Article

Public Transit Ridership and Car-Oriented Cities: The Case of the Dallas Region

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Abstract: U.S. cities have invested large amounts of sums on public transit and urban rail in the last few decades, but the transit usage in most of these car-oriented cities is very low, and previous efforts to increase ridership have been mostly fruitless. This research examines the factors affecting transit ridership in a large car-oriented metropolitan setting and uses the Dallas region in the United States as a case for the study to identify factors that could help in increasing ridership. Most previous studies of transit ridership have not included many 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.

Keywords: transit ridership; rail transit; bus transit; Dallas Area Rapid Transit (DART); intelligent transit information systems (ITIS)

1. Introduction

Transit ridership is at the heart of transportation policy-making and the success of any transit system. In recent years, the energy component of 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 rise in energy price will mean that North America must adapt, as energy gets more expensive and scarcer. One of the areas of adaptations needs to be made in transportation, as transportation consumes large quantities of energy. Recent studies estimate that a large percentage of air pollutants is generated by the transportation sector. In 2017, transportation accounted for the largest portion (29%) of total U.S. GHG emissions, 82% of which derive from road transport (Fast Facts 2019). The transport sector currently accounts for 54% of the total oil consumption (EIA 2018). The number of cars is expected to double by 2035 when their total number reaches 1.7 billion. This rise is mainly related to the development of emerging economies like China, India, and the Middle East. Also, the expected increase in urbanization is likely to cause severe congestion problems in the next decades in most cities all over the world (Borghesi et al. 2014).

Transit ridership is essential for policymaking and the success of any transportation system. Automobile dependence is a concern for many reasons, including congestion in urban areas, pollution, and environmental damages caused by pollution. 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). This study will examine transit ridership in the Dallas metropolitan area as an example of a quintessential car-oriented metro area in the United States. It will examine the factors affecting transit ridership in a case study applied to the Dallas Area Rapid Transit (DART), a regional

transit agency in the Dallas metropolitan in Texas, as a sample of large low-density car-oriented cities in the United States for a ten-year period of monthly data. We also include a measure of auto ridership in the models in order to measure the responsiveness of demand for transit to a relative change in auto usage. Also, as part of these factors, it explores the impact of intelligent transit information systems (ITIS) on transit ridership. In recent years, the introduction of intelligent transit information systems (ITIS) applications that provide real-time information to transit users created new hope for increased transit ridership. We examine the price elasticity of demand for transit and how it could help us in understanding changes in transit as an effect of other essential variables. As part of ongoing research, 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 the demand for transit ridership.

The primary purpose of this study is to shed light on the significant factors that influence transit ridership. The research question for the study is: What are the factors affecting transit ridership? This study also examines 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 transit in the study area. In this type of research, quite frequently one is interested in interpreting the effect of a percent increase of an independent variable on the dependent variable, which 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 fare, income, or ITIS usage is explored, and the policy implications out of these elasticities are discussed. We select the Dallas Area Rapid Transit as a prime sample of a car-oriented city to examine these questions. The research contributes to transportation planning literature and provides opportunities to improve transit for transit and non-transit users, including the poor and underserved population. It is expected that the results of this research will help policymakers with decisions on increasing transit ridership, which is relatively very small in American car-oriented cities and other cities around the world where their public transportation is losing ground to car dominance.

2. Literature Review

Transit ridership literature shows that ridership depends on several economic and social characteristics, such as urban geography, economic activity, and population characteristics (Taylor et al. 2009). 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 commuter money, and travel time, a transit agency is likely to gain a new rider (Armbruster 2010). It is reasonable to assume that if car drivers had a better alternative, they might be willing to use it. In theory, that alternative is public transportation—buses, commuter trains, light rail, streetcars, and subway systems (Wallace 2017). At its best, public transportation is as reliable as driving, more efficient, less stressful, and cheaper. Most American cities fall well short of that ideal.

Other influential factors, which were identified using a literature search on factors that affect ridership levels, include gas prices, education, and socioeconomic characteristics (Taylor et al. 2009) as well as intelligent transit information systems (ITIS). It is believed that factors such as gas price changes over the last decade have 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). Several studies have shown that the immediate benefits of ITIS accrue because riders appreciate the information and use it. A reduction of wait times, associated uncertainties, and onboard connection information systems could be examples of the primary factors linking it to increased transit use (Gosselin 2011; Weigel et al. 2010).

