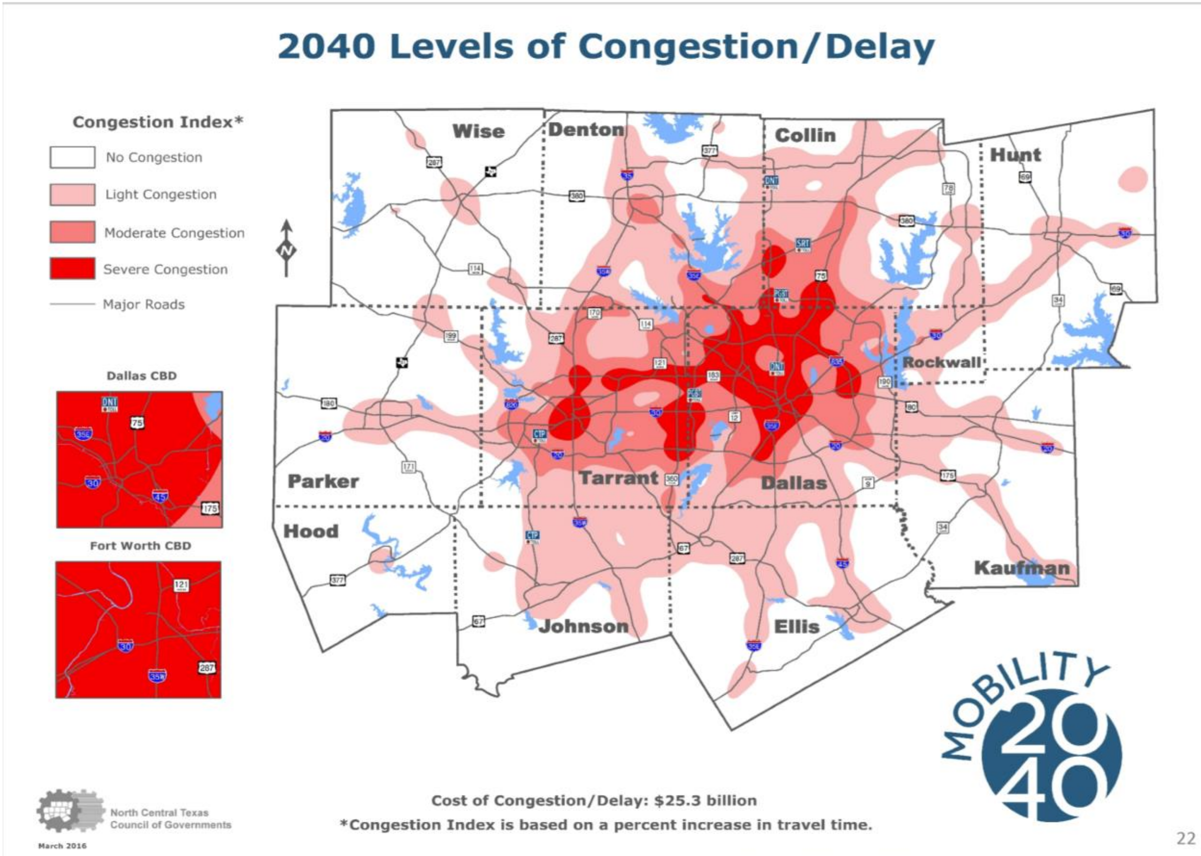

Figure 5-4 2040 Levels of Congestion/ Delay

(Source: Mobility 2040 Presentation, NCTCOG)

Switching to more sustainable and environmentally friendly transportation modes, and less congesting, such as public transit, is likely to be an effective solution to most of these problems. Moreover, in DART study area, the population is expected to grow significantly due to the influx of people moving from other States into the DFW area (See fig. 5-5). Employment level is also expected to increase substantially in the DFW area (See fig. 5-6). Population and employment increases are expected to have positive impact on transit ridership.

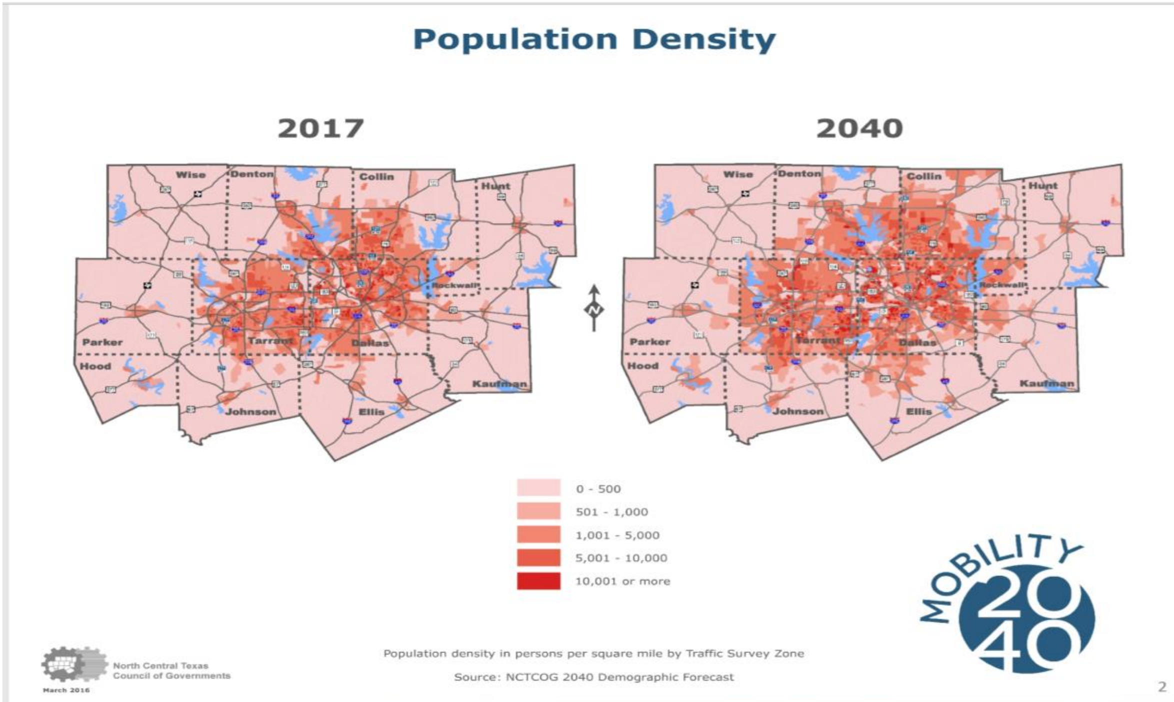

Figure 5-5 Population density

(Source: Mobility 2040 Presentation, NCTCOG)

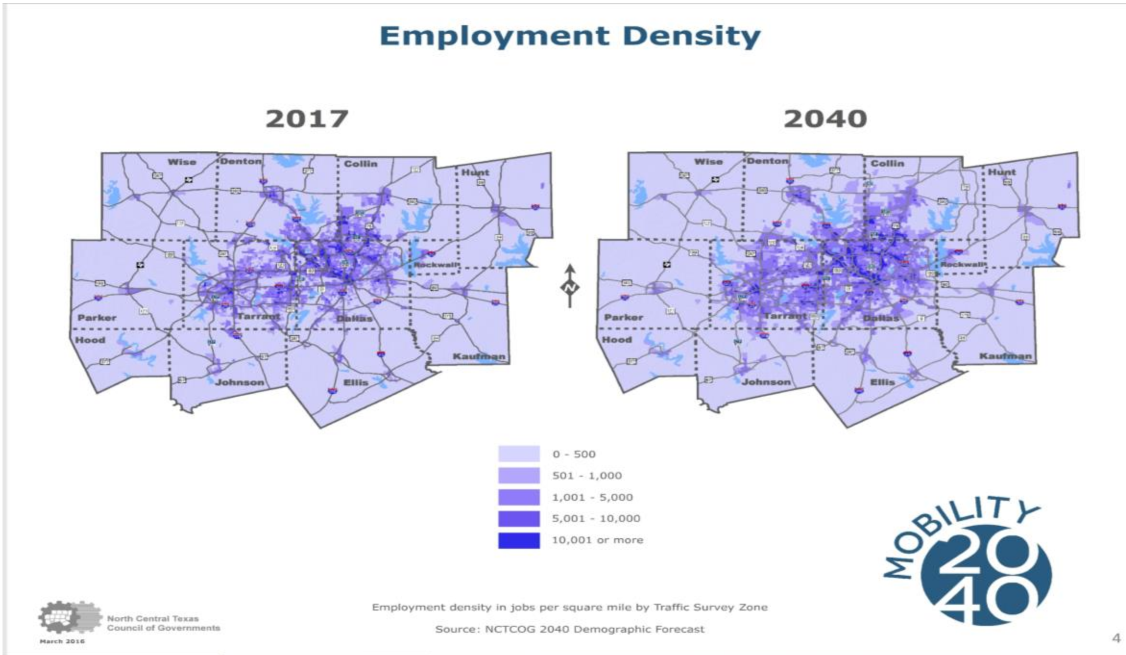

Figure 5-6 Change in Employment density

(Source: Mobility 2040 Presentation, NCTCOG)

5.4 DART Intelligent Transit Information Systems (ITIS) Applications Overview

In 2010, Trapeze ITS, a provider of solutions to public passenger transportation industry, has been chosen by DART for its intelligent transit transportation system implementations. DART selected Trapeze INFO-Web for its online trip planning software. "The fact that Trapeze INFO-Web required absolutely no additional data maintenance was a huge factor in selecting the company as a vendor by DART," said Alan Gorman, Senior DART's Manager, Transit IT Systems. Buses and trains equipped with GPS based Automatic Vehicle Location (AVL), Automatic passenger counters and a private radio system for operator voice communications to Dispatch vehicle location data every 90 seconds 4G wireless. This information will help DART like many other public transit systems reach its full potential and address concerns about uncertainty of arrival time, limited connectivity, in addition to safety and comfort. DART has strived to collect more information about the location of their vehicles and to provide this information to their customers. The availability of global positioning system (GPS) data was a necessary step for addressing the uncertainty concerns, but it was only part of the solution because location information had to be communicated in real time to the public. ITIS applications on user-friendly devices such as smart phones, PDAs, and Desktops can provide that missing link.

Integration with the existing schedule data was another factor as changes to the schedules are immediately reflected on their website. There's no need for manual updating or uploading of data. Trapeze is also characterized by its system's simplicity: riders enter a starting point, a destination, and a preferred departure or arrival time, and itineraries are generated using scheduling and routing data from the Trapeze FX scheduling system. Results can be sorted by total trip time, number of transfers, and walking distances. Drop-down menus also allow riders to select landmarks such as shopping centers or hospitals as their origin and destination points. "DART has also implemented TransitMaster from Trapeze as the application underlying a new radio communications system which will provide a trove of real-time (or close) trip data for operational metrics and analysis," said Allan Steele, Vice President/Chief Information Officer at DART. Using business intelligence tools this will be linked to data from other modules to deliver management information routinely and on demand. Additionally, DART has made strides in delivering information to riders. Using a desktop or mobile browser, riders can receive real-time predicted bus arrival time at a stop. Smartphones can also be used to locate the nearest DART stop, with a street view, and then show routes at that stop, trip planning and predicted bus or train arrival time. Text capability has been added, using the bus stop ID and short code to extend the arrival prediction service to riders with regular cell phones. Subscriptions to social media sites and email enable direct messages to riders about incidents on their chosen routes. The following ITIS transit information systems tools and applications have been implemented and available via desktops and mobile devices:

1. DART Trip Planner app enables customers to plan bus and rail trips from the convenience of their personal computers with the online DART Trip Planner available on DART.org.
2. Google Transit: Create personalized trip plans for DART buses, DART Rail, TRE and DCTA A-train. Google Transit features interactive Google Maps.
3. DART Travel Agent: The DART Travel Agent shows how visitors, shoppers, fun seekers and sports fans can get around by bus, train or a combination of both.
4. My Ride North Texas: The goal for My Ride North Texas app is to provide a one-stop transportation resource, where anyone can find a ride in the 16 county North Central Texas region, and transportation providers can support their communities. This website was created to meet the transportation needs for military veteran's face every day, and has been extended to serve the needs of everyone in the North Texas region.
5. Where's My DART STOP: Use this stop location tool to find the nearest DART stop and service to your location. Where's My DART Stop, utilizes interactive Google Maps with Street View, so finding your way around once you get off the bus or train just got easier.
6. Where My Bus App: Before you go, find out when your bus will actually be at your stop. Select your route, direction of travel and stop and you are all set.

7. Where My Train: Use this app to find out when your train will actually be at your stop. Select your route, direction of travel and stop and you are all set.
8. DART's GoPass app: The GoPassSM mobile ticketing application is launched in 2012 as the new way to buy passes for the region's three transit agencies. This Mobile ticketing App for Apple & Android makes discovering everything DARTable a breeze. Whether you are traveling by rail, bus or both, you've got a great travel tool literally at your fingertips. You can purchase DART passes on the app, and learn when the next bus or train will arrive or leave from any station. The app also features a trip planner to help you get to your destination, and even offers a section highlighting local events accessible by transit.

5.5 Transit Ridership Figures

DART ridership trend figures between 2007 and 2017 for the three types of mass transit namely: Rail, Bus, and Transit are shown in figure 5.7.

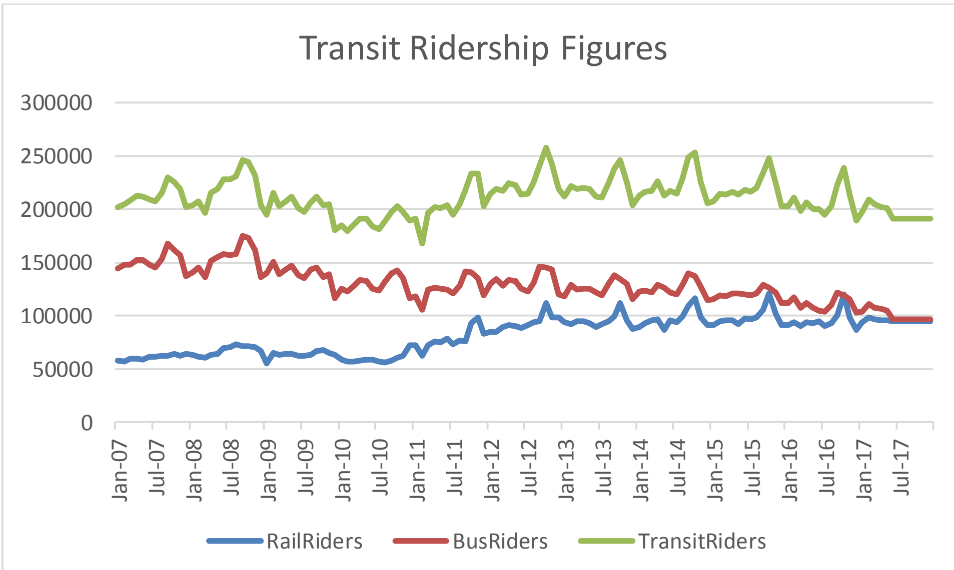

Figure 5-7 Transit Ridership Figures

Chapter 6

Methodology

6.1 Introduction

This chapter introduces the statistical models used to understand factors impacting transit ridership in the Dallas Area Rapid Transit. The methodology and variables of this study will be taken and analyzed from many prior articles and studies. In addition, this chapter provides some details on the databases that will be utilized for this study and different quantitative measurement that will be utilized to address the research questions. Three time series regression models will be developed to explain three dependent variables for ridership in DART area for transit, rail and bus ridership. The models considered in this section explain transit ridership for rail, bus, and for the combined ridership using several independent variables selected based on a comprehensive review of the theoretical and empirical literature. Models are estimated separately for rail, bus, and for transit ridership to evaluate the determining factors on each mode.

6.2 Regression Models Overview

Three models will be developed to explain the following dependent variables:

1. Monthly transit ridership in DART area (Transit)
2. Monthly rail ridership in DART area (Rail)
3. Monthly bus ridership in DART area (Bus)

6.2.1 Regression Equations

In general transit ridership equation will be:

> **Total Monthly Transit Ridership for DART Area** = α + *b1 Monthly Unemployment + b1 Monthly Gas Prices + b1 Monthly Fares + b1 Average Monthly Temperatures + b1 Average Monthly Precipitation+ b1 Monthly Number of Days When Temperatures Dropped to 32 F or Below+ b1 Monthly Amount of Snowfall+ b1 Monthly ITIS Applications Usage+ b1 Education+ b1 Income + b1 Car Trips + b1 Net Migration Flow + b1 Estimate of People in Poverty.*

Or

$$Y_t = \alpha + \beta X_t + \varepsilon_t \quad \text{For } t = 1, .., T$$

Where**:**

- **Y** is the dependent variable (Transit Ridership); Which is the monthly transit ridership for DART Area;
- **α** is the unobserved time-invariant individual effect;
- **X** is a vector of explanatory variables consists of Unemployment Rates (UNEMP), Gas Prices (GAS), Fares (FARE), Average Temperatures (TEMP), Average Precipitation (PRECIPITATION), Number of days below 32 F (FREEZE), Amount of Snowfall (SNOW), ITIS Applications Usage (ITIS), Education Attainment (EDUC), Car Trips (CARTRIPS) Income (INCOME), Net Migration Flow (MIGFLOW), Estimate of People in Poverty (POVERTY) in DFW;

- **ε** is the error term;
- **T** is the number of time periods/months in the data set (120).