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 prices (Chen et al. 2011; 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 have 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 necessities (Alam 2009; Holtzclaw et al. 2010; 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). 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 the 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 the transit riders are low-income, African Americans, Latinos, women, and older adults, who are unable to afford an automobile due to financial constraints (Alam et al. 2015).

The literature about factors impacting transit ridership is quite mixed. This study addresses these gaps by testing multiple factors, measuring population, technology, geography, and socioeconomic characteristics. This study of transit ridership is examined in a case study applied to the Dallas Area Rapid Transit (DART).

3. Study Area

This study covers transit ridership in the 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 ten year period in a monthly base and the incremental exposure to ITIS technology.

Rail passenger transportation in the Dallas–Fort Worth Metropolitan Area is provided by three regional transit agencies—including Dallas Area Rapid Transit (DART), Denton County Transportation Authority (DCTA), and Trinity Railway Express (TRE)—and serves four urban counties (Collin, Dallas, Denton, and Tarrant) as shown in Figure 1, (NCTCOG 2013). Most of the figures in the paper are from the North Central Texas Council of Government (NCTCOG), which is the regional council for this urban region. In these four counties, 20 cities are served by 74 rail stations along 146 miles of light and commuter rail, as shown in Figure 1. DART is the largest agency that provides rail services. It covers 13-member cities along 90 miles of light rail transit (59 rail stations). TRE as a commuter rail links downtown Fort Worth and downtown Dallas in this twin center combined metropolitan region with roughly 35 miles of commuter rail service (10 stations) in four cities; DCTA provides 21 miles of commuter rail that serves three cities (6 stations) (NCTCOG 2015). As mentioned earlier, one motivating factor for doing this study is that the DFW area has the longest rail transit system,

but no major study has examined its impact. Also, cities served by transit in the DFW metropolitan area are low-density and automobile-oriented cities, and therefore these systems do not improve transit accessibility or attract more residents and commercial activities next to rail stations.
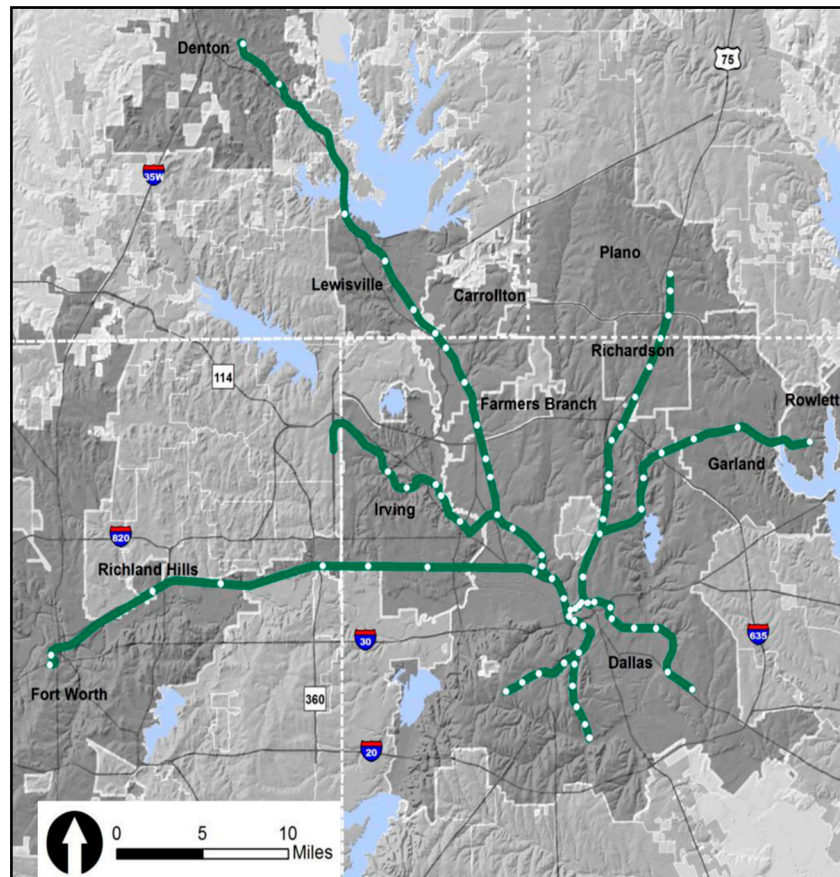

Figure 1. Dallas–Fort Worth area rail transit systems. (Source: NCTCOG 2013).