In this study, the following equations will be estimated to explain transit ridership in DART Area for the following three dependent variables: Total Monthly Transit Ridership, Total Monthly Rail Ridership, and Total Monthly Bus Ridership, all as function of aforementioned explanatory variables and others which may be implicated from the results of a comprehensive literature review. Therefore, in mathematical terms, the regression equations are written as:

1- Transit = α + β_1 (UNEMP) + β_2 (GAS) + β_3 (FARE) + β_4 (TEMP) + β_5 (PRECIPITATION)+ β_6 (FREEZE)+ β_7 (SNOW)+ β_8 (ITIS)+ β_9 (EDUC)+ β_{10} (INCOME) + β_{11} (CARTRIPS) + β_{12} (MIGRFLOW) + β_{13} (POVERTY) (1)

2- Rail = α + β_1 (UNEMP) + β_2 (GAS) + β_3 (FARE) + β_4 (TEMP) + β_5 (PRECIPITATION)+ β_6 (FREEZE)+ β_7 (SNOW)+ β_8 (ITIS)+ β_9 (EDUC)+ β_{10} (INCOME) + β_{11} (CARTRIPS) + β_{12} (MIGRFLOW) + β_{13} (POVERTY) (2)

3- Bus = α + β_1 (UNEMP) + β_2 (GAS) + β_3 (FARE) + β_4 (TEMP) + β_5 (PRECIPITATION)+ β_6 (FREEZE)+ β_7 (SNOW)+ β_8 (ITIS)+ β_9 (EDUC)+ β_{10} (INCOME) + β_{11} (CARTRIPS) + β_{12} (MIGRFLOW) + β_{13} (POVERTY) (3)

Table 6.1 below presents all explanatory variables, along with a definition, and data source:

Table 6-1 Definition of variables used in the equations 1, 2, and 3

Variable abbreviation	Definition	source
UNEMP	Monthly Unemployment Rates	Federal Reserve Economic Data
GAS	Monthly Gas Prices	NCTCOG
FARE	Monthly Fares	DART
TEMP	Average Monthly Temperatures	Weather website
PRECIPITATATION	Average Monthly Precipitation	Weather website
FREEZE	Average Monthly Number of Days When the temperature dropped to 32 F or below	Weather website
SNOWFALL	Average Monthly Amount of Snowfall	Weather website
ITIS	Monthly Intelligent Transit Information Systems Applications Usage in DART Area	DART
EDUC	Educational Attainment (Percentage of population with college degree)	American Community Survey (ACS)
INCOME	Income Data (Per Capita Personal Income in DFW. Dollars, Monthly)	Federal Reserve Economic Data
CARTRIPS	Average monthly weekday traffic counts which include the counts registered at Automatic Traffic Recorder (ATR) stations	NCTCOG
MIGRATFLOW	Net Migration Flow in DFW	U.S. Bureau of the Census
PPOVERTY	Estimate of People of All Ages in Poverty	U.S. Bureau of the Census

In this type of research quite frequently, one may be interested in interpreting the effect of a percent change of an independent variable on the dependent variable, which can be also achieved through a double-log (log-log) model. This can be transformed by taking the logarithm from both sides.

$Log\ y = log\alpha + \beta_1 logx_1 + \beta_2 logx_2 + \beta_3\ logx_3 + e$

Where: $e = log\ \varepsilon$

In the full logarithm nonlinear form, the *b* coefficients will constitute elasticities. Essentially, if we run the model proposed in this study, the coefficients will constitute the elasticities.

Log Transit Ridership = $\log\alpha + \beta_1 \log\text{Income} + \beta_2 \log\text{ITIS} + \ldots + \beta 24 \log\text{Fare} + e$

Therefore, in mathematical terms, the regression equations might be written as:

4- Log TRANSIT = Log α + β_1 Log (UNEMP) + β_2 Log (GAS) + β_3 Log (FARE) + β_4 Log (TEMP) + β_5 Log (PRECIPITATATION) + β_6 Log (FREEZE)+ β_7 Log (SNOW)+ β_8 Log (ITIS)+ β_9 Log (EDUC)+ β_{10} Log (INCOME) + β_{11} Log (CARTRIPS) + β_{12} Log (MIGRFLOW) + β_{13} Log (POVERTY) (4)

5- Log RAIL = = Log α + β_1 Log (UNEMP) + β_2 Log (GAS) + β_3 Log (FARE) + β_4 Log (TEMP) + β_5 Log (PRECIPITATATION) + β_6 Log (FREEZE)+ β_7 Log (SNOW)+ β_8 Log (ITIS)+ β_9 Log (EDUC)+ β_{10} Log (INCOME) + β_{11} Log (CARTRIPS) + β_{12} Log (MIGRFLOW) + β_{13} Log (POVERTY) (5)

6- Log BUS = = Log α + β_1 Log (UNEMP) + β_2 Log (GAS) + β_3 Log (FARE) + β_4 Log (TEMP) + β_5 Log (PRECIPITATATION) + β_6 Log (FREEZE)+ β_7 Log (SNOW)+ β_8 Log (ITIS)+ β_9 Log (EDUC)+ β_{10} Log (INCOME) + β_{11} Log (CARTRIPS) + β_{12} Log (MIGRFLOW) + β_{13} Log (POVERTY) (6)

6.2.2 Hypothesis

During building regression models, authors hope to accept the model; thus, the null hypothesis (Ho) is usually constructed to make its rejections possible and get the desired result which is alternative hypothesis (Ha).

6.2.2.1 Hypothesis 1

The null hypothesis (H0: β = 0) for the first research question might be written as:

I. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with ITIS.

II. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Fare.

III. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Gas Price.

IV. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Temperature.

V. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Precipitation.

VI. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Freeze.

VII. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Snow.

VIII. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Car Trips.

IX. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Unemp.

X. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Poverty.

XI. Transit ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Income.

However, the alternate hypothesis (Ha: $\beta \neq 0$) is that all independent variables have a statistically significant impact on transit ridership for the period between 2007 and 2017. Hypotheses have been stated based on the expected results. So, hypothesis for the first research question will be:

I. Hypothesis: As the ITIS application usage increases, transit ridership will increase. So, ITIS increases transit ridership because it reduces negative aspects and cost of using transit through providing information, saving time and other attributes, and makes transit more competitive with the automobile

II. As Fare increases, transit ridership will decrease

III. As Gas Price increases, transit ridership will increase

IV. As Temp increases, transit ridership will increase

V. As Precipitation increases, transit ridership will decrease

VI. As Freeze increases, transit ridership will decrease

VII. As Snow increases, transit ridership will decrease

VIII. As Car Trips (Congestion) increases, transit ridership will increase

IX. As Unemp increases, transit ridership will decrease

X. As Poverty increases, transit ridership will increase

XI. As Income increases, transit ridership will decrease

6.2.2.2 Hypothesis 2

The null hypothesis (H0: $\beta = 0$) for the second research question might be written as:

I. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with ITIS.

II. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Fare.

III. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Gas Price.

IV. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Temperature.

V. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Precipitation.

VI. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Freeze.

VII. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Snow.

VIII. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Car Trips.

IX. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Unemp.

X. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Poverty.

XI. Rail ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Income.

However, the alternate hypothesis (Ha: $\beta \neq 0$) is that all independent variables have a statistically significant impact on rail ridership for the period between 2007 and 2017. Hypotheses have been stated based on the expected results. So, hypothesis for the second research questions will be:

I. Hypothesis: As the ITIS application usage increases, rail ridership will increase

II. As Fare increases, rail ridership will decrease

III. As Gas Price increases, rail ridership will increase

IV. As Temp increases, rail ridership will increase

V. As Precipitation increases, rail ridership will decrease

VI. As Freeze increases, rail ridership will decrease

VII. As Snow increases, rail ridership will decrease

VIII. As Car Trips (Congestion) increases, rail ridership will increase

IX. As Unemp increases, rail ridership will decrease

X. As Poverty increases, rail ridership will increase

XI. As Income increases, rail ridership will decrease

6.2.2.3 Hypothesis 3

The null hypothesis (H0: $\beta = 0$) for the third research question might be written as:

I. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with ITIS.

II. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Fare.

III. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Gas Price.

IV. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Temperature.

V. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Precipitation.

VI. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Freeze.

VII. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Snow.

VIII. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Car Trips.

IX. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Unemp.

X. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Poverty.

XI. Bus ridership for the period between 2007 and 2017 in the DART area does not exhibit any significant relationship with Income.

However, the alternate hypothesis (Ha: $\beta \neq 0$) is that all independent variables have a statistically significant impact on bus ridership for the period between 2007 and 2017. Hypotheses have been stated based on the expected results. So, hypothesis for the above research questions will be:

I. Hypothesis: As the ITIS application usage increases, bus ridership will increase

II. As Fare increases, bus ridership will decrease

III. As Gas Price increases, bus ridership will increase

IV. As Temp increases, bus ridership will increase

V. As Precipitation increases, bus ridership will decrease

VI. As Freeze increases, bus ridership will decrease

VII. As Snow increases, bus ridership will decrease

VIII. As Car Trips (Congestion) increases, bus ridership will increase

IX. As Unemp increases, bus ridership will decrease

X. As Poverty increases, bus ridership will increase

XI. As Income increases, bus ridership will decrease

6.3 Data Sets and Sources

In this study, the datasets consist of ridership data for the DART Area, socio-economic data for DART, and ITIS applications usage data for the entire DART Area from January of 2007 to present in a monthly base. Given that the intelligent transit information systems applications were implemented in 2012, this enables the models to capture any seasonal changes over this period, or roughly few years before the implementation of ITIS transit applications to few years after. The required data for this study will be obtained from a wide variety of sources:

6.3.1 U.S. Census Data

This study of the Dallas Area Rapid Transit (DART) covers the period between 2007 and 2017. In addition, this study uses time series perspective to examine changes in transit ridership over 10 years period in a monthly base to capture the incremental exposure to ITIS technology. Most of the socioeconomic data can be found in Census and the American Community Survey (ACS). The changes in these socioeconomic data impact on transit system in DFW area help to answer the research questions.

6.3.2 North Central Texas Council of Governments (NCTCOG)

The NCTCOG Regional Data Center provides objective data and analysis on the development of the NCTCOG region related to urban planning and economic activities such as development data, employment estimates, and Geographic Information System (GIS) layers. This source also provides some data related to DART and Dart area and all geocoded information needed for converting some data from other jurisdictions into DART operation area.

6.3.3 Dallas Area Rapid Transit (DART)

DART is going to provide the following ITIS data for relatively the entire 10 years study period. However, if the data is not available then DART will provide the data for the years in which the data is/was available:

1- Monthly Intelligent Transit Information Systems Applications Usage in DART Area (ITIS): Currently ITIS application visits counts are recorded and reported to DART. The application visit statistics represent the number of times transit applications are opened.

2- DART will also provide the Wi-Fi data on the trains.

3- DART also promised to provide additional ITIS data collected on the trains

6.4 Dependent Variables

The dependent variables are monthly average transit, rail, and bus for the DART Area from January 2007 to July 2017. Models were estimated separately for buses, trains, and for transit ridership. The models consist of the following dependent variables:

1. Monthly transit ridership for DART Area
2. Monthly rail ridership for DART Area
3. Monthly bus ridership for DART Area

6.5 Independent Variables

The following independent variables are the explanatory contributing factors that may impact transit ridership in Dallas Area:

1. Monthly Unemployment Rates (UNEMP): The monthly unemployment rates in DART Area will be obtained from the Federal Reserve Economic Data website
2. Monthly Gas Prices (GAS): This data will be obtained from the NCTCOG website
3. Monthly Fares (FARE): Monthly fares data will be obtained from DART
4. Monthly Average Temperatures (TEMP): Average Monthly Temperatures in DART Area will be obtained from the weather website
5. Monthly Average Precipitation (PRECIPITATION): Average Monthly Precipitation in DART Area will be obtained from the weather website

6. Monthly Number of days below 32 F (FREEZE): Average Monthly Number of Days When the temperature in DART Area dropped to 32 Fahrenheit or below will be obtained from the weather website
7. Monthly Amount of Snowfall (SNOW): Average Monthly Amount of Snowfall in DART Area will be obtained from the weather website
8. Monthly Intelligent Transit Information Systems Applications Usage in DART Area (ITIS): Currently ITIS application visits counts are recorded and reported to DART. The application visit statistics represent the number of times transit applications are opened.

   Note: The ITIS transit application usage data for the study period will be obtained from DART.
9. Educational Attainment (EDUC): Education data is available from American Community Survey (ACS)
10. Income (INCOME): Income data is available from ((Federal Reserve Economic Data)
11. Car Trips (CARTRIPS): Average monthly weekday traffic counts in DART area which include the counts registered at Automatic Traffic Recorder (ATR) stations maintained by TxDOT
12. Net Migration Flow (MIGFLOW): Net Migration Flow for Dallas County data is available from U.S. Bureau of the Census
13. Estimate of People in Poverty (POVERTY): Estimate of People of All Ages in Poverty for Dallas County, TX data is available from U.S. Bureau of the Census

Table 6.2 below presents all explanatory variables, along with a definition, data source, and the sign of their expected impact on transit ridership based on the literature.

Note, a positive (+) sign indicates that it is expected to have a positive relationship with the dependent variable. A negative sign (-) means a hypothesized negative relationship between the dependent and independent variable, and (?) means an uncertain relationship.

Table 6-2 Definition of variables and the expected impact

Variable abbreviation	Definition	source	Expected Sign
	Dependent Variable		
Rail	Monthly rail ridership for DART Area (2007-2017)	NCTGOC	
BUS	Monthly bus ridership for DART Area (2007-2017)	NCTGOC	
TRANSIT	Monthly transit ridership for DART Area (2007-2017)	NCTGOC	
	Independent Variables		
UNEMP	Monthly Unemployment Rates	Federal Reserve Economic Data	-
GAS	Monthly Gas Prices	NCTCOG	+
FARE	Monthly Fares	DART	-
TEMP	Average Monthly Temperatures	Weather website	-
PRECIPITATATION	Average Monthly Precipitation	Weather website	-
FREEZE	Average Monthly Number of Days When the temperature in DART Area dropped to 32 Fahrenheit or below	Weather website	-

SNOWFALL	Average Monthly Amount of Snowfall in DART Area	Weather website	-
ITIS	Monthly Intelligent Transit Information Systems Applications Usage in DART Area	DART	+
EDUC	Educational Attainment (Percentage of population with college degree)	American Community Survey (ACS)	?
INCOME	Income Data (Per Capita Personal Income in DFW. Dollars, Monthly)	Federal Reserve Economic Data	-
CARTRIPS	Average monthly weekday traffic counts in DART area which include the counts registered at Automatic Traffic Recorder (ATR) stations maintained by TxDOT	NCTCOG	+
MIGRATFLOW	Net Migration Flow in DFW	U.S. Bureau of the Census	?
PPOVERTY	Estimate of People of All Ages in Poverty	U.S. Bureau of the Census	+

6.6 Research Methods

Time Series / Multiple Regression methods will be used on the dataset to estimate the relationship between the models' variables. Time Series analysis was selected for the following reasons:

1. To identify changes in the dependent variables (Transit Ridership, Rail Ridership, and Bus Ridership) with variations in independent variables (Unemployment

Rates (UNEMP), Gas Prices (GAS), Fare Price (FARE), Average Temperatures (TEMP), Average Precipitation (PRECIPITATION), Number of days below 32 F (FREEZE), Amount of Snowfall (SNOW), ITIS Applications Usage (ITIS), Education Attainment (EDUC), Car Trips (CARTRIPS), Income (INCOME), Net Migration Flow (MIGFLOW), Estimate of People in Poverty (POVERTY) in the Dallas Area) over 10 years period/ Time series.

2. To assess the strength of impact of the independent variables on the dependent variable (Ridership) for the entire length of the 10 years' timeframe.

   To explore the effect of a percent change of an independent variable on the dependent variable, which we can be achieved through a double-log (log-log) model. As such, the elasticity of demand for transit with respect to some of the factors in the model such as percent change in fare, income or the research question variable, ITIS usage, are examined.

6.7 Descriptive Statistics

Descriptive statistics for the dependent and independent variables are presented in Table 6-3. The mean transit ridership in DART area between 2007 and 2017 was estimated to be 211092. The mean rail ridership was 82225 and the mean bus ridership was 128866. The ITIS application usage mean was estimated to be 53280. The mean Car Trips was 20959 and the mean per capita Income was \$ 44620. The mean Gas price per gallon was \$ 2.74 and the mean Fare was 1.62. The average Temperature was 65.6 F and the average Precipitation was 2.78. The average number of days when the temperature dropped to 32 Fahrenheit or below (Freeze) was 1.78 and the average amount of

Snowfall was 0.11. The mean of people of all ages in Poverty was estimated to be 438222 and the mean Unemployment rate was 6.3.

Table 6-3 Descriptive Statistics

Descriptive Statistics

	N	Mean	Std. Deviation
Transit Riders	132	211092.22	16688.655
Rail Riders	132	82225.91	16801.411
Bus Riders	132	128866.31	16882.794
ITIS	132	53280.69	31233.763
Car Trips	132	20959.54	5377.765
Income	132	44620.42	5119.189
Gas Price/ Gallon	132	2.74229	.654949
Fare	132	1.615	.1928
Temperatures (F)	132	65.638	16.0895
Precipitation	132	2.7829	2.52864
Freeze	132	1.78	3.541
snowfall (ASN)	132	.11	.403
Poverty (EPP)	132	438222.73	33550.477
Unemp	132	6.2821	1.62116
Valid N (listwise)	132		

Chapter 7

Regression Analysis

7.1 Selection of Multiple Regression Models

Regression model building can assist in determining the factors most heavily affect the dependent variable, and therefore, choosing the best model cannot be achieved unless one considers all possible models (Berenson et al., 2009). A good number of independent variables were obtained from the literature review for examining the factors affecting transit, rail, and bus ridership. All three models have many independent variables, but models will be revisited by both employing different set of models and variables combinations to find the best model explaining the dependent variable (Anjomani & Shebeeb, 2003; Berenson, Levine & Krehbiel, 2009). All needed statistical procedures such as testing for the absence of high degree of multicollinearity will be applied; multicollinearity means that two or more variables are highly correlated with each other which mean two or more of the independent variables are not independent of each other (Lewis-Beck, 1980; Berenson, 2009). As a result, some of the independent variables may be eliminated. To carry out all the procedures and regression models, this study will use SPSS software.