The 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 13 August 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 has served 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's extensive network of Light Rail, Trinity Railway Express commuter rail, bus routes, and paratransit services move more than 220,000 passengers per day across a 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 Figures 2 and 3).
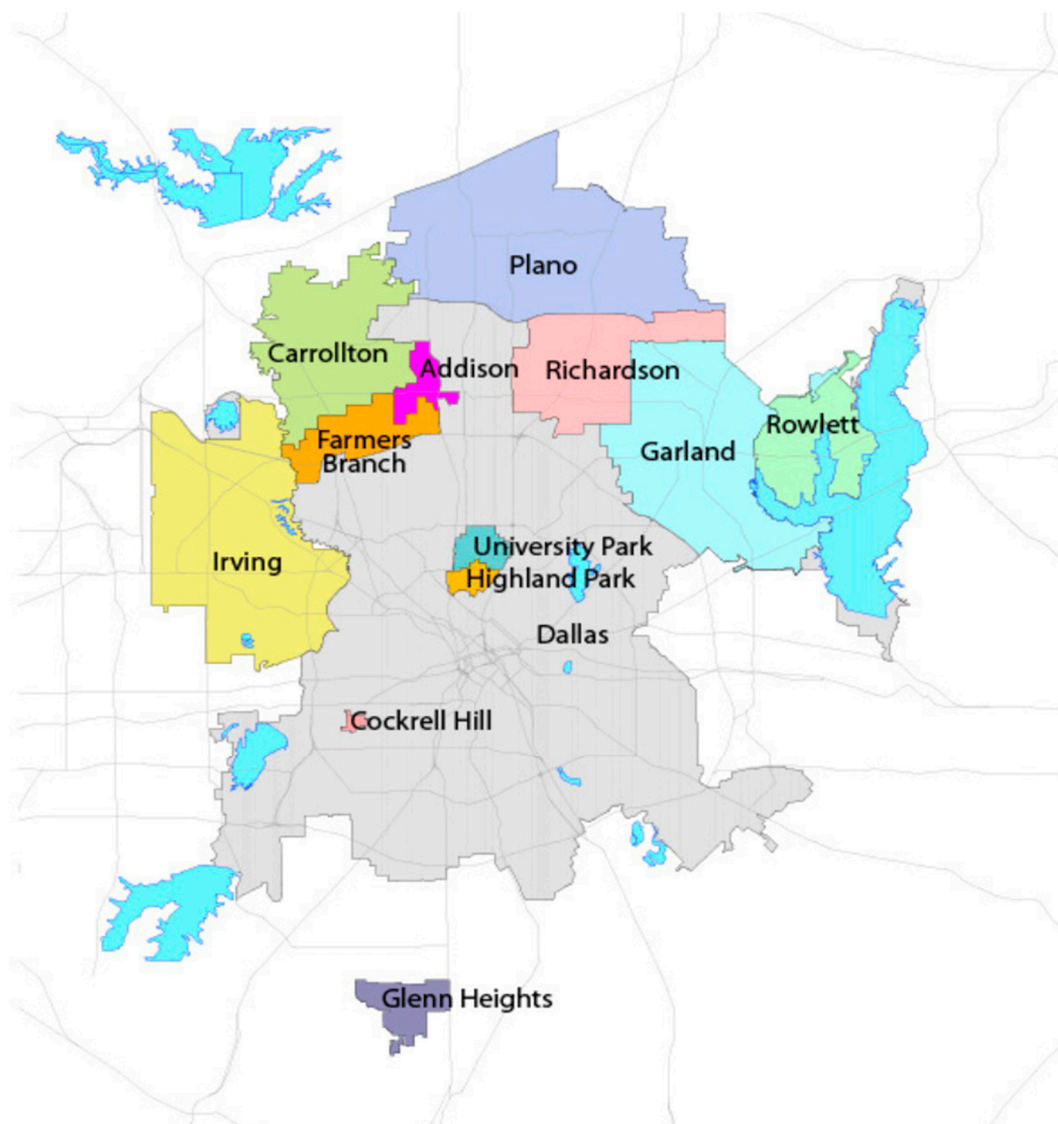
Figure 2. DART Service Area. (Source: DART 2017).

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 damage caused by pollution. The level of congestion/delay is expected to increase substantially in the DFW area between the year 2017 and 2040 (see Figures 4 and 5).

Switching to more sustainable, environmentally friendly and less congesting transportation modes, such as public transit, is likely to be an effective solution to most of these problems. Moreover, in the 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 Figure 6). The employment level is also expected to increase substantially in the DFW area (see Figure 7). Population and employment increases are expected to have a positive impact on transit ridership.
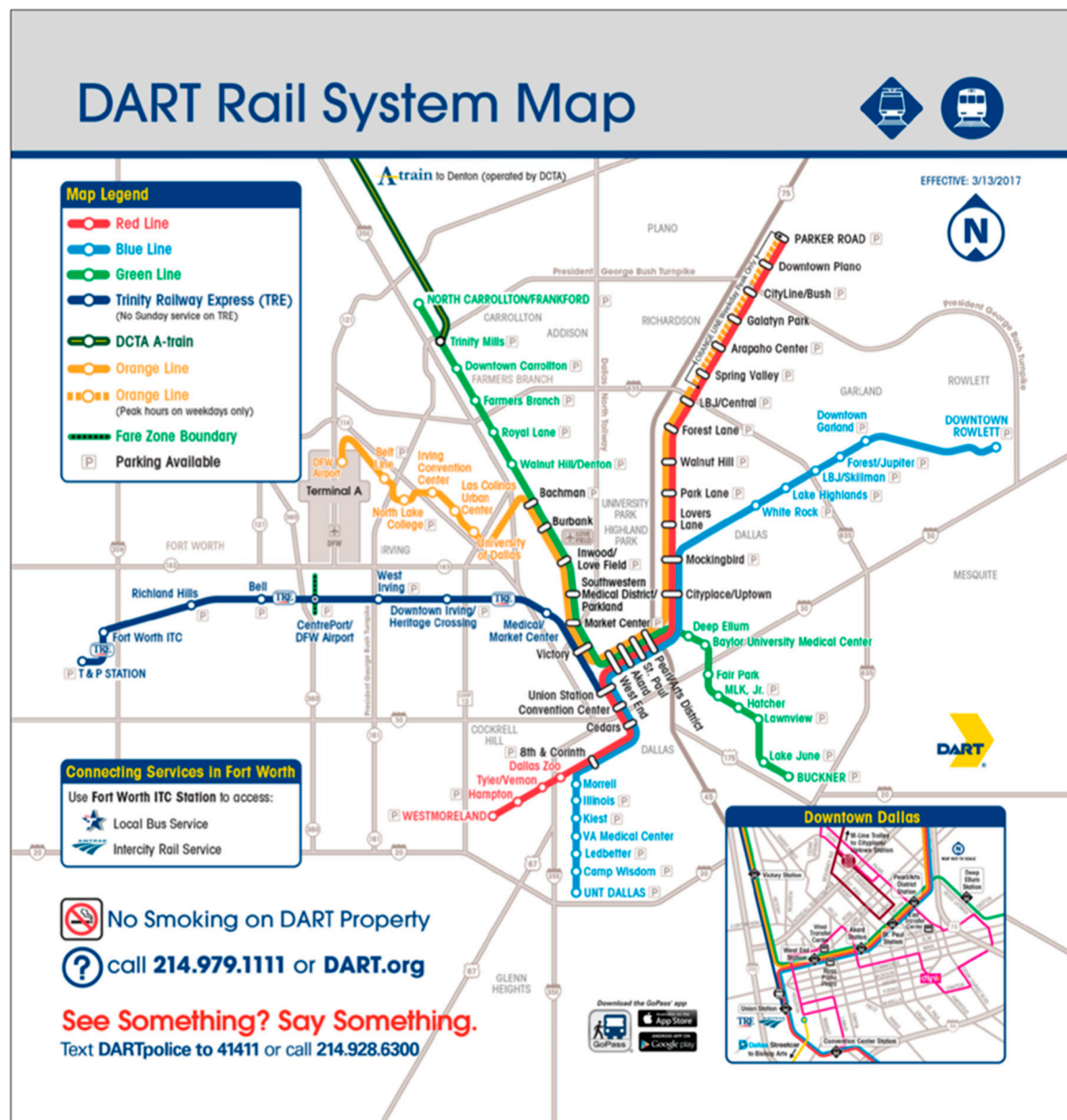
Figure 3. DART Rail System Map. (Source: DART 2017).