After testing the VIF, normality, multicollinearity, and homoscedasticity, a modified approach based on Berenson et al. (2009) was utilized to evaluate all possible models for the independent variables and to determine the best fitted model. Berenson et al. (2009) employed two criterions to determine the best model. They are the higher adjusted R2 and the Cp statistic that is close to or less than the number of independent variables plus one (K+1) (Berenson et al., 2009). Figure 7-1 summarizes the steps involved in model building. First, we run the regression model with only the independent variables related to the research question or (ITIS), and then make a hierarchy of remaining independent variables based on the literature review. In other words, after adding the major factors first, we added those remaining independent variables, one by one, into the regression model and run the model with the added variable. Next, we used three criteria based on Rao and Miller (1971) to decide whether to keep or drop the added independent variable, including the significance of the variable, the improvement of t-value, and the improvement of adjusted R2 (Anjomani, 2016).

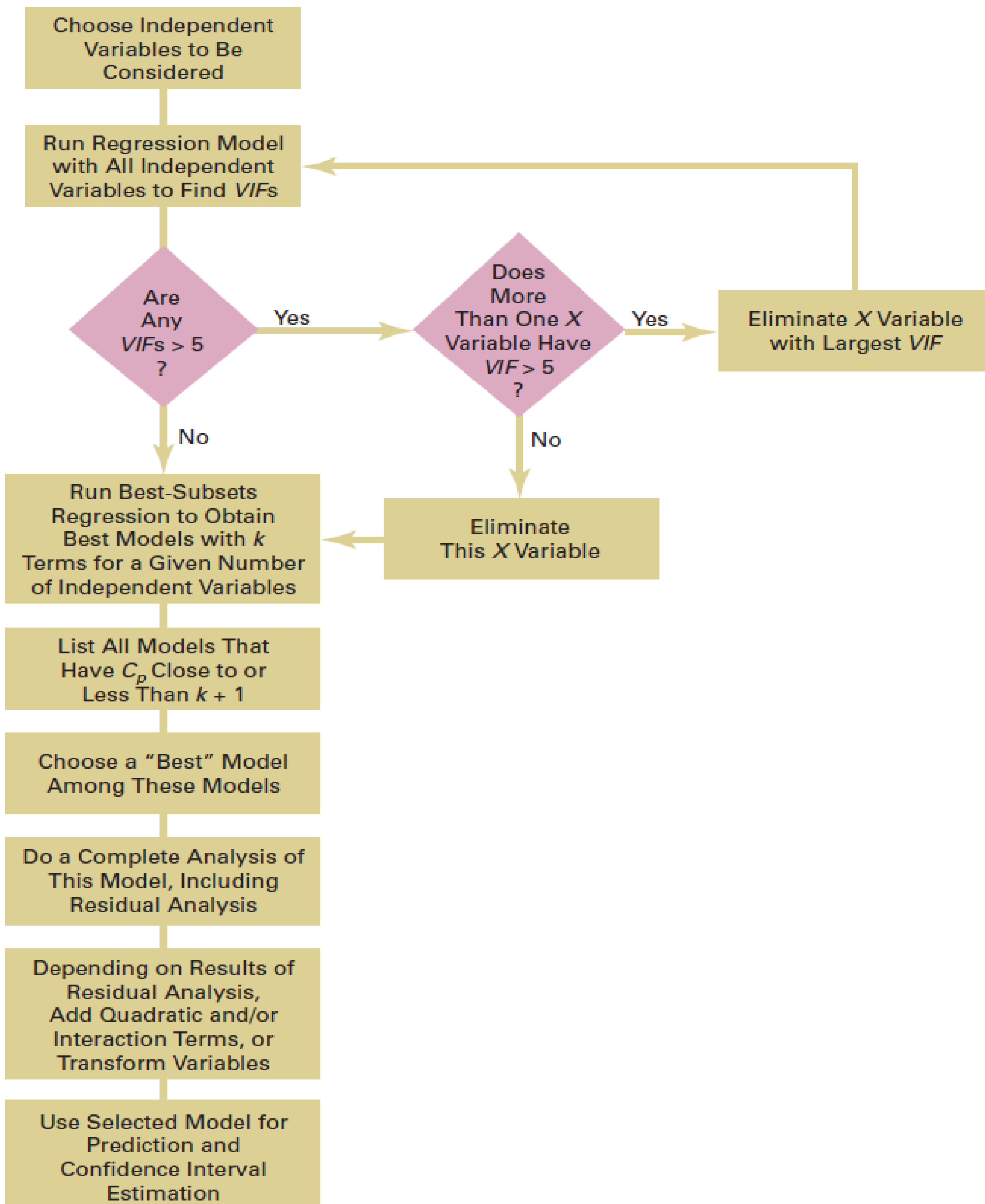

Figure 7-1 Summary of steps involved in model building

(Source: Berenson et al., 2009)

Moreover, the assumption of normality was checked to identify if the data were normally distributed (Ghasemi & Zahediasl, 2012; Thode, 2002). Our test of the normality showed that the initial dependent variables (Transit, Rail, and Bus) were not normally distributed. Therefore, a transformation of the data was used to achieve the normality of the variables. We used the most popular transformation method – the natural logarithm (Wooldridge, 2013).

7.2 Test for Variance Inflation Factor (VIF) for the Models

The first step of Berenson's model building is to measure the amount of collinearity between two or more independent variables through a variance inflation factor (VIF) (Berenson et al., 2009). If the VIF is greater than 5.0, the multicollinearity is high, meaning a severe correlation across the independent variables, however the smaller the value of VIF, the lower the possibility of correlations between explanatory variables (Berenson et al., 2009). As observed in table 7-1, table 7-2, and table 7-3 the models are free of collinearity problems. In addition, after running Pearson's correlation tests, none of the regression models had multicollinearity problems.

Table 7-1 Variance inflation factors (VIF) for the Equation: LnTransit

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	LnITIS	.384	2.521
	LnCarTrips	.547	1.829
	LnIncome	.237	3.214
	LnGas	.534	1.872
	LnFare	.636	1.573
	LnTemp	.470	2.129
	LnPrecipitation	.930	1.075
	LnFreeze	.435	2.298
	LnSnow	.733	1.365
	LnPoverty	.397	2.519
	LnUnemp	.635	1.576

a. Dependent Variable: LnTransit

Table 7-2 Variance inflation factors (VIF) for the Equation: LnRail

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	LnITIS	.384	2.521
	LnCarTrips	.547	1.829
	LnIncome	.237	3.214
	LnGas	.534	1.872
	LnFare	.636	1.573
	LnTemp	.470	2.129
	LnPrecipitation	.930	1.075
	LnFreeze	.435	2.298
	LnSnow	.733	1.365
	LnPoverty	.397	2.519
	LnUnemp	.635	1.576

a. Dependent Variable: LnRail

Table 7-3 Variance inflation factors (VIF) for the Equation: LnBus

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	LnITIS	.384	2.521
	LnCarTrips	.547	1.829
	LnIncome	.237	3.214
	LnGas	.534	1.872
	LnFare	.636	1.573
	LnTemp	.470	2.129
	LnPrecipitation	.930	1.075
	LnFreeze	.435	2.298
	LnSnow	.733	1.365
	LnPoverty	.397	2.519
	LnUnemp	.635	1.576

a. Dependent Variable: LnBus

7.3 Test of Normality

The assumption of normality should be tested to identify if the data are normally distributed. The test of normality should be carried out for continuous dependent variables especially with variables that have many observations (Anjomani, 2016; Ghasemi & Zahediasl, 2012; Wooldridge, 2013). The test of normality was carried out in SPSS and also the normal Q-Q plots were checked. Generally the Kolmogorov-Smirnov and Shapiro–Wilk test were carried. The null hypothesis for this test is that the data was normally distributed. The null hypothesis was accepted if the P value was above 0.05. Accordingly, for this test all our variables must be above 0.05, to accept the null hypothesis. Table 7.4 describes the results of the test for normality. It shows the P values for all dependent variables (LnTransit, LnRail, and LnBus) are greater than 0.05, which means the data is normally distributed.

Table 7-4 Test for Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
LnRail	.058	132	.200*	.985	132	.173
LnBus	.057	132	.200*	.986	132	.196
LnTransit	.052	132	.200*	.992	132	.682

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

One of the best graphical methods of testing for normality is the Q-Q Plot. An ideal normal distribution will be positioned exactly on the line. The Q-Q plot also indicates that all data points fall very close to the diagonal line. The result depicted in figure 7-2 shows that all variables are normally distributed and the assumption of normality for all selected variables was satisfied.

Moreover, the normality test of residuals was also computed using a histogram and P-P plot of standardized residuals in SPSS as shown in Figure 7-3. The P-P Plots should show data points fall very close to the diagonal line and histogram should form a bell shape. The results in Figure 7-4 indicate that residuals are normally distributed.

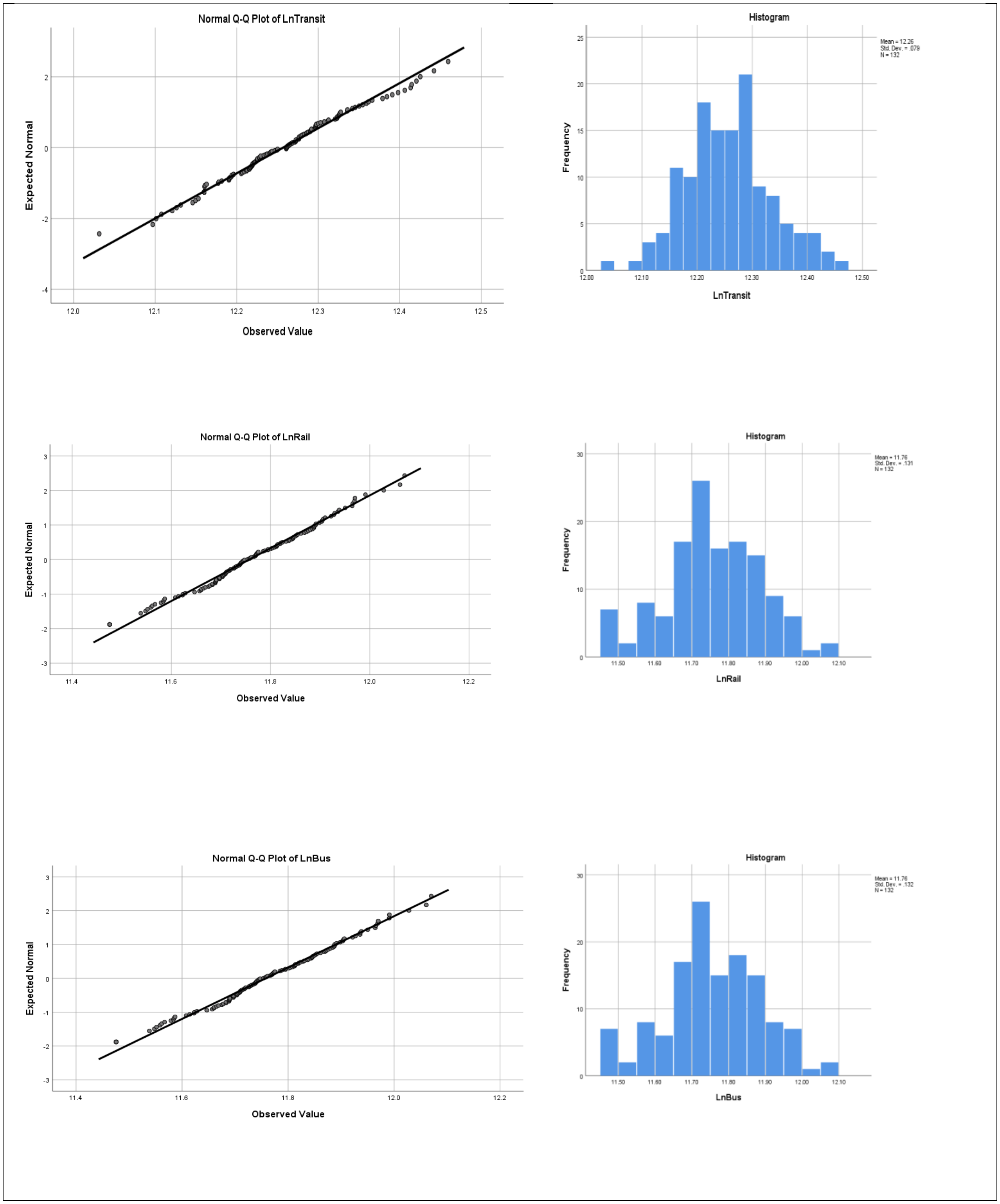

Figure 7-2 Q-Q Plots (left) and Histograms (right) of the selected dependent variables

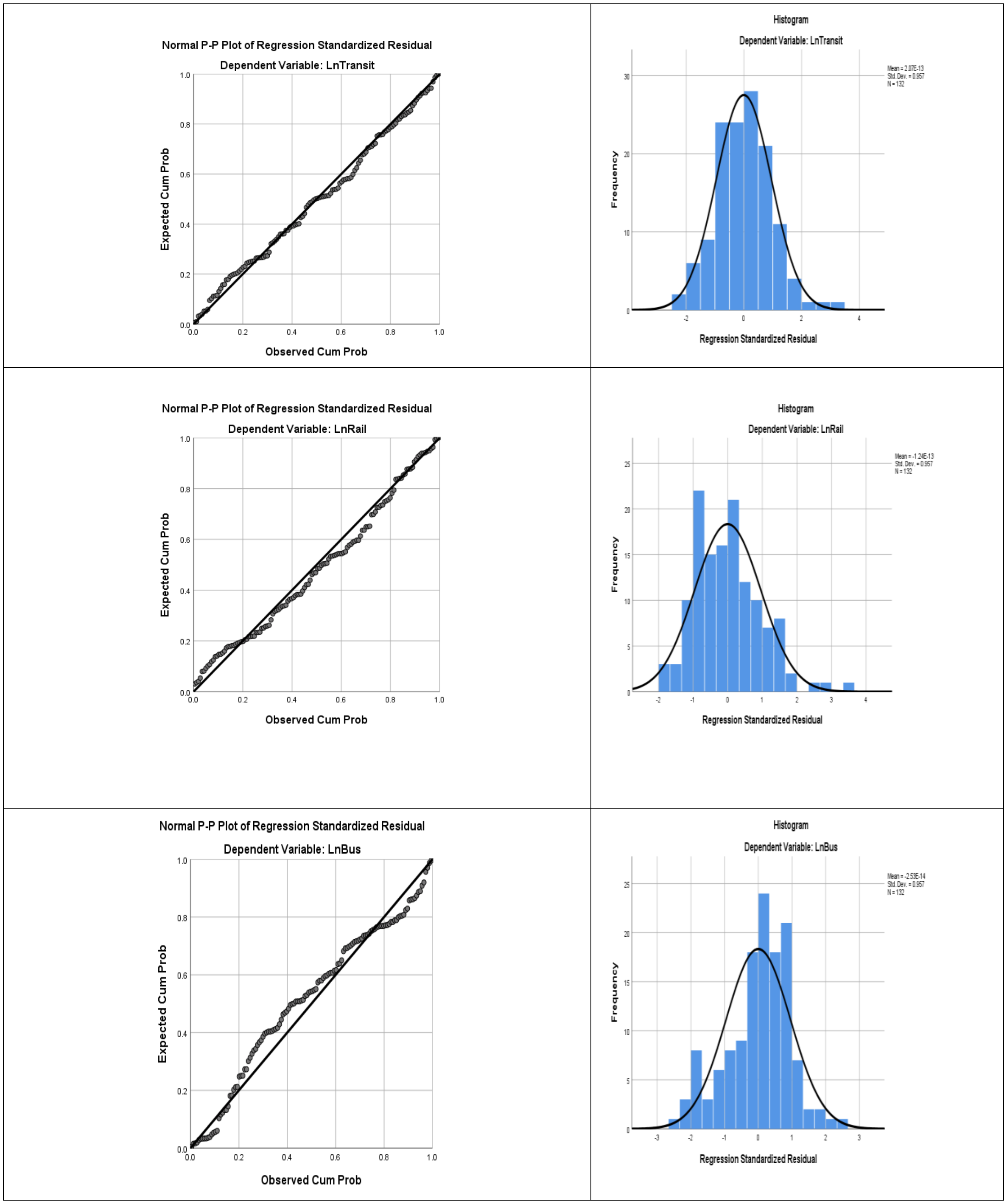

Figure 7-3 P-P Plots (left) and Histograms (right) of the selected dependent variables

7.4 Test for Homoscedascity

Residual plots were checked to identify whether there was a constant variance in the errors. Generally the residual plot should be distributed randomly without any specific pattern and should be equally distributed, which means that there is a constant variance. If a pattern exists it indicates that a non-linear regression is present and the homoscedasticity assumption is violated. As observed in figure 7.4, 7.5, and 7.6 the residual plots show that the variance of the errors were distributed randomly and the relationships between variables in all models are linear. Please note that Figure 7.4, 7.5, and 7.6 describe the regression standardized residual with the predicted Z value on the X axis and the Predicted Standardized Residual on the Y axis for the dependent variables (LnTransit, LnRail, and LnBus) respectively.