Dallas–Fort Worth is the fourth largest metropolitan area in the United States after New York, Los Angeles, and Chicago. The Dallas–Fort Worth–Arlington metropolitan area's 2018 population was 7,405,564, and it had a 146,000-population increase that year, which was the most of any metro area and Maricopa County. Historically, the Dallas metro area attracts large numbers from both international and domestic migration. Many of the other largest metro areas in the country rely mostly on international migration and a natural increase for growth (U.S. Census Bureau 2018). The metropolitan area's growth since 1980 has averaged about 30% per decade. In 2017, the Dallas–Fort Worth–Arlington metropolitan area, Texas, had a population of 7.4 million people with a median age of 34.9 and a median household income of $67,382. Between 2016 and 2017, the population of Dallas–Fort Worth–Arlington, Texas, grew from 7.23 to 7.4 million, a 2.32% increase, and its median household income grew from $63,812 to $67,382, a 5.59% increase. The population density of the metropolitan area was 634/sq mi (245/km^2) in 2010 and was 3005/sq mi (1160/km^2) in the Dallas county.
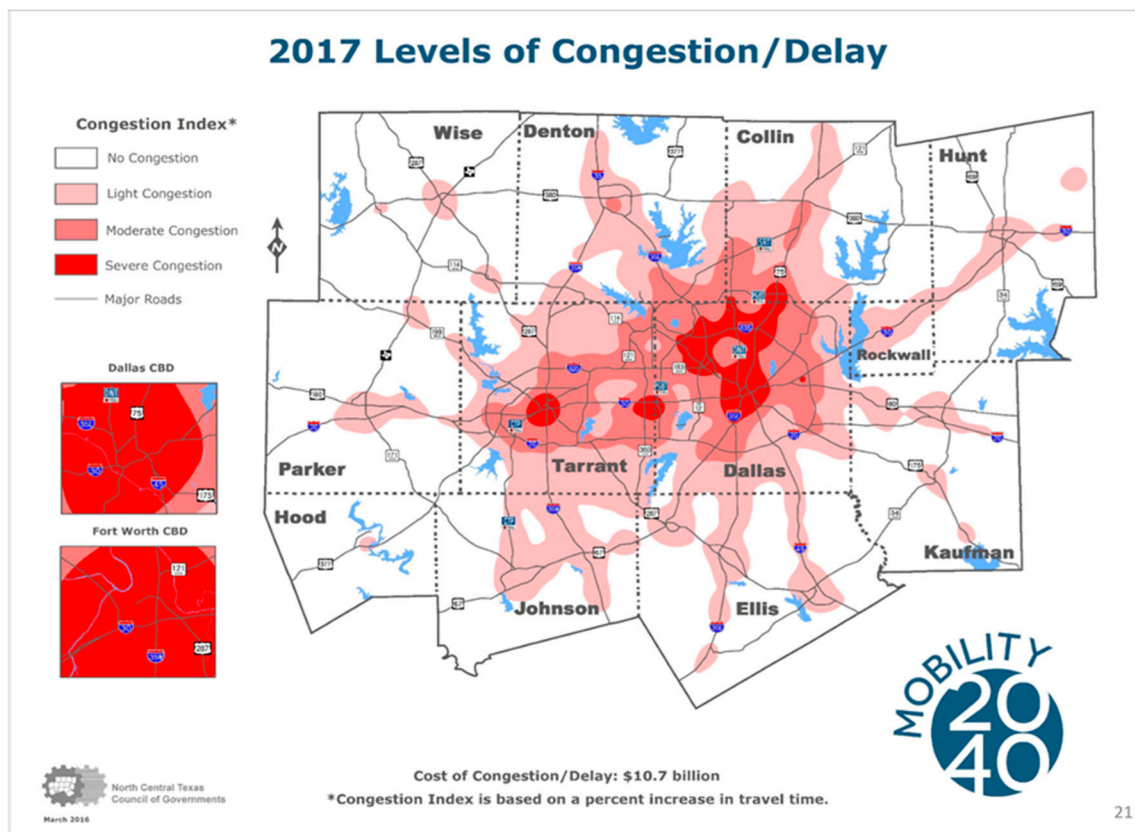
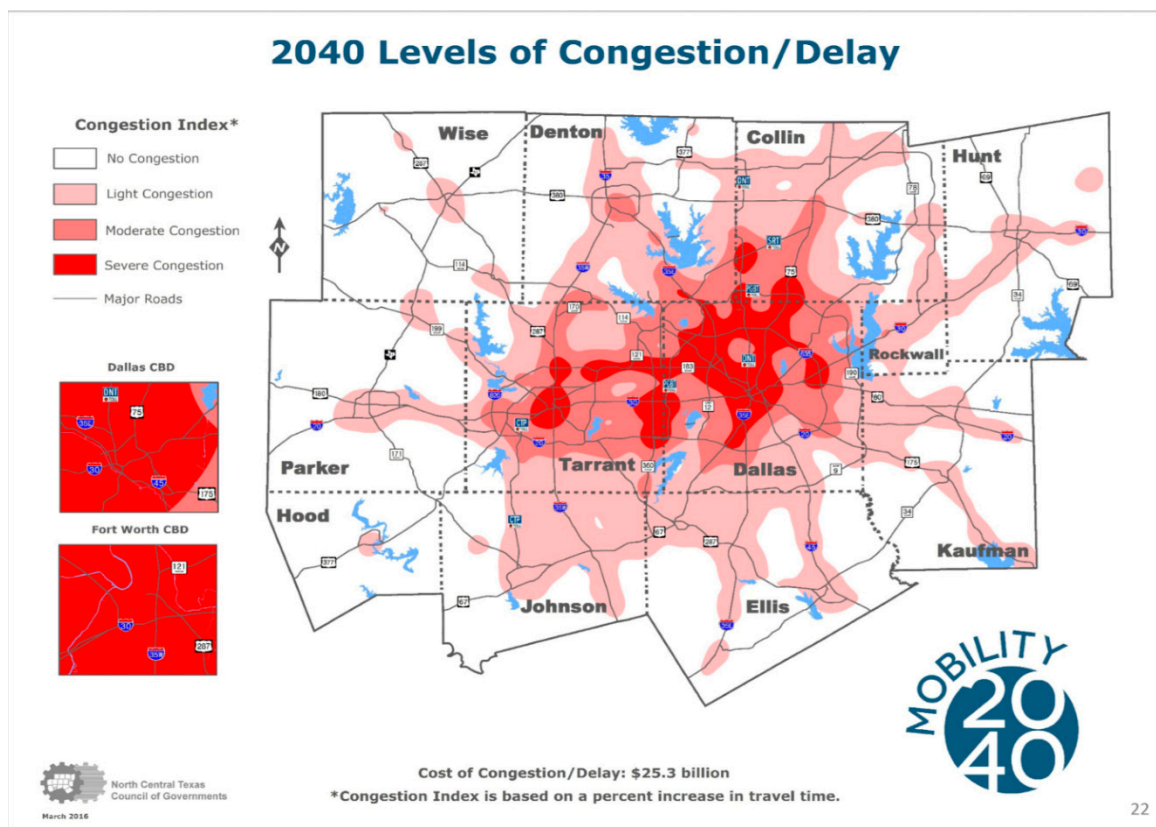**Figure 4.** 2017 Levels of Congestion/ Delay. (Source: NCTCOG 2017).