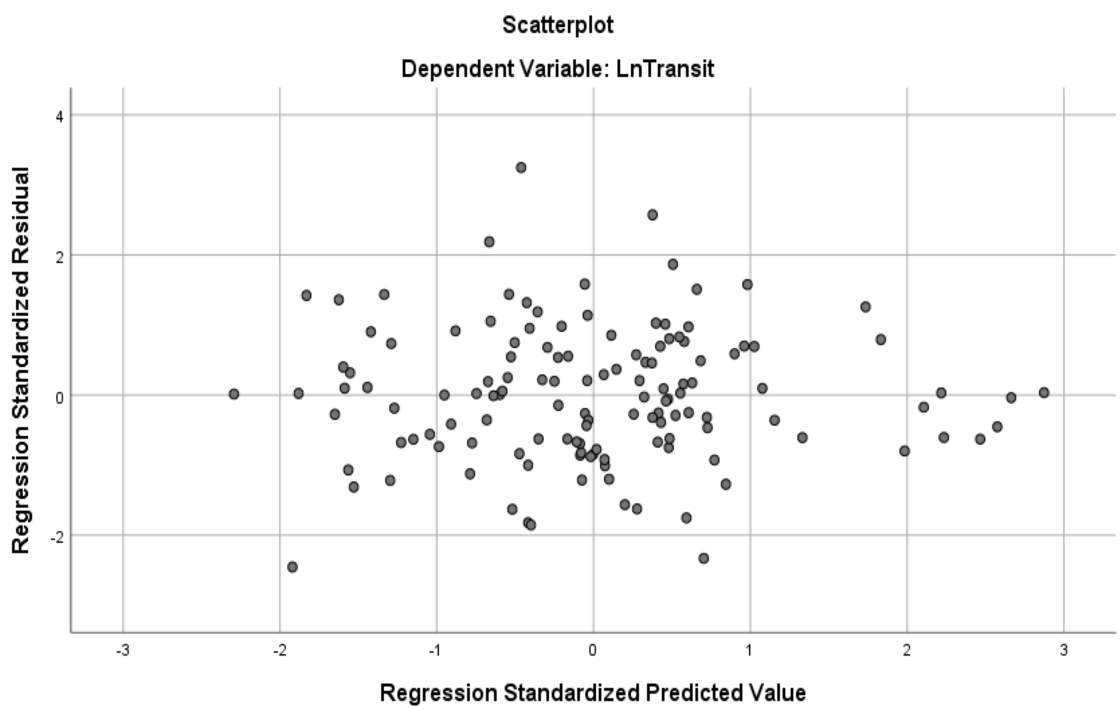

Figure 7-4 Residual plot for Equation 1: LnTransit

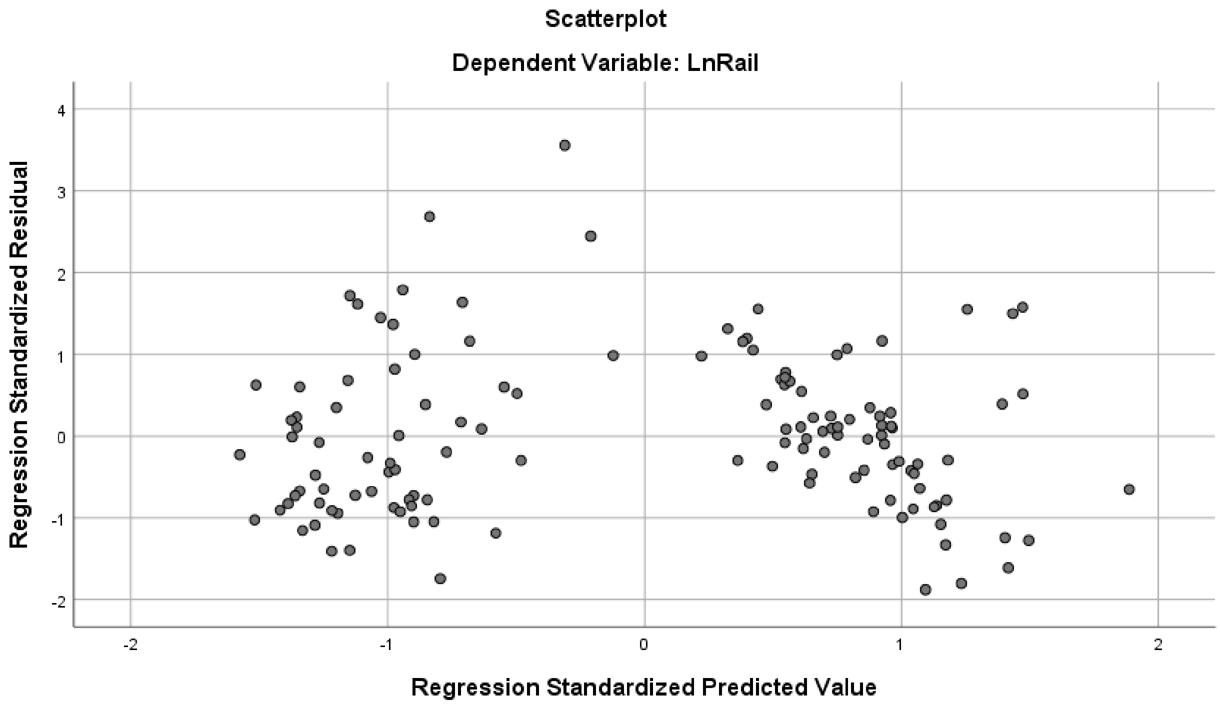

Figure 7-5 Residual plot for Equation 1: LnRail

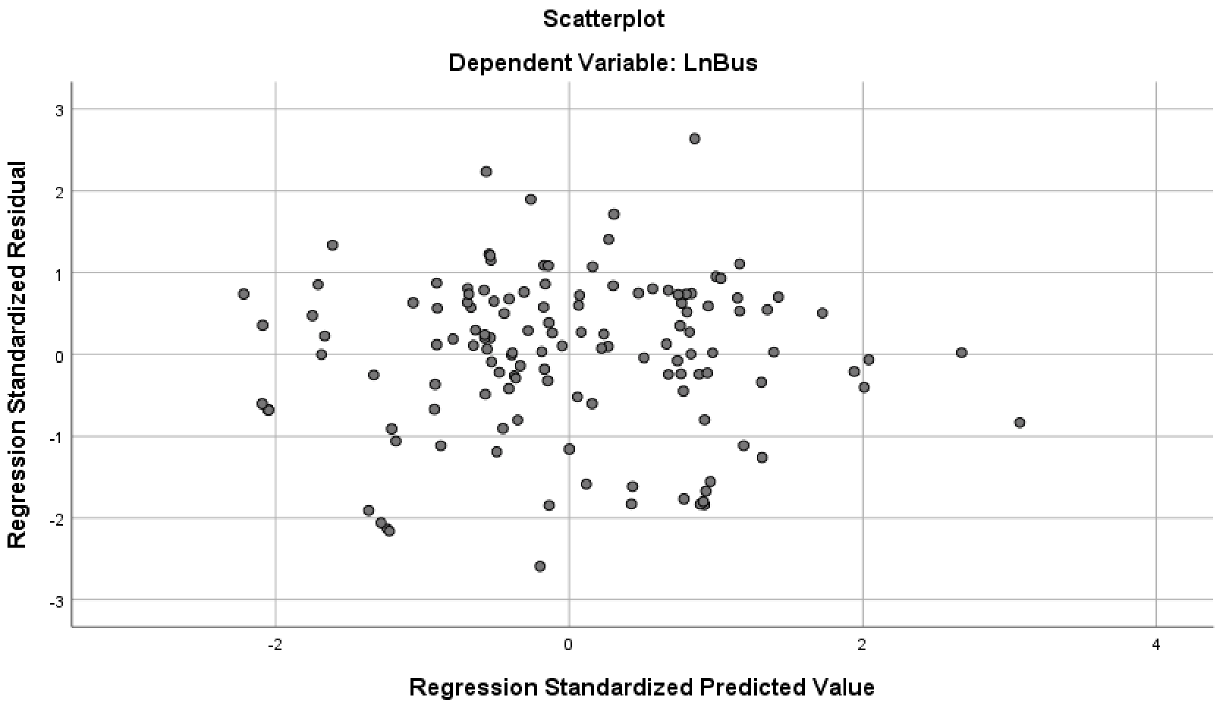

Figure 7-6 Residual plot for Equation 1: LnBus

7.5 Procedures and Analysis

The multiple regression models were conducted using SPSS to examine the impact of the independent variables on the dependent variables in the study area. The models were built by including most factors that may have an impact on the dependent variables based on various theories and empirical studies. As indicated earlier, the regression models for this study are in the log-log (double log) form and, as such, the coefficients will constitute the elasticities. In other words, an interpretation of their coefficients as elasticities indicates a percent change of the explanatory variables between 2007 and 2017 will lead to a percent change for the coefficient in the dependent variable (Transit Ridership) between 2007 and 2017.

7.5.1 Regression Analysis and Results for Research Question 1: Transit Ridership (2007-2017)

The first regression model estimates transit ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. The model is formulated to examine the impact of ITIS on transit ridership as follows:

$$Ln(TRANSIT) = \alpha + \beta 1\ (LnITIS) + \beta 2\ (LnCarTrips) + \beta 3\ (LnIncome) + \beta 4\ (LnGas) + \beta 5\ (LnFare) + \beta 6\ (LnTemp) + \beta 7\ (LnPrecipitation) + \beta 8\ (LnFreeze) + \beta 9\ (LnSnow) + \beta 10\ (LnPOVERTY) + \beta 11\ (LnUnemp) + \beta 12\ (LnMigFlow) + \beta 13\ (LnEduc) \qquad (1)$$

In the initial formulation of the regression model, the independent variables that directly relate to the research question were considered. Subsequently, the control variables that are not considered to be major factors were first added into the regression model, if the variable was found to be not significant, it was removed from the equation. As a result, the Net Migration Flow and Education variables were included in the model, but both became insignificant, so they were dropped from all equations; then, all regression models were evaluated based on the same criteria, including the improvement of the adjusted R2, the improvement of the t test, and the Cp statistic that should be close to or less than (K+1). Table 7-5 shows the ANOVA output for the transit model which illustrates the model significance. The results show that this model is significant, meaning that there is a relationship between the independent variables and the dependent variable.

Table 7-5 Model 1 Transit ANOVA Output

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.642	11	.058	42.242	.000[b]
	Residual	.166	120	.001		
	Total	.808	131			

a. Dependent Variable: LnTransit

b. Predictors: (Constant), LnUnemp, LnFreeze, LnPrecipitation, LnITIS, LnGas, LnCarTrips, LnSnow, LnFare, LnTemp, LnPoverty, LnIncome

Table 7-6 shows the summary of the best model explaining transit ridership which depicts the R Square is .795. This means the independent variables explain approximately 80% of the variation in Transit Ridership. Moreover, the highest adjusted R2 found in this model is .776.

Table 7-6 Model 1 Transit Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.891[a]	.795	.776	.03717

a. Predictors: (Constant), LnUnemp, LnFreeze, LnPrecipitation, LnITIS, LnGas, LnCarTrips, LnSnow, LnFare, LnTemp, LnPoverty, LnIncome

b. Dependent Variable: LnTransit

Table 7-7 below also shows that the Mean of Residual is equal to zero which indicates normal distribution.

Table 7-7 Model 1 Transit Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	12.0965	12.4581	12.2570	.07000	132
Residual	-.09122	.12072	.00000	.03558	132
Std. Predicted Value	-2.293	2.873	.000	1.000	132
Std. Residual	-2.454	3.248	.000	.957	132

a. Dependent Variable: LnTransit

Table 7-8 shows the results of the chosen multiple regression model that includes the coefficients and the corresponding significant levels (p-values).

Table 7-8 Results of the best multiple regression model of Transit Ridership

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	11.664	1.119		10.420	.000
	LnITIS	.064	.011	.440	5.669	.000
	LnCarTrips	.100	.017	.338	6.038	.000
	LnIncome	-.184	.059	-.266	-3.129	.002
	LnGas	.069	.019	.211	3.728	.000
	LnFare	-.138	.033	-.217	-4.179	.000
	LnTemp	-.054	.019	-.174	-2.881	.005
	LnPrecipitation	-.004	.003	-.048	-1.112	.268
	LnFreeze	-.017	.006	-.194	-3.088	.003
	LnSnow	-.031	.016	-.095	-1.966	.052
	LnPoverty	.146	.067	.143	2.178	.031
	LnUnemp	-.078	.015	-.265	-5.108	.000

a. Dependent Variable: LnTransit

All the independent variables namely ITIS, CarTrips, Income, Gas, Fare, Temperature, Freeze, Snow, Poverty, and Unemployment are considered statistically significant since their significance (p) value was < 0.05. The regression coefficients (B) help in identifying the nature and the strength of the relationship with the dependent variable. It was also observed that ITIS, CarTrips, Gas, and Poverty have a positive relationship towards the dependent variable. On the other hand, Income, Fare, Temperature, Freeze, Snow, and Unemployment have a negative relationship towards the dependent variable. Over all, the results show that there was a significant relationship between the dependent variable and independent variables.

Based on the information observed in Table 7-8, ITIS is statistically significant and its coefficient 0.064 indicates that, holding all independent variables as fixed, a 1% increase in ITIS is predicted to increase transit ridership by 0.064. This means that as ITIS increases by 10%, transit ridership increases by 0.64%. Accordingly, the null hypothesis can be rejected at a 95% confidence level, meaning that there is a relationship between ITIS and transit ridership in the DART area. Considering the Beta coefficients, IT IS Beta-coefficient is about 0.45 which is the largest between all Beta coefficients, which means ITIS is the most important variable contributing to the ridership increase. Not surprisingly, the car trips has the second largest value, which considering its positive sign indicates impact of congestion increases on improving the ridership.

This study also sought to answer the secondary research question: What are some controlling factors impacting transit ridership? From Table 7-8, the following conclusions can be drawn. Car Trips variable is significant and its coefficient 0.100 indicates that, holding all independent variables as fixed, a 1% increase in Car Trips is predicted to increase transit ridership by 0.100. This means that as Car Trips (Congestion on highways in the study area) increases by 10%, transit ridership increases by around 1.0%.

Likewise Gas price was also statistically significant (Sig = .000) and has positive relationship with the dependent variable. Its coefficient .069 indicates that a one percentage increase in gas price per gallon is predicted to increase transit ridership in the study area by .069, while controlling for all other variables. This finding is consistent with our previous analysis. When gas price increases in DFW area, it will most likely cause auto ridership to be more expensive and transit ridership to be cheaper; thereby increasing transit ridership. As expected, Fare price on the other hand, has a negative relationship with the dependent variable and was statistically significant. Its coefficient -0.138 indicates that, holding all independent variables as fixed, a 1% increase in fare prices is predicted to decrease transit ridership by 0.138. This means that as fare price increases by 10%, transit ridership decreases by around 1.4% - Which indicates the importance of this variable.

In this model, it is observed that all selected socioeconomic variables are statistically significant and conform to expectations. Income and Unemployment have a negative relationship with the dependent variable, while Poverty has a positive relationship with the dependent variable. Literal interpretation follows that for every 1% increase in individual income within the DFW area, transit ridership decrease by .184% when the effects of all the other variables are held constant. This indicates that low income individuals are most likely to rely on transit for access to employment and other household’s necessities. In addition, a 1% increase in Unemployment in the study area leads to a .078% decrease in transit ridership, while controlling for all other variables. Furthermore the Poverty variable showed statistically significant (sig= .031) and has positive relationship with the dependent variable. Its coefficient .146 indicates that a 1% increase in Poverty increased transit ridership by approximately 0.15% over the study period, with the effects of all the other variables held constant.

It is also observed that most of the weather variables are statistically significant and has negative relationship with the dependent variable, which again conforms to expectations. The findings show that Temperature, Freeze, and Snowfall coefficients are negative. This means that extreme weather conditions such as low temperatures, freeze, and snow decreases transit ridership in the study area. Precipitation on the other hand, is not significant. Yet, this variable is considered one of the major factors affecting transit ridership and is consistently mentioned in the theoretical literature review, so it has been kept in this model and the remainder of the regression models. Anjomani (2016) states that if the purpose of the research is to establish a relationship and if there is an independent variable that the literature suggests should be in the model, the variable should be kept in the model regardless of its significance.

The final regression model taking into consideration all significant independent variables (plus LnPrecipitation) can be written as follows:

$$Ln(TRANSIT) = 11.664 + .064\ (LnITIS) + .100\ (LnCarTrips) - .184\ (LnIncome) + .069\ (LnGas) - .138\ (LnFare) - .054\ (LnTemp) - .004\ (LnPrecipitation) - .017\ (LnFreeze) - .031\ (LnSnow) + .146\ (LnPOVERTY) - .078\ (LnUnemp) + \varepsilon \qquad (1)$$

7.5.2 Regression Analysis and Results for Research Question 2: Rail Ridership (2007-2017)

The second regression model estimates rail ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. The model is formulated to examine the impact of ITIS on rail ridership as follows:

$$Ln(Rail) = \alpha + \beta 1\ (LnITIS) + \beta 2\ (LnCarTrips) + \beta 3\ (LnIncome) + \beta 4\ (LnGas) + \beta 5\ (LnFare) + \beta 6\ (LnTemp) + \beta 7\ (LnPrecipitation) + \beta 8\ (LnFreeze) + \beta 9\ (LnSnow) + \beta 10\ (LnPOVERTY) + \beta 11\ (LnUnemp) + \beta 12\ (LnMigFlow) + \beta 13\ (LnEduc) \quad (2)$$

Just as for the transit model building steps discussed earlier, the same methodology was followed in the formulation of the rail regression model. All regression models were evaluated based on the same criteria, including the improvement of the adjusted R2, the improvement of the t test, and the Cp statistic that should be close to or less than (K+1). Table 7-9 shows the ANOVA output for the rail model which illustrates the model significance. The results show that this model is significant, meaning that there is a relationship between the independent variables and the dependent variable.