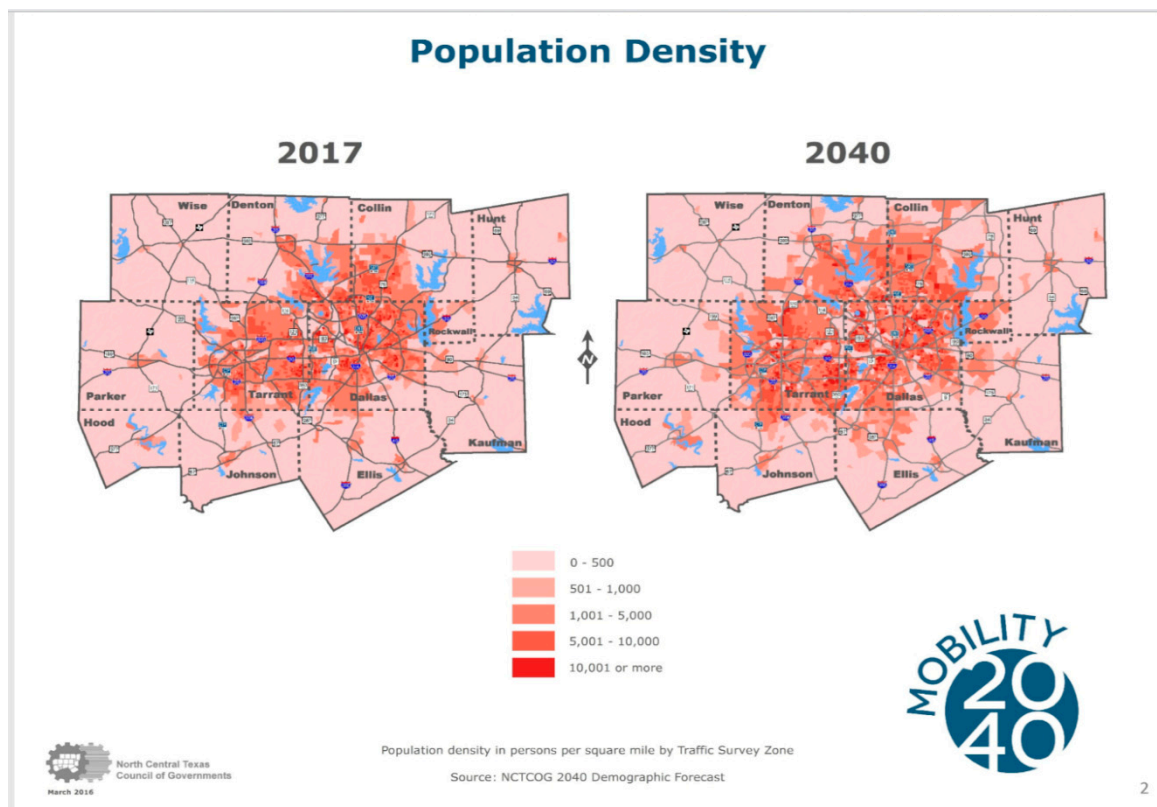**Figure 5.** 2040 Levels of Congestion/Delay. (Source: NCTCOG 2017).

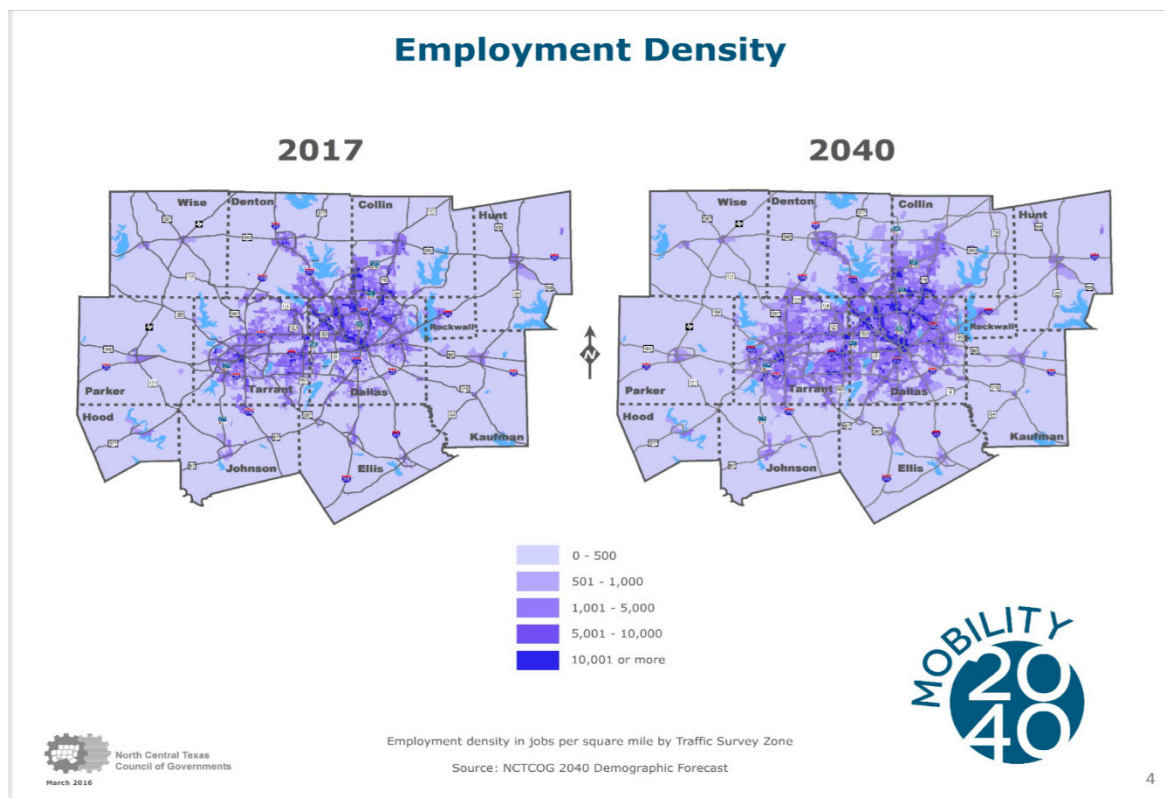**Figure 6.** Population density. (Source: NCTCOG 2017).