Table 7-9 Model 2 Rail ANOVA Output

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.201	11	.473	84.432	.000[b]
	Residual	.672	120	.006		
	Total	5.873	131			

a. Dependent Variable: LnRail

b. Predictors: (Constant), LnUnemp, LnFreeze, LnPrecipitation, LnITIS, LnGas, LnCarTrips, LnSnow, LnFare, LnTemp, LnPoverty, LnIncome

Table 7-10 shows the summary of the best model explaining rail ridership which depicts the R Square is .886. First, it is noted that this model has the highest R2 of the 3 models, and so has the best explanatory power. This means the independent variables explain approximately 89% of the variation in Rail Ridership. Moreover, the highest adjusted R2 found in this model is .875.

Table 7-10 Model 2 Rail Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.941[a]	.886	.875	.07483

a. Predictors: (Constant), LnUnemp, LnFreeze, LnPrecipitation, LnITIS, LnGas, LnCarTrips, LnSnow, LnFare, LnTemp, LnPoverty, LnIncome

b. Dependent Variable: LnRail

Table 7-11 below also shows that the Mean of Residual for this model is equal to zero which again indicates a normal distribution.

Table 7-11 Model 2 Rail Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	10.9816	11.6713	11.2955	.19926	132
Residual	-.14047	.26610	.00000	.07162	132
Std. Predicted Value	-1.575	1.886	.000	1.000	132
Std. Residual	-1.877	3.556	.000	.957	132

a. Dependent Variable: LnRail

Table 7-12 shows the results of the chosen multiple regression model for Rail that includes the coefficients and the corresponding significant levels (p-values).

Table 7-12 Results of the best multiple regression model of Rail Ridership

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	6.535	2.254		2.900	.004
	LnITIS	.304	.023	.775	13.372	.000
	LnCarTrips	.117	.033	.146	3.486	.001
	LnIncome	.205	.118	.110	1.732	.086
	LnGas	.098	.038	.111	2.623	.010
	LnFare	-.137	.037	-.165	-3.658	.000
	LnTemp	.109	.066	.064	1.650	.102
	LnPrecipitation	-.006	.006	-.029	-.921	.359
	LnFreeze	-.024	.011	-.097	-2.079	.040
	LnSnow	-.049	.032	-.056	-1.539	.127
	LnPoverty	.120	.135	.044	.890	.375
	LnUnemp	.059	.031	.075	1.924	.057

a. Dependent Variable: LnRail

Results for model 2 are presented in Table 7-12. In this model the following independent variables namely ITIS, CarTrips, Gas, Fare, Freeze, and Unemployment are considered statistically significant since their significance (p) value was < 0.05. It was also observed that ITIS, CarTrips, Gas, and Unemployment have a positive relationship towards the dependent variable. On the other hand, Fare, and Freeze have a negative relationship towards the dependent variable. Over all, the results show that there was a significant relationship between the dependent variable and independent variables.

Similar to the results of the transit study related to the considering of the Beta coefficients, ITIS Beta-coefficient is about 0.78, which is the largest with a wide margin from the next vale between all Beta coefficients. This means ITIS is the most important variable contributing to the rail ridership increase. Car trips has the second largest value with a 0.15 score, which considering its positive sign indicates impact of congestion increases on improving the rail ridership.

Interestingly, ITIS is statistically significant in this model and its coefficient 0.304 indicates that, holding all independent variables as fixed, a 1% increase in ITIS is predicted to increase rail ridership by 0.304. This means that as ITIS increases by 10%, Rail ridership increases by 3% - Which indicates the importance of this variable. Accordingly, the null hypothesis can be rejected at a 95% confidence level, meaning that there is a relationship between ITIS and Rail ridership in the DART area.

Based on the information observed in Table 7-12, a higher unemployment rate increases rail ridership, which is surprising. Unemployment was statistically significant (Sig = .05) and has positive relationship with the dependent variable. Its coefficient .059 indicates that a one percentage increase in unemployment is predicted to increase rail ridership in the study area by .059, while controlling for all other variables. As expected, however, a fare increase decreases rail ridership. Fare has a negative relationship with the dependent variable and was statistically significant.

This study also sought to answer the secondary research question: What are some controlling factors affecting rail ridership? From Table 7-12, the following conclusions can be drawn. Car Trips variable is significant and its coefficient 0.117 indicates that, holding all independent variables as fixed, a 1% increase in Car Trips is predicted to increase rail ridership by approximately 0.12. This means that as Car Trips (Congestion on highways in the study area) increases by 10%, rail ridership increases by around 1.2%.

Likewise Gas price was also statistically significant (Sig = .010) and has positive relationship with the dependent variable. Its coefficient .098 indicates that a one percentage increase in gas price per gallon is predicted to increase rail ridership in the study area by .098, while controlling for all other variables. In this model, however, weather variables do not seem to have the same impact on Rail as they do on rail with the exception of LnFreeze variable. LnFreeze is statistically significant and its coefficient -0.024 indicates that, holding all independent variables as fixed, a 1% increase in LnFreeze is predicted to decrease rail ridership by 0.024.

Moreover, it is observed that Poverty is not significant in this model; however, this variable is consistently mentioned in the theoretical literature review, so it has been kept in the model and the remainder of the regression models.

The final Rail regression model taking into consideration all significant independent variables (plus the weather variables) can be written as follows:

$$Ln(Rail) = 6.535 + .304\,(LnITIS) + .117\,(LnCarTrips) + .205\,(LnIncome) + .098\,(LnGas) - .137\,(LnFare) + .109\,(LnTemp) - .006\,(LnPrecipitation) - .024\,(LnFreeze) - .049\,(LnSnow) + .120\,(LnPOVERTY) + .059\,(LnUnemp) + \varepsilon \quad (2)$$

7.5.3 Regression Analysis and Results for Research Question 3: Bus Ridership (2007-2017)

The third regression model estimates bus ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. The model is formulated to examine the impact of ITIS on bus ridership as follows:

$$Ln(Bus) = \alpha + \beta 1\ (LnITIS) + \beta 2\ (LnCarTrips) + \beta 3\ (LnIncome) + \beta 4\ (LnGas) + \beta 5\ (LnFare) + \beta 6\ (LnTemp) + \beta 7\ (LnPrecipitation) + \beta 8\ (LnFreeze) + \beta 9\ (LnSnow) + \beta 10\ (LnPOVERTY) + \beta 11\ (LnUnemp) + \beta 12\ (LnMigFlow) + \beta 13\ (LnEduc) \quad (3)$$

Just as for the transit and the rail models building steps discussed earlier, the same methodology was followed in the formulation of the bus regression model. All regression models were evaluated based on the same criteria, including the improvement of the adjusted R2, the improvement of the t test, and the Cp statistic that should be close to or less than (K+1). Table 7-13 shows the ANOVA output for the bus model which illustrates the model significance. The results show that this model is significant, meaning that there is a relationship between the independent variables and the dependent variable.

Table 7-13 Model 3 Bus ANOVA Output

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.771	11	.161	38.393	.000[b]
	Residual	.503	120	.004		
	Total	2.274	131			

a. Dependent Variable: LnBus

b. Predictors: (Constant), LnUnemp, LnFreeze, LnPrecipitation, LnITIS, LnGas, LnCarTrips, LnSnow, LnFare, LnTemp, LnPoverty, LnIncome

Table 7-14 shows the summary of the best model explaining bus ridership which depicts the R Square is .779. This means the independent variables explain approximately 78% of the variation in Bus Ridership. Moreover, the highest adjusted R2 found in this model is .758.

Table 7-14 Model 3 Bus Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.882[a]	.779	.758	.06476

a. Predictors: (Constant), LnUnemp, LnFreeze, LnPrecipitation, LnITIS, LnGas, LnCarTrips, LnSnow, LnFare, LnTemp, LnPoverty, LnIncome

b. Dependent Variable: LnBus

Table 7-15 below also shows that the Mean of Residual for this model is equal to zero which again indicates a normal distribution.

Table 7-15 Model 3 Bus Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	11.5002	12.1148	11.7580	.11627	132
Residual	-.16779	.17066	.00000	.06198	132
Std. Predicted Value	-2.217	3.069	.000	1.000	132
Std. Residual	-2.591	2.635	.000	.957	132

a. Dependent Variable: LnBus

Table 7-16 shows the results of the chosen multiple regression model for Bus that includes the coefficients and the corresponding significant levels (p-values).

Table 7-16 Results of the best multiple regression model of Bus Ridership

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	12.523	1.950		6.422	.000
	LnITIS	-.049	.032	-.056	-1.539	.127
	LnCarTrips	.092	.029	.184	3.166	.002
	LnIncome	-.424	.102	-.365	-4.139	.000
	LnGas	.059	.032	.107	1.821	.071
	LnFare	-.289	.057	-.271	-5.033	.000
	LnTemp	.004	.032	.008	.128	.898
	LnPrecipitation	-.003	.006	-.022	-.504	.615
	LnFreeze	-.010	.010	-.065	-.995	.322
	LnSnow	-.018	.028	-.032	-.647	.519
	LnPoverty	.249	.117	.145	2.131	.035
	LnUnemp	-.145	.027	-.294	-5.463	.000

a. Dependent Variable: LnBus

Results for model 3 are presented in Table 7-16. Unlike the previous two models, the variable of most interest to this research (ITIS) is not statistically significant, which is quite surprising. One possible explanation is that perhaps a high percentage of bus riders either do not have digital phone or IPad to use ITIS or that are not versed with the software. The other possible explanation might be that (ITIS) for bus is not sufficient to convince people to leave their automobiles and ride the bus. Another possibility is that bus riders may need a different set of ITIS apps or perhaps more targeted apps. Running the model with a more refined and detailed ITIS data which would separate the bus users from the other rail could help to derive more accurate results and better interpretations. In terms of Beta coefficients, car trips has the highest score with a negative sign implying that car trips is the most important contributor to the decrease of bus ridership.

In this model, it’s observed that the following independent variables namely: CarTrips, Income, Fare, Poverty, and Unemployment are considered statistically significant since their significance (p) value was < 0.05. CarTrips, and Poverty have a positive relationship towards the dependent variable. On the other hand, Income, Fare, and Unemployment have a negative relationship towards the dependent variable. Over all, the results show that there was a significant relationship between the dependent variable and most of the independent variables.

Based on the information presented in Table 7-16, a higher unemployment rate decreases bus ridership. Unemployment was statistically significant (Sig = .000) and has negative relationship with the dependent variable. Its coefficient .145 indicates that a one percentage increase in unemployment is predicted to decrease bus ridership in the study area by .145, while controlling for all other variables. As expected, however, a fare increase decreases bus ridership. Fare has negative relationship with the dependent variable and was statistically significant, and its coefficient -.289 indicates that, holding all independent variables as fixed, a 1% increase in fare is predicted to decrease bus ridership by 0.289. This means that as bus fare increases by 10%, bus ridership decreases by around 2.9%.

From Table 7-16, the following conclusions can be drawn. Car Trips variable is significant and its coefficient 0.092 indicates that, holding all independent variables as fixed, a 1% increase in Car Trips is predicted to increase rail ridership by approximately 0.09. This means that as Car Trips (Congestion on highways in the study area) increases by 10%, bus ridership increases by around 0 .92%.

Likewise Gas price was also statistically significant and has positive relationship with the dependent variable, and its coefficient .059 indicates that, holding all independent variables as fixed, a one percentage increase in gas price per gallon is predicted to increase bus ridership in the study area by .059. In this model, it is also observed that the weather variables do not have much impact on bus ridership in the study area. Furthermore the Poverty variable showed statistically significant (sig= .035) and has positive relationship with the dependent variable. Its coefficient .249 indicates that a 1% increase in Poverty increased bus ridership by approximately 0.249% over the study period, with the effects of all the other variables held constant.

The final Bus regression model taking into consideration all significant independent variables (Plus ITIS and the weather variables) can be written as follows:

$$Ln(Bus) = 12.523 - .085\,(LnITIS) + .092\,(LnCarTrips) - .424\,(LnIncome) + .059\,(LnGas) - .289(LnFare) + .004\,(LnTemp) - .003\,(LnPrecipitation) - .010\,(LnFreeze) - .018\,(LnSnow) + .249\,(LnPOVERTY) - .145\,(LnUnemp) + \varepsilon$$

7.6 Regression Analysis Using the Lag Dependent Variables:

From the literature scan, there are really mix feelings about inclusion or exclusion of Lag dependent variables in the models. Achen (2001) points out that the decision to include a lagged dependent variable in the model is really a theoretical question. It makes sense to include a lagged dependent variable if you expect that the current level of the dependent variable is heavily determined by its past level. In that case, not including the lagged dependent variable will lead to omitted variable bias and your results might be unreliable.

For this study, we decided lagging the dependent variable in the three transit models namely: Transit, Rail, and Bus. Using a lagged dependent variable among the independent variables may be theoretically important. It may also allow to compare the models' outputs with the original models' outputs to test and analyze any significant difference or impact.

7.6.1 Regression Analysis and Results for Research Question 1 Using Lag Dependent Variable: Transit Ridership (2007-2017)

The first regression model estimates transit ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. The model is formulated to examine the impact of ITIS on transit ridership using the lag dependent variable as follows:

$$Ln(TRANSIT) = \alpha + \beta 1\ (LnITIS) + \beta 2\ (LnCarTrips) + \beta 3\ (LnIncome) + \beta 4\ (LnGas) + \beta 5\ (LnFare) + \beta 6\ (LnTemp) + \beta 7\ (LnPrecipitation) + \beta 8\ (LnFreeze) + \beta 9\ (LnSnow) + \beta 10\ (LnPOVERTY) + \beta 11\ (LnUnemp) + \beta 12\ (LnMigFlow) + \beta 13\ (LnEduc) + \beta 14\ (LnTransitLag1)$$

(1)

Table 7-17 shows the ANOVA output for the transit model with the lag dependent variable LnTransitLag1 which illustrates the model significance. The results show that this model is significant, meaning that there is a relationship between the independent variables and the dependent variable.

Table 7-17 Model 4 Transit ANOVA Output Using Lag Dependent Variable

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.663	12	.055	45.606	.000[b]
	Residual	.143	118	.001		
	Total	.806	130			

a. Dependent Variable: LnTransit

b. Predictors: (Constant), LnTransitLag1, LnPrecipitation, LnITIS, LnUnemp, LnTemp, LnGas, LnCarTrips, LnSnow, LnFare, LnFreeze, LnPoverty, LnIncome

Table 7-18 shows the summary of the best model explaining transit ridership which depicts the R Square is .823. This means the independent variables explain approximately 82% of the variation in Transit Ridership. Moreover, the highest adjusted R2 found in this model is .805.

Table 7-18 Model 4 Transit Summary Using Lag Dependent Variable

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.907[a]	.823	.805	.03481

a. Predictors: (Constant), LnTransitLag1, LnPrecipitation, LnITIS, LnUnemp, LnTemp, LnGas, LnCarTrips, LnSnow, LnFare, LnFreeze, LnPoverty, LnIncome

Table 7-19 below also shows that the Mean of Residual is equal to zero which indicates normal distribution.

Table 7-19 Model 4 Transit Residual Statistics Using Lag Dependent Variable

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	12.0967	12.4653	12.2573	.07142	131
Residual	-.07232	.10720	.00000	.03317	131
Std. Predicted Value	-2.249	2.913	.000	1.000	131
Std. Residual	-2.077	3.079	.000	.953	131

a. Dependent Variable: LnTransit

Table 7-20 shows the results of the chosen multiple regression model that includes the coefficients and the corresponding significant levels (p-values).

Table 7-20 Multiple regression model of Transit Ridership Using Lag Dependent Variable

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	11.107	1.056		10.517	.000
	LnITIS	.062	.011	.423	5.827	.000
	LnCarTrips	.092	.016	.309	5.864	.000
	LnIncome	-.183	.055	-.264	-3.317	.001
	LnGas	.053	.018	.161	2.955	.004
	LnFare	-.127	.031	-.201	-4.118	.000
	LnTemp	-.052	.017	-.168	-2.997	.003
	LnPrecipitation	-.004	.003	-.053	-1.308	.193
	LnFreeze	-.016	.005	-.176	-3.010	.003
	LnSnow	-.025	.016	-.072	-1.577	.117
	LnPoverty	.196	.064	.190	3.053	.003
	LnUnemp	-.082	.014	-.279	-5.682	.000
	LnTransitLag1	.253	.063	.173	3.997	.000

a. Dependent Variable: LnTransit

7.6.2 Regression Analysis and Results for Research Question 2 Using Lag Dependent Variable: Rail Ridership (2007-2017)

The second regression model estimates rail ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. The model is formulated to examine the impact of ITIS on rail ridership using the lag dependent variable as follows:

$$Ln(Rail) = \alpha + \beta 1\ (LnITIS) + \beta 2\ (LnCarTrips) + \beta 3\ (LnIncome) + \beta 4\ (LnGas) + \beta 5\ (LnFare) + \beta 6\ (LnTemp) + \beta 7\ (LnPrecipitation) + \beta 8\ (LnFreeze) + \beta 9\ (LnSnow) + \beta 10\ (LnPOVERTY) + \beta 11\ (LnUnemp) + \beta 12\ (LnMigFlow) + \beta 13\ (LnEduc) + \beta 14\ (LnRailLag1) \qquad (2)$$

Table 7-21 shows the ANOVA output for the rail model with the lag dependent variable LnRailLag1 which illustrates the model significance. The results show that this model is significant, meaning that there is a relationship between the independent variables and the dependent variable.

Table 7-21 Model 5 Rail ANOVA Output Using Lag Dependent Variable

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.151	12	.429	82.853	.000[b]
	Residual	.611	118	.005		
	Total	5.763	130			

a. Dependent Variable: LnRail

b. Predictors: (Constant), LnRailLag1, LnPoverty, LnTemp, LnIncome, LnPrecipitation, LnSnow, LnFare, LnUnemp, LnCarTrips, LnGas, LnFreeze, LnITIS

Table 7-22 shows the summary of the best model explaining rail ridership which depicts the R Square is .894. This means the independent variables explain approximately 89% of the variation in Rail Ridership. Moreover, the highest adjusted R2 found in this model is .883.

Table 7-22 Model 5 Rail Summary Using Lag Dependent Variable

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.945[a]	.894	.883	.07198

a. Predictors: (Constant), LnRailLag1, LnPoverty, LnTemp, LnIncome, LnPrecipitation, LnSnow, LnFare, LnUnemp, LnCarTrips, LnGas, LnFreeze, LnITIS

b. Dependent Variable: LnRail

Table 7-23 below also shows that the Mean of Residual is equal to zero which indicates normal distribution.

Table 7-23 Model 5 Rail Residual Statistics Using Lag Dependent Variable

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	10.9586	11.6913	11.2980	.19906	131
Residual	-.14904	.25015	.00000	.06858	131
Std. Predicted Value	-1.705	1.975	.000	1.000	131
Std. Residual	-2.071	3.475	.000	.953	131

a. Dependent Variable: LnRail

Table 7-24 shows the results of the chosen multiple regression model that includes the coefficients and the corresponding significant levels (p-values).

Table 7-24 Multiple regression model of Rail Ridership Using Lag Dependent Variable

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.688	2.238		2.095	.038
	LnITIS	.292	.022	.748	13.170	.000
	LnCarTrips	.088	.033	.110	2.646	.009
	LnIncome	.242	.115	.131	2.111	.037
	LnGas	.068	.037	.077	1.816	.072
	LnFare	.124	.064	.073	1.946	.054
	LnTemp	-.126	.036	-.152	-3.486	.001
	LnPrecipitation	-.007	.006	-.037	-1.176	.242
	LnFreeze	-.021	.011	-.085	-1.883	.062
	LnSnow	-.034	.033	-.036	-1.033	.303
	LnPoverty	.255	.136	.093	1.875	.063
	LnUnemp	.044	.030	.056	1.462	.147
	LnRailLag1	.353	.103	.116	3.411	.001

a. Dependent Variable: LnRail

7.6.3 Regression Analysis and Results for Research Question 3 Using Lag Dependent Variable: Bus Ridership (2007-2017)

The third regression model estimates bus ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. The model is formulated to examine the impact of ITIS on bus ridership using the lag dependent variable as follows:

$$Ln(Bus) = \alpha + \beta 1\ (LnITIS) + \beta 2\ (LnCarTrips) + \beta 3\ (LnIncome) + \beta 4\ (LnGas) + \beta 5\ (LnFare) + \beta 6\ (LnTemp) + \beta 7\ (LnPrecipitation) + \beta 8\ (LnFreeze) + \beta 9\ (LnSnow) + \beta 10\ (LnPOVERTY) + \beta 11\ (LnUnemp) + \beta 12\ (LnMigFlow) + \beta 13\ (LnEduc) + \beta 14\ (LnBusLag1) \quad (3)$$

Table 7-25 shows the ANOVA output for the bus model with the lag dependent variable LnBusLag1 which illustrates the model significance. The results show that this model is significant, meaning that there is a relationship between the independent variables and the dependent variable.

Table 7-25 Model 6 Bus ANOVA Output Using Lag Dependent Variable

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.844	12	.154	43.659	.000[b]
	Residual	.415	118	.004		
	Total	2.259	130			

a. Dependent Variable: LnBus

b. Predictors: (Constant), LnBusLag1, LnIncome, LnPrecipitation, LnCarTrips, LnTemp, LnPoverty, LnSnow, LnUnemp, LnFare, LnGas, LnFreeze, LnITIS

Table 7-26 shows the summary of the best model explaining bus ridership which depicts the R Square is .816. This means the independent variables explain approximately 82% of the variation in Bus Ridership. Moreover, the highest adjusted R2 found in this model is .797.

Table 7-26 Model 6 Bus Summary Using Lag Dependent Variable

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.903[a]	.816	.797	.05933

a. Predictors: (Constant), LnBusLag1, LnIncome, LnPrecipitation, LnCarTrips, LnTemp, LnPoverty, LnSnow, LnUnemp, LnFare, LnGas, LnFreeze, LnITIS

b. Dependent Variable: LnBus

Table 7-27 below also shows that the Mean of Residual is equal to zero which indicates normal distribution.

Table 7-27 Model 6 Bus Residual Statistics Using Lag Dependent Variable

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	11.4721	12.1091	11.7570	.11910	131
Residual	-.14253	.13640	.00000	.05652	131
Std. Predicted Value	-2.392	2.956	.000	1.000	131
Std. Residual	-2.403	2.299	.000	.953	131

a. Dependent Variable: LnBus

Table 7-28 shows the results of the chosen multiple regression model that includes the coefficients and the corresponding significant levels (p-values).

Table 7-28 Multiple regression model of Bus Ridership Using Lag Dependent Variable

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	12.488	1.788		6.983	.000
	LnITIS	-.054	.018	-.333	-4.514	.128
	LnCarTrips	.088	.027	.176	3.308	.001
	LnIncome	-.448	.094	-.386	-4.757	.000
	LnGas	.039	.030	.070	1.284	.202
	LnFare	-.277	.053	-.261	-5.271	.000
	LnTemp	-.005	.030	-.010	-.173	.863
	LnPrecipitation	-.002	.005	-.017	-.423	.673
	LnFreeze	-.009	.009	-.061	-1.020	.310
	LnSnow	-.002	.028	-.003	-.074	.941
	LnPoverty	.279	.107	.162	2.601	.010
	LnUnemp	-.147	.024	-.299	-6.010	.000
	LnBusLag1	.435	.092	.201	4.705	.000

a. Dependent Variable: LnBus

Tables 7-17 thru 7-28 showed that the inclusion of the lag variables namely: LnTransitLag1, LnRailLag1, LnBusLag1 did not have any significant impact on the previous models outputs. Since the results of the previous models have not changed much, the detailed interpretations of these models namely: models 4, 5, and 6 will not be present.

Chapter 8

Conclusions, Summary of Findings, and Policy Implications

8.1 Conclusions

This research contributes to the field of urban planning and public policy by developing empirical evidence that analyzes the impact of intelligent information systems (ITIS) on transit ridership. The study explores ITIS and the factors impacting transit ridership in Dallas Area Rapid Transit (DART), and how can transit ridership be increased to determine if policy and/or actions can be taken to improve ridership in the study area. This study covered the period extending from January 2007 to December 2017. To accomplish the goal of the study this research specifically examined and tested the following research questions:

1- Does ITIS impact Transit Ridership in Dallas Area Rapid Transit?

2- Does ITIS impact Rail Ridership in Dallas Area Rapid Transit?

3- Does ITIS impact Bus Ridership in Dallas Area Rapid Transit?

In addition, this study examined factors that influence transit usage in the presence of intelligent transit information systems (ITIS).

Multiple regression models were formulated using SPSS to examine the impact of the independent variables namely: ITIS, Car Trips, Income, Gas, Fare, Temperature, Precipitation, Freeze, Snowfall, Poverty, Unemployment, Net Migration Flow, and Education on the dependent variables (Transit, Rail, and Bus) ridership in the study area between 2007 and 2017. Results of the first two models (transit and rail) were in accordance with the hypothesis. Accordingly, the statistical analysis found that ITIS has significant impact on both transit and Rail modes. In addition, IT IS had the highest value in terms of Beta coefficients, which indicated it is the most important variable contributing to the increase of transit and rail ridership. However, results of the regression analysis did not support the hypothesis for ITIS impact on bus mode, and the statistical analysis found that ITIS has no effect on bus mode. One possible explanation is that ITIS apps is not sufficient to convince people to leave their automobiles and ride the bus, or perhaps bus riders in the Dallas-Fort Worth area do not rely on ITIS apps as much as Transit and Rail riders. Finally, the ITIS variable in the models does not trach mode choice information associated with each trip; it only captures the number of times an ITIS app was opened which can be perceived as a limitation to this study. Comparing the results of the three models it becomes clear that the ITIS rail effect and bus effect are in the two end of the range and the transit effect is just the average of the two effects. With the advancement of Information and tracking technologies, future research should focus on more comprehensive ITIS app indicator, which tracks mode choice information. In other words, it captures what mode was chosen for each trip. More precisely, there is need for the breakdown of IT IS data by rail and bus that the models could be run with the actual data as opposed to the aggregate data which our study had access to and used.

8.2 Summary of Findings for Research Question 1

Research Question 1: Does ITIS impact Transit Ridership in Dallas Area Rapid Transit?

The first regression model estimates transit ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. For this model, the findings below show the significant independent variables which have an impact on transit ridership within the study area:

- ITIS: ITIS app usage in the study area shows a positive correlation with transit ridership. In this model ITIS is also a test of causation; as the ITIS app usage increases, transit ridership also increases. This is supported by some of the available literature that suggests that ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes, and makes transit more competitive with the automobile. The results showed that ITIS is affecting transit ridership. More importantly, it showed that ITIS is one of the most important contributors to transit ridership increase.

- Car Trips: The results show a significant positive correlation between Car Trips and transit ridership. As Car Trips increase, transit ridership increases. This means that when congestion on the highways in the study area increases, transit ridership also increases.
- Gas: Gas price was also statistically significant and has positive correlation with transit ridership. This finding is consistent with our previous analysis. When gas price increases in DFW area, it will most likely cause auto ridership to be more expensive and transit ridership to be cheaper; thereby increasing transit ridership.
- Fare: As expected, Fare price has a negative correlation with transit ridership and was statistically significant. This finding conforms to existing literature and suggests as fare increases, transit ridership decreases within the study area.
- Income: Income has a negative correlation with transit ridership. As income increases, transit ridership decreases. This finding suggests that low income individuals are most likely to rely on transit for access to employment and other household's necessities.
- Unemployment: Likewise, unemployment has a negative correlation with transit ridership. This means that as unemployment increases in the study area, transit ridership decreases. This finding conforms to employment literature witch suggests that a change in employment level will change transit use due to the

change of demand (Mattson, 2008). During Great Depression of 1930s, transit ridership had decreased by 25% nationwide (APTA, 2001).

- Poverty: Poverty has a positive correlation with transit ridership. This means that as poverty increases, transit ridership increases. This finding suggests that Poor individuals are most likely to choose transit for access to employment and other household's necessities.
- Weather: Weather variables namely: Temp, Freeze, and Snowfall are statistically significant and have negative correlation with transit ridership, which again conforms to expectations. This means that extreme weather conditions decrease transit ridership in the study area. The findings conform to existing literature. Guo et al. (2007) used the Chicago Transit Authority in Illinois as a case study to investigate the impact of five weather elements (temperature, rain, snow, wind, and fog) on transit ridership, and found that weather condition affects transit ridership: Good weather increase transit use, while bad weather decrease such usage.

8.3 Summary of Findings for Research Question 2

Research Question 2: Does ITIS impact Rail Ridership in Dallas Area Rapid Transit? The second regression model estimates rail ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. For this model, the findings below show the significant independent variables which have an impact on rail ridership within the study area:

- ITIS: ITIS app usage in the study area shows a positive correlation with rail ridership. As the ITIS app usage increases, rail ridership increases. Interestingly, ITIS coefficient 0.304 indicates that, holding all independent variables as fixed, a

1% increase in ITIS is predicted to increase rail ridership by 0.304. This means that as ITIS increases by 10%, Rail ridership increases by 3% - Which indicates the importance of this variable. This finding is supported by some of the available literature that suggests that ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes, and makes transit more competitive with the automobile.

- Car Trips: The results show a significant positive correlation between Car Trips and rail ridership. As Car Trips increase, rail ridership increases. This means that when congestion on the highways in the study area increases, rail ridership also increases.
- Gas: Gas price was also statistically significant and has positive correlation with rail ridership. This finding is consistent with our previous analysis. When gas price increases in DFW area, it will most likely cause auto ridership to be more expensive and transit ridership to be cheaper; thereby increasing transit/rail ridership.
- Fare: As expected, Fare price has a negative correlation with rail ridership and was statistically significant. This finding conforms to existing literature and suggests as fare increases, rail ridership decreases within the study area.
- Unemployment: Unemployment has a positive correlation with rail ridership. This means a higher unemployment rate increases rail ridership, which is somewhat surprising.
- Weather: Freeze (When the temperature in DFW Area dropped to 32 Fahrenheit or below) has a negative correlation with rail ridership. This means that extreme weather conditions decrease rail ridership in the study area. This again conforms to expectations.

8.4 Summary of Findings for Research Question 3

Research Question 3: Does ITIS impact Bus Ridership in Dallas Area Rapid Transit? The third regression model estimates bus ridership between 2007 and 2017 as a function of ITIS, weather, and other socioeconomic factors in the DFW area. For this model, the findings below show the significant independent variables which have an impact on bus ridership within the study area:

- ITIS: Unlike the previous two models, the variable of most interest to this research (ITIS) is not statistically significant in this model, which is quite surprising. One possible explanation is perhaps a high percentage of bus riders either do not have digital phone or IPad to use ITIS or that are not versed with the software. The other possible explanation might be that (ITIS) for bus is not sufficient to convince people to leave their automobiles and ride the bus. Another possibility is that bus riders may need a different set of ITIS apps or perhaps more targeted ITIS apps.
- Car Trips: The results show a significant positive correlation between Car Trips and bus ridership. As Car Trips increase, bus ridership increases. This means that when congestion on the highways in the study area increases, bus ridership also increases.
- Poverty: Poverty has a positive correlation with transit ridership. This means that as poverty increases, bus ridership increases. This finding suggests that Poor individuals are most likely to choose public transportation for access to employment and other household's necessities.

- Fare: As expected, Fare price has a negative correlation with bus ridership and was statistically significant. This finding conforms to existing literature and suggests as fare increases, bus ridership decreases within the study area.
- Unemployment: Likewise, unemployment has a negative correlation with bus ridership. This means that as unemployment increases in the study area, bus ridership decreases. This finding conforms to employment literature witch suggests that a change in employment level will change transit use due to the change of demand (Mattson, 2008). During Great Depression of 1930s, transit ridership had decreased by 25% nationwide (APTA, 2001).
- Income: Income has a negative correlation with transit ridership. As income increases, bus ridership decreases. This finding suggests that low income individuals are most likely to rely on public transportations for access to employment and other household's necessities.

8.5 Policy Implications

This research contributes to the field of urban planning and public policy by developing empirical evidence that analyzes the impact of intelligent information systems (ITIS) on transit ridership. Thereby emphasizes the integrations of ITIS applications as a policy tool for increasing transit ridership in DFW area. The outcomes of this research have several policy implications. Knowledge of ITIS elasticities will help North American cities and Dallas Area Rapid Transit specifically to develop strategies that attempt to increase transit ridership for a variety of reasons including: reduce the energy use of transportation in cities, curb congestion, reduce pollution, and provide other social, economic and environmental benefits. It will aid policy makers in their decision making regarding further investments in transit ITIS applications. In addition, the use of these data by transit operators, transportation planners, and transit marketers presents significant opportunities for both short-term and long-term gains in transit use. Transit properties that leverage objective customer information from these systems may be able to be more proactive in serving transit customers (Under TCRP Project B-29, "Transit Market Research: Leveraging ITS and Transit ITS Data". This research provides opportunities to improve transit services because ITIS reduces negative aspects and cost of using transit through providing information, saving time and other attributes for transit users and non-transit users including the poor and underserved population. It will also enable service providers to target services towards those areas (or customers) that are most likely to increase transit use because of these services, design improved ITIS, and develop transit promoting programs. In addition, the underlying reasons for deploying this kind of applications include both economic and social considerations. Transit agencies expect these systems to boost the ridership, and hence revenues, by attracting more passengers. From transit users' perspective, the availability of real-time transit information at their fingertips and the time saved by real-time transit information is certainly an economic benefit. Besides, transit agencies may boost their public images by making such visible efforts to improve their service. Perhaps a deeper social consideration is that social inequity in American cities, worsened by suburbanization and segregation, may be narrowed to some extent by improving transit service for the disadvantaged population who are largely captive transit riders. This analysis will also help DART's transit managers increase their operational efficiency and provide better real-time customer information to retain existing customers and perhaps attract new customers.

The implementations of Intelligent Transit Information Systems (ITIS) radically changed the way people communicate and get information. The ITIS applications aid transportation operators and emergency response personnel as they monitor traffic, detect and respond to incidents, and inform the public of traffic conditions via the Internet, roadway devices, and the media. The availability of ITIS applications has the potential to change several aspects of people's lives and to influence their travel choices. Today some of the ITIS applications provide real-time transit information making transit more attractive to users. Such systems enable trip makers to make informed decisions by providing them with the information on the projected vehicle arrival and departure time at stations/stops, projected vehicle connection information, and expected origin-destination travel time (U.S. Department of Transportation, 2010). Originally available through Variable Message Signs at transit facilities or through the Internet, software developers now have built application software for smart phones and Personal Digital Assistants that use the underlying transit vehicle location data, making such information ubiquitously available.

The availability of this information has the potential to change people's attitudes toward public transit and to boost ridership. Public transit systems play an important role in combating traffic congestion, reducing carbon emissions, and promoting compact, sustainable urban communities (Taylor et al., 2008). The development of real-time ITIS applications is one of the new strategies for high-quality transit service. These systems provide timely and accurate information to current and potential riders to enable them to make better pre-trip and en-route decisions. The most frequently provided real-time transit information includes vehicle arrival times, service disruptions and delays. In addition, there are various types of travel information. These include pre-trip as well as en-route information.

Over all, the DFW metropolitan area is considered an auto-oriented environment where public funds are mainly invested in highway improvements. Accordingly, an investment in transit ITIS applications needs to be incorporated into local and regional policies. Adopting such polices would make transit more competitive with private automobiles and potentially increase transit ridership. Furthermore, with the widespread dissemination of the Internet and personal mobile devices, the ways by which public transit agencies serve travel information to the public are undergoing great improvements. Recent technological advances in dynamic information systems are changing the experience for transit travelers and transit managers. New mobile technologies allow for en-route decision making and, thus, changing the nature of the transit experience. Further advances in interoperability are supporting advances in content, format, and delivery—making it easier to access and use multi-source data, facilitating multi-modal connections. DART has been involved in the planning, programming, and implementation of ITIS programs and projects. This research clearly demonstrated that ITIS is affecting rail ridership and in general the transit ridership. More importantly, it showed that ITIS is one of the most important contributors to the transit and rail ridership. In particular, regarding the rail ridership it was the most significant by a wide margin compared to the rest of the variables. All these verify and confirm DART's efforts in implementing the ITIS technology and its fruitfulness. Finally, findings from this research should help DART and other transit agenesis better understand the correlation between ITIS applications and transit ridership.

References

Abdel-Aty, M. (2001). Using ordered probit modeling to study the effect of ATIS on transit ridership. Transportation Research, Part C, Emerging Technologies 9 (4), 265–277.

Abdel-Aty, M., & Abdalla, M., (2004). Modeling drivers' diversion from normal routes under ATIS using generalized estimating equations and binomial probit link function. Transportation 31 (3), 327–348.

Alam, B. M., (2009). "Transit Accessibility to Jobs and Employment Prospects of Welfare Recipients Without Cars." Transportation Research Record: Journal of the Transportation Research Board 2110: 78–86.

Alam, B. M. (2015). "Investigating the Determining Factors for Transit Travel Demand by Bus Mode in US Metropolitan Statistical Areas." Transportation Research Record: Journal of the Transportation Research Board 2110: 78–86.

American Public Transit Association. (2009). Public transportation facts at a glance. Technical report, 2009.

Anjomani, A., & Shebeeb, O. (2003). Safety and Efficiency: Regression Analysis Results for Left-turn Movements. *Proceedings of the 82nd Annual meetings of the Transportation Research Board, CD ROM.* Washington D.C. Retrieved from http://www.ltrc.lsu.edu/TRB_82/TRB2003-002126.pdf

Anjomani, A. (2016). Interactions and model building [PowerPoint slides].

APTA. (2008). Rising Fuel Costs: Impacts on Transit Ridership and Agency Operations: Survey Results, American Public Transportation Association (www.apta.com); at www.apta.com/resources/reportsandpublications/Documents/fuel_survey_0809.pdf.

APTA. (2011). Potential Impact of Gasoline Price Increases on U.S. Public Transportation Ridership, 2011 -2012, American Public Transportation Association (www.apta.com); at http://tinyurl.com/cuy2hl7.

Armbruster B. (2010). Factors Affecting Transit Ridership at the Metropolitan Level 2002-2007, A Thesis for the Degree of Master of Public Policy, Georgetown University.

Arthur, W. B. (2011). The nature of technology: What it is and how it evolves.New York: Free Press.

Bass, F. M., 1969, A New Product Growth for Model Consumer Durables, Management Science 15, 215-227.

Asquith, B. J. (2011). Income Elasticity of Demand for Large, Modern Rapid Transit Rail Networks. Undergraduate Economic Review: Vol. 7: Iss. 1, Article 20.

Battelle Memorial Institute and Multisystems, Inc. (2003). Customer Preferences for Transit ATIS. Prepared for Federal Transit Administration. Report No. FTA-OH-26-7015-2003.1

Beaudoin, J. Y., Farzin, H. & Lawell, C. L. (2015). “Public Transit Investment and Sustainable Transportation: A Review of Studies of Transit’s Impact on Traffic Congestion and Air Quality,” Research in Transportation Economics, 52: 15-22.

Bell, D. R. & Song. S. (2004). Neighborhood Effects and Trial on the Internet: Evidence from Online Grocery Retailing, Mimeo, Wharton.

Berenson, M., Levine, D., & Krehbiel, T. (2009). *Basic business statistics: Concepts and applications*. Prentice Hall: New Jersey

Blanchard, C. (2009). The Impact of Rising Gasoline Prices on US Public Transit Ridership, Masters Thesis, Duke University; at http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/1379/Blanchard,%20Christopher.pdf;jsessionid=CFD50E95C8DC8F6F35783C67FEF302BE?sequence=1.

Boarnet, M. R. & Crane, R. (2001). Travel by design: The influence of urban form on travel. Oxford, New York: Oxford University Press, 2001.

Brand, D. (2009). Impacts of Higher Fuel Costs, Federal Highway Administration, (www.fhwa.dot.gov); at www.fhwa.dot.gov/policy/otps/innovation/issue1/impacts.htm.

Brown, J., Hess, D. & Shoup, D. (2001), Unlimited Access. Transportation, Volume 28, number 3, 2001, pp. 233-267; at UCLA Institute of Transportation Studies website: www.sppsr.ucla.edu/res_ctrs/its/UA/UA.pdf.

Borghesi, S., Calastri, C. & Fagiolo, G. (2014). How do people choose their commuting mode? An evolutionary approach to transport choices, LEM Papers Series, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy

Cain, A. (2007). Center for Urban Transportation Research, “Are Printed Transit Information Materials a Significant Barrier to Transit Use?,” Journal of Public Transportation, 10(2): 33-52, 2007.

CBO. (2008). Effects of Gasoline Prices on Driving Behavior and Vehicle Markets, Congressional Budget Office (www.cbo.gov); at www.cbo.gov/ftpdocs/88xx/doc8893/01-14GasolinePrices.pdf.

Cham, L. G., Darido, D., Jackson, R., Laver, A. H. & Schneck, D. (2006). Real-time Bus Arrival Information Systems Return-on-investment Study – Final Report. National Technical Information Service, Federal Transit Administration, Washington, D.C., 2006.

Chen, C., Varley, D. & Chen, J. (2011). What Affects Transit Ridership? A Dynamic Analysis Involving Multiple Factors, Lags and Asymmetric Behaviour. Urban Studies 48 (9): 1893–1908.

Chiang, W., Robert A. R., & Timothy L. U. (2011). Forecasting Ridership for a Metropolitan Transit Authority. Transportation Research Part A: Policy and Practice 45.7 696-705. Web.

Chorus, C., E. Molin, B. Van Wee, T. Arentze, & Timmermans. H. (2006). Responses to Transit Information among Car-drivers: Regret-based Models and Simulations. Transportation Planning & Technology, Vol. 29, No. 4, 2006, pp. 249-271.

Coleman, J., Katz, E. & Menzel, H. (1957). The Diffusion of an Innovation Among Physicians Sociometry 20, 253-270.

Cooper, R. B. & Zmud, R. W. (1990). Information Technology Implementation Research: A Technological Diffusion Approach. Management Science, Vol. 36, No. 2, 1990, pp. 123-139.

Crane, R. (2000). The Impacts of Urban Form on Travel: An Interpretive Review. Journal of Planning Literature, 15(2000): 3-23.

CTA. (2009). CTA Bus Tracker: Select Stop – Estimated Arrival Times. Retrieved from: http://www.ctabustracker.com/bustime/eta/eta.jsp.

Currie, G. & Phung, J. (2007). Transit Ridership, Auto Gas Prices and World Events – New Drivers of Change? Transportation Research Board Annual Meeting (www.trb.org).

Currie, G. & Phung, J. (2008). Understanding Links Between Transit Ridership and Automobile Gas Prices: U.S. and Australian Evidence, Transportation Research Board 87th Annual Meeting (www.trb.org).

Curtin, J. F. (1968). Effect of Fares on Transit Riding. Highway Research Record, 213 (1968), 8-19.

Dallas Area Rapid Transit DART. (2017). DART Reference Book. Available at: (https://www.dart.org/about/dartreferencebookmar17.pdf).

Dargay, J. & Hanly, M. (1999). Bus Fare Elasticities. ESRC Transport Studies Unit, University College London, (www.ucl.ac.uk).

Dargay, J., Hanly, M., Bresson, G. M., Boulahbal, J., Madre, L. & Pirotte, A. (2002). The Main Determinants of the Demand for Public Transit: A Comparative Analysis of

Great Britain and France, ESRC Transport Studies Unit, University College London (www.ucl.ac.uk).

David, P. A. (1969). A contribution to the Theory of Diffusion Stanford Center for Research in Economic. Department for Transport (U.K.).

David, P. A. (1990). The Dynamo and the Computer: An Historical Perspective on the Modern.

Department for Transport (U.K.), Productive Use of Rail Travel Time and the Valuation of Travel Time Savings for Rail Business Travelers: Final Report, June 2009.

Deakin, E. & Sonju, K. (2011). Transportation Technologies: Implications for Planning.

De Graaff, T. & Rietveld, P. (2003). ICT and substitution between out-of-home and at-home work. <http://www.tinbergen.nl/discussionpapers/03061.pdf> (retrieved 15.02.05).

De Graaff, T. & Rietveld, P. (2004). Telework, frequency of working out-of-home and commuting: a labor supply model and an application to the Netherlands.

Dittmar, H. (1995). A broader context for transportation panning: not just an end in itself. J. Am. Plan. Associ. 61 (1), 7-13.

Dutzik, T. & Madsen, T. (2013). A New Way to Go. The Transportation Apps and Vehicle-Sharing Tools that Are Giving More Americans the Freedom to Drive Less. Frontier Group Phineas Baxandall, Ph.D. U.S. PIRG Education Fund.

Dziekan, K. & Vermeulen, A. (2006). Psychological Effects of and Design Preferences for Real-Time Information Displays. Journal of Public Transportation, Vol. 9, No. 1, 2006, pp. 71-89.

Elster, J. (1989). Nuts and Bolts for the Social Sciences. Cambridge: Cambridge University Press.

Elster, J. (1991). Patterns of Causal Analysis in Tocqueville's Democracy in America. Rationality and Society 3(3):277-97.

Elster, J. (1992). Political Psychology. Cambridge: Cambridge University Press.

Eirikis, D., & Eirikis, M. (2010). Friending Transit: How Public Transit Agencies Are Using Socal Media to Expand Their Reach and Improve Their Image. Mass Transit, 7.

Farias, J., & Almeida, J. (2014). Technology adoption in service organizations: A framework proposal for studying ICT diffusion in healthcare and hospital services. XXIV International Conference of RESER, Helsinki.

Farias, J. S., Guimaraes, T. A., & Vargas, E. R. (2012). Innovation in Brazilian and Spanish hospitals: The managers' perception upon electronic patient record. Brazilian Business Review, 9(3), 23–44 (Art. 2).

Federal Highway Administration. (2004). Traffic Congestion and Reliability: Linking Solutions to Problems, prepared by Cambridge with Texas Transportation Institute, 2004.

Federal Highway Administration. (2012). Analysis of Automobile Travel Demand Elasticities With Respect To Travel Cost. Report prepared by Oak Ridge National

Laboratory for the Federal Highway Administration Office of Highway Policy Information.

Fehr & Peers. (2004). Direct Ridership Forecasting: Out of the Black Box, Fehr & Peers (www.fehrandpeers.com).

Ferris, B., Watkins, K. E. & Borning, A. (2010). One Bus Away: Behavioral and Satisfaction Changes Resulting from Providing Real-Time Arrival Information for Public Transit, submitted to the 2011 Transportation Research Board Annual Meeting, 14 November 2010.

Frank, L., & Engelke, P. O (2008). Urban Form, Travel Time, And Cost Relationships With Tour Complexity And Mode Choice. Transportation, Vol. 35, No. 1, January, pp. 37-54; at www.springerlink.com/content/9228326786t53047.

FTA. (2001). National Transit Summaries and Trends, Federal Transit Administration (www.fta.gov); at www.ntdprogram.com/NTD/NTST.nsf/NTST/2001/$File/01NTST.pdf.

Gaylord, C. (2013). The App-Driven Life: How Smartphone Apps Are Changing Our Lives. Christian Science Monitor, 27 January 2013.

Glaeser, E. L. & Kahn, M. E. (2004). Sprawl and Urban Growth. Handbook of Regional and Urban Economics. Volume 4, 2481-2527.

Global Positioning System. (2009). In Wikipedia, The Free Encyclopedia. Retrieved from: http://en.wikipedia.org/w/index.php?title=Global_Positioning_System&oldid=283848264.

Golob, T. F. (2000). Activity approaches to modeling the effects of information technology on personal travel. TravelBehavior.com: UCI-ITS-AS-WP-00-1, Institute of Transportation Studies University of California, Irvine, USA, p. 46.

Golob, T. F. & Regan, A.C. (2001). Impacts of information technology on personal travel and commercial vehicle operations: research challenges and opportunities. Transportation Research Part C – Emerging Technologies 9, 87–121.

Goolsbee, A. & Klenow, P. (2002). Evidence on learning and network externalities in the diffusion of home computers, Journal of Law and Economics 45, 317-343.

Google. (2010). Google Latitude. Retrieved from: http://www.google.com/mobile/default/latitude.html.

Google. (2013). Google Transit Feed Specification. Retrieved from: http://code.google.com/transit/spec/transit_feed_specification.html.

Google. (2014). Google Transit Partner Program. Retrieved from: http://maps.google.com/help/maps/transit/partners/participate.html.

Gordon, P. & Willson, R. (1985). The Determinants of Fixed Rail Transit Demand—An International Cross-Sectional Comparison," a chapter in International Railway Economics, eds. K. Button and D.E. Pittfield. Hants, England: Gower, 1985, pp. 159-175.

Goodwin, P. (1992). Review of New Demand Elasticities With Special Reference to Short and Long Run Effects of Price Changes. Journal of Transport Economics, Vol. 26, No. 2, May, pp. 155171.

Gosselin, K. (2011). Latitude Research, Deprivation Study Finds Access to Real-Time Mobile Information Could Raise the Status of Public Transit, 16 March 2011.

Haire, A. R., & Machemehl, R. B. (2007). Impact of Rising Fuel Prices on US Transit Ridership. Transportation Research Record 1992, TRB (www.trb.org), pp. 11-19; at http://pubsindex.trb.org/view.aspx?id=802405.

Hamilton, B. A. (2008). CityRail Fare Elasticities, Independent Pricing and Regulatory Tribunal (www.ipart.nsw.gov.au); at www.ipart.nsw.gov.au/files/CityRail%20fare%20elasticities%20-%20Booz%20%20website%20final%20document%20%20June%202008.PDF.

Han, S. & Lee, C. W. (2009). Oil Price and Travel Demand, Korea Transport Institute (http://english.koti.re.kr).

Hansen, O. S. (2016). Understanding Public Transit Ridership through Gasoline Demand: Case Study in San Francisco Bay Area, CA Advised by: Professor Michael Anderson. Department of Economics University of California, Berkeley.

Hensher, D. A. (2008). Assessing Systematic Sources of Variation in Public Transport Elasticities: Some Comparative Warnings," Transportation Research A, Vol. 42, Issue 7 (www.elseevier.com/locate/tra), pp. 1031-1042.

Hickey, R. (2005). Impact of Transit Fare Increase on Ridership and Revenue: Metropolitan Transportation Authority, New York City. Transportation Research Record: Journal of the Transportation Research Board 1927: 239–248.

Hojin, J., Gun, J. Y. & Kyoung, K. (2016). Investigating the Effect of Gasoline Prices on Transit Ridership and Unobserved Heterogeneity. Journal of Public Transportation, Vol. 19, No. 4, pp. 56-74 (DOI: http://dx.doi.org/10.5038/2375-0901.19.4.4); at: http://scholarcommons.usf.edu/jpt/vol19/iss4/4.

Holmgren, J. (2007). Meta-analysis of Public Transit Demand. Transportation Research Part A: Policy and Practice, Volume 41, Issue 10, Dec. 2007, pp. 1021-1035.

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D. & Haas, P. (2010). Location Efficiency: Neighborhood and Socio-Economic Characteristics Determine Auto Ownership and Use - Studies in Chicago, Los Angeles and San Francisco, Transportation Planning and Technology, 25:1, 1-27, DOI: 10.1080/03081060290032033

International Energy Agency. (2013). CO2 Emissions from fuel combustion highlights 2013. Paris. Technical report.

Iseki, H. & Ali, R. (2014), Net Effects Of Gasoline Price Changes On Transit Ridership In U.S. Urban Areas, Report 12-19, Mineta Transportation Institute

Kain, J. F. & Liu, Z. (1999). Secrets of Success: assessing the large increases in transit ridership achieved by Houston and San Diego transit providers. Transportation Research Part A: Policy and Practice, 33(7/8): 601-24.

Kelly, K. (2012). Para onde nos leva a tecnologia. São Paulo: Bookman.Laudon, K. K. C., & Laudon, J. P. (2007). Sistemas de Informa¸cão Gerenciais(7 ed. 4areimp). São Paulo: Pearson Prentice Hall.

Kenneth, J.B. (Eds.), Handbook of Transport Modelling. Pergamon, pp. 449–462.

King County. (2009). Tracker Map Real-time Transit Vehicle Locations. Retrieved from: http://tracker-map.metrokc.gov/tracker-map-launch.jsp.

Khattak, A. J., Yim, Y. & Stalker, P. L. (2003). Willingness to Pay for Travel Information in Transportation Research, Part C, Vol. 11C, 137-159

Kohn, H. M. (1999). Factors affecting urban transit ridership. Statistics Canada. Knol. Eindhoven: Eindhoven University of Technology, 1999. ISBN 90-386-0593-5 (ECIS research report) - NUGI 684.

Kuby, M., Barranda, A. & Upchurch, C. (2004). FACTORS INFLUENCING LIGHT-RAIL STATION BOARDINGS IN THE UNITED STATES. Transportation Research Part A: Policy and Practice, Volume 38, Issue 3, p. 223-247.

Lane, B. W. (2008), Gasoline Costs, Public Transit, And Sustainability, Peer Reviewed Conference Paper, Berkeley Electronic Press (http://works.bepress.com); at http://works.bepress.com/bradleywlane/8.

Lane, B. W. (2010). "The Relationship between Recent Gasoline Price Fluctuations and Transit Ridership in Major US Cities." Journal of Transport Geography 18 (2): 214–225.

Lane, B. (2012). A Time-series Analysis of Gasoline Prices and Public Transportation in US Metropolitan Areas. Journal of Transport Geography 22 (2012): 221–235.

Lee Rainie, L. (2012). Pew Internet and American Life Project, Two-Thirds of Young Adults and Those with Higher Income Are Smartphone Owners, 11 September 2012.

Leggatt, H. (2013). Mobile Accounted for 11% of Ecommerce Sales in 2012," BizReport, 10 January 2013.

Lewis, D. & Williams, F. L. (1999). Policy and Planning as a Public Choice: Mass Transit in the United States. Ashgate Publishing: Brookfield, VT.

Lewis-Beck, M. (1980). *Applied regression: An introduction*. SAGE: Newbury Park, CA

Litman, T. (2006). Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior, Victoria Transport Policy Institute (www.vtpi.org); at www.vtpi.org/elasticities.pdf.

Litman, T. (2012). "Changing North American Vehicle-Travel Price Sensitivities: Implications For Transport and Energy Policy" Transport Policy

Litman, T. (2017). Transit Price Elasticities and Cross-Elasticities. Victoria Transport Policy Institute, (www.vtpi.org).

Litman, T. (2004). Transit Price Elasticities and Cross-Elasticities," Journal of Public Transportation, Vol. 7, No. 2, (www.nctr.usf.edu/jpt/pdf/JPT 7-2 Litman.pdf), 2004, pp. 37-58.

Luk, J. & Hepburn, S. (1993). New Review of Australian Travel Demand Elasticities, Australian Road Research Board (www.arrb.org.au).

Maley, D. W. & Weinberger, R. (2009). Rising Gas Price and Transit Ridership: Case Study of Philadelphia, Pennsylvania, Transportation Research Record 2139, Transportation Research Board (www.trb.org), pp. 183-188.

Mattson, J. (2008). Effects of Rising Gas Prices on Bus Ridership for Small Urban and Rural Transit Systems, Upper Great Plains Transportation Institute (www.ugpti.org); at www.ugpti.org/pubs/pdf/DP201.pdf; summarized in Community Transportation, Spring, pp. 38-41; at http://web1.ctaa.org/webmodules/webarticles/articlefiles/Effects_Rising_Gas_Prices_Transit_Ridership.pd f.

McFadden, D. (1974). The Measurement of Urban Travel Demand. Journal of Public Economics, 3(4): 303-328.

McFadden, D. & Train, K. (2000). Mixed MNL Models for Discrete Response. Journal of Applied Econometrics. Vol. 15, No. 5 (Sep. - Oct., 2000), pp. 447-470 .

Mishalani, R. & McCord, M. (2006). Passenger Wait Time Perceptions at Bus Stops: Empirical Results and Impact on Evaluating Real-Time Bus Arrival Information. In Journal of Public Transportation, Vol. 9, No. 2, 2006.

Molin, E. & Timmermans, H. (2006). Traveler Expectations and Willingness-to-pay for Web-enabled Public Transport Information Services. In Transportation Research Part C 14(2006) 57-67.

Mokhtarian, P. L. (2004). A conceptual analysis of the transportation impacts of B2C e-commerce. Transportation 31, 25–284.

Mokhtarian, P. L. (2005). Travel as a desired end, not just a means. Transportation research Part A 39, 93–96.

Mokhtarian, P. L., Neufeld, A. J., Dong, Z. & Circella, G. (2013). Did Free Wi-Fi Make a Difference to Amtrak's Capital Corridor Service? An Evaluation of the Impact on Riders and Ridership, February 2013.

Mokhtarian, P. L. (2002). Telecommunications and Travel: The Case for Complementarity. Journal of Industrial Ecology, 6(2): 43-57, April 2002, doi: 10.1162/108819802763471771. 39 Alexander Malokin,

Mokhtarian, P. L. & Giovanni, C. (2013). Multi-Tasking Aficionados and Mode Choice: Untapped Potential for Transit Ridership? Powerpoint presentation to University of California Transportation Center 2013 Research Conference, 1 March 2013.

Moskowitz, E. (2013). T Riders Happier with Countdown Signs for Next Train. Boston Globe, 23 January 2013.

Murray, S. (2010). Public transit passengers face rough ride. Wall Street Journal, January 2. http://online.wsj.com/article_email/SB126238967349812961-lMyQjAxMTIwNjAyMjMwODI5Wj.html

Mussi, F. B., & Canuto, K. C. (2008). Percepc¸ão dos Usuários sobre os Atrib-utos de uma Inovac¸ão. Revista de Gestão USP, 15(n. especial), 17–30. SãoPaulo.

Nelson, P., Baglino, A., Harrington, W., Safirova, E., & Lipman,R. (2006). “Transit in Washington, DC: Current Benefits and Optimal Level of Provision,” Journal of Urban Economics, 62(2): 231-51.

Nijkamp, P. & Pepping, G. (1998), “Meta-Analysis for Explaining the Variance in Public Transport Demand Elasticities in Europe,” Journal of Transportation Statistics, Vol. 1, No. 1, Jan., pp.1-14; at http://ntl.bts.gov/lib/7000/7100/7104/nijkamp.pdf.

Nielsen. (2012). Smartphones Account for Half of All Mobile Phones, Dominate New Phone Purchases in the U.S., 29 March 2012.

North Central Texas Council of Governments (NCTCOG), (2017). Mobility 2035 Presentation. Available at: (www.nctcog.org/trans/tip/17-20/documents).

North Central Texas Council of Governments (NCTCOG), (2017). Mobility 2040 Presentation. Available at: (http://www.nctcog.org/trans/mtp/2040/documents/MapPackage.pdf).

Oram, R. & Stark, S. (1996). “Infrequent Riders: One Key to New Transit Ridership and Revenue,” Transportation Research Record 1521, TRB (www.trb.org), pp. 37-41.

O’Sullivan, A. (2012). Urban Economics (8th Ed.). New York, NY: McGraw Hill.

Paulley, N., Balcombe, R., & Mackett , R. (2006), “The Demand For Public Transport: The Effects of Fares, Quality Of Service, Income and Car Ownership,” Transport Policy, Vol. 13, No. 4 (www.elsevier.com/locate/tranpol), July 2006, pp. 295-306.

Perloff, J. (2008). Microeconomics Theory & Applications with Calculus. Pearson.

Polzin, S. E., Xuehao, C. & Joel R. R. (2000). Density and Captivity in Public Transit Success: Observations from the 1995 Nationwide Personal Transportation Study. Transportation Research Record: Journal of the Transportation Research Board 1735: 10–18.in

Pucher, J. (2002). Renaissance of Public Transport in the United States? Transportation Quarterly 56 (1): 33–49.

Pucher, J. & Renne, J. L. (2003). Socioeconomics of Urban Travel: Evidence from the 2001 NHTS. Transportation Quarterly 57 (3): 49–77.

Renne, J. L. (2009). From Transit-adjacent to Transit-oriented Development. Local Environment 14 (1): 1–15.

Rogers, E. M. (1983). Diffusion of innovations (3rd ed.). New York: The Free Press, New York.

Rogers, E. M. (1995). The Diffusion of Innovations, Fourth Edition. Free Press, New York.

Rojas, F. (2013). Effective Disclosure Through Open Data. Transparency Policy Project, Ash Center for Democratic Governance and Innovation, Harvard Kennedy School, Transit Transparency. Spring 2012, accessed at www.transparencypolicy.net/assets/ FINAL_UTC_TransitTransparency_ 8%2028%202012.pdf, July 21, 2013.

Ryan, B. & Gross, N.C. (1943). The Diffusion of Hybrid Seed Corn in Two Iowa Communities, Rural Sociology 8, 15-24.

Salomon, I. (2000). Can telecommunications help solve transportation problems. In: Hinsher, D.A.

Salomon, I. (1998). Technological change and social forecasting: the case of telecommuting as a travel substitute. Transportation Research Part C 6, 17–45.

Sebastian, B., Ajzen, I. & Schmidt, P. (2010). Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action, Basic and Applied Social Psychology, 25:3, 175-187, DOI: 10.1207/S15324834BASP2503_01

Schelling, T. C. (1978). Micromotives and Macrobehavior. New York: W. W. Norton.

Schweiger, C.L. (2003). Real-Time Bus Arrival Information Systems. Transit Cooperative Research Program (TCRP) Synthesis Report 48, published by Transportation Research Board, Washington.

Schenker, E. & Wilson, J. (1967). The Use of Public Mass Transportation in the Major Metropolitan Areas of the United States. Land Economics, 43(3), 361-367

Schmenner, R. W. (1976). The Demand for Urban Bus Transit: A Route-by Route Analysis. The Journal of Transport Economics and Policy, 10(1), 68-86.

Schwieterman, J. P., Forst, R. & Nelson, D. (2012). Staying Connected En Route: The Growing Use of Tablets and other Portable Electronic Devices on Intercity Buses, Trains, and Planes. DePaul University, Chaddick Institute for Metropolitan Development, Tablets and e-Readers Leap Past Music Players and Regular Cell Phones as “Technologies of Choice” on Commuter Trains (press release), 23 May 2012.

Schwieterman, J. P., Forst, R. & Nelson, D. (2013). The Digitally Connected Commuter: The Rapidly Rising Use of Personal Electronic Devices on Chicago’s Suburban Trains 2012-2013, 15 June 2013.

Sheng, L. (1998). Adoption and Diffusion of Telemedicine Technology in HealthCare Organizations: A Comparative Case Study in Hong Kong. Unpublished paper. 1998.

Small, K. & Verhoef, E. (2007). The Economics of Urban Transportation. New York: Routledge

Smith, A. (2013). Smartphone Ownership – Pew Research Center, 2013 Update, 5 June 2013.

Stoneman, P. (2002). The Economics of Technological Diffusion. Blackwell Publishers, Oxford UK.

Stroeken, J. H. M. & Knol, W. H. C. (1999). The stimulation of the diffusion and adoption of information technology in small and mediumsized enterprises through IT scenarios. Research Report Eindhoven Centre for Innovation Studies, Eindhoven University of Technology.

Stal, E. (2007). Inovac¸ão Organizacional e Tecnológica. In D. Moreira, & A.Queiroz (Eds.), Inova¸cão Tecnológica, Sistemas Nacionais de Inova¸cão e

Tang, L. & Thakuriah, P. (2007). Ridership Effects of Real-Time Bus Information System: A Case Study in the City of Chicago. Transportation Research Part C, 22: 146–161, 1 January 2012.

Tang, L. (2010). Design and Implementation of Advanced Transit Information Systems, University of Illinois at Chicago, 2010.

Taylor, B. D., Miller, D., Iseki, H. & Fink, C. (2009). Nature And/or Nurture? Analyzing the Determinants of Transit Ridership across US Urbanized Areas. Transportation Research Part A: Policy and Practice 43.1 (2009): 60-77. Web.

Taylor, B. D. & Fink, C. (2009). The Factors Influencing Transit Ridership: A Review and Analysis of the Ridership Literature, UCLA Department of Urban Planning, University of California Transportation Systems Center (www.uctc.net); at www.uctc.net/papers/681.pdf.

Tang, L. & Thakuriah, P. (2007). An Analysis of Behavioral Responses to Real Time Transit Information Systems. Chicago. University of Illinois at Chicago.

The Victoria Transport Policy Institute. (2007). Valuing Transit Service Quality Improvements: Considering Comfort and Convenience in Transport Project Evaluation, Victoria, Canada.

TRACE. (1999). Elasticity Handbook: Elasticities for Prototypical Contexts, Prepared for the European Commission, Directorate-General for Transport, Contract No: RO-97-SC.2035, (www.hcg.nl/projects/trace/trace1.htm).

Transit Cooperative Research Programs. (2003). Real-Time Bus Arrival Information Systems. TCRP Synthesis No. 48. Retrieved from: http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_syn_48.pdf

Transit Cooperative Research Program. (1998). Strategies to Attract Auto Users to Public Transportation. TCRP Report Number 40.

Transit Cooperative Research Program. (2016). Real-Time Bus Arrival Information Systems. TCRP Report Number 48.

Turnbull, K. F. & Pratt, R. H. (2003). Transit Information and Promotion: Traveler Response to Transport System Changes, Chapter 11, Transit Cooperative Research Program Report 95; Transportation Research Board (www.trb.org).

Tigre, P. B. (2006). Gestão da Inova¸cão: A economia da tecnologia no Brasil.Rio de Janeiro: Elsevier.

U.S. Department of Transportation. (2010). Advanced Public Transportation Systems Deployment in the United States — Year 2010 Update, Washington, D.C., 2010.

U.S. Urban Personal Vehicle & Public Transport Market Share from 1900. Retrieved from: http://www.publicpurpose.com/ut-usa2007ann.pdf

Venkatesh, V. & Davis, F. D. (2003). User acceptance of information technology: toward a unified view. MIS Quarterly,27(September 3), 425–478.

Wallace N. (2017). The Best Cities for Public Transpiration, University of Washington, 2017.

Watkins, K. E., Ferris, B., Borning, A. G., Rutherford, S. & Layton, D. (2011). Where Is My Bus? Impact of Mobile Real-time Information on the Perceived and Actual Wait Time of Transit Riders. Transportation Research Part A: Policy and Practice 45.8 839-48.

Wardman, M. (2004). “Public Transport Values of Time,” Transport Policy, 11(4): 363-377.

Weigel, L. (2010). Transportation for America, Future of Transportation National Survey, March 2010. Transportation Statements.

Wooldridge, J. (2013). Introductory Econometrics: A modern approach. (5th ed.). Mason, OH: South-Western Cengage Learning.

Young, C. A. (2012). MBTA Ridership Growth Contributes to Nationwide Surge. Boston Globe, 4 June 2012.

Zhang, F., Q. Shen, & Clifton, K., J. (2008). Examination of Traveler Responses to Real-time Information about Bus arrivals using Panel data. Transportation Research Record, Vol. 2082, 2008, pp. 107-115.

Zhang, F. (2010). Traveler Responses to Real-Time Passenger Information Systems (dissertation), 2010.

Zhou, J. & Schweitzer, L. (2011). Getting Drivers to Switch: Transit Price and Service Quality among Commuters. Journal of Urban Planning and Development 137 (4): 477–483.

Biographical Information

Ahmed Ismail Daqrouq graduated with his Bachelor of Science degree in Computer Information Systems from the University of Texas at Arlington in 2000. He then worked at Accenture LLP in Dallas, Texas as a business analyst providing consulting solutions to various clients. He earned his Masters of Science degree in Computer Information Systems from the University of Texas at Arlington in 2009. He graduated with 4.0 GPA. He worked with several clients across multiple verticals including Version, AT&T, Dynegy, Geneva, Trinity Industries, PDX Enterprise Pharmaceutical Systems, Sonexus Health, Cardinal Health, Bank of America, ADT security services, Premier Designs, Visionet Systems, Tribune, Ashely Furniture, Masonite, and Northrup Grumman as a consultant and technical leader. In a consulting role, he worked on the creation of formal master project plans, Fit-gap analysis, process mapping, data migrations, and employee training. He also worked on providing technical solutions, business analysis, and process design. Ahmed ssuccessfully executed multiple end to end implementation projects in Supply Chain, Trade and Logistics, Procurement & Sourcing, Inventory and Warehouse Management, Finance, Product Information Management, and Sales & Marketing. Ahmed has been involved in Full Cycle implementations of numerous distributions such as enterprise data, billing, e*commerce, retail, telecommunication, financial, pharmaceutical, aerospace, enterprise resource planning ERP, and CRM systems. Ahmed is currently working for Microsoft as a Dynamics AX & Dynamics 365 engineer working as a technical leader to solve technically complex Dynamics AX problems, integrate cross-product solutions, and drive the discovery of potentially unique solutions for each customer situation. His research interests are in the field of transportation planning and design, Information technology, urbanizations issues and equity. Ahmed is married and has four children.