Figure 7. Change in Employment density. (Source: NCTCOG 2017).

The population of Dallas–Fort Worth–Arlington metropolitan area is 46.3% White Alone, 28.9% Hispanic or Latino, and 15.4% Black or African American Alone. From 2016 to 2017, employment in Dallas–Fort Worth–Arlington, Texas, grew at a rate of 2.75%, from 3.61 to 3.71 million employees. Households have a median annual income of $67,382, which is more than the median annual income of $60,336 across the entire United States. Using averages, employees in Dallas–Fort Worth–Arlington have a longer commute time (27 min) than the normal US worker (25.5 min). Additionally, 1.92% of the workforce in the region have "super commutes" for more than 90 min. The public transit use has been merely at the 8% level. In 2017, the most common method of travel for workers in the Dallas–Fort Worth–Arlington area was Drove-alone, 80.9%, followed by those who carpooled, 9.61% (Data USA 2018).

4. Intelligent Transit Information Systems (ITIS) Applications Overview

In 2010, Trapeze ITS, a provider of solutions to the public passenger transportation industry, was chosen by DART for its intelligent transit transportation system implementations. DART selected Trapeze INFO-Web for its online trip-planning software. Buses and trains were 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 s by 4G wireless. This information has helped DART, like many other public transit systems, reach its full potential and address concerns about the uncertainty of arrival times and 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 smartphones, personal digital assistants (PDAs), and desktops can provide that missing link.

Integration with the existing schedule data was another factor as changes to the schedules were immediately reflected on their website, with no need for manual updating or uploading of data. The system is also characterized by its 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 scheduling system. Results can be sorted by total trip time, a 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 an application underlying a new radio communications system which provides a trove of real-time (or close) trip data for operational metrics and analysis. Using business intelligence tools, this system 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 times 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 times. 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.

5. Methods and Techniques

To understand the impact of important socioeconomic variables and ITIS on transit ridership in the Dallas Area Rapid Transit, this study covers the period between 2007–2017. The analysis considered in this section attempts to explain transit ridership for the combined ridership of rail and bus and studies several independent variables selected based on the literature. The focus is on transit ridership to evaluate the effect of factors on its decline or increase. The analysis attempts to understand the variation of ridership for public transit, considering several independent variables selected based on a

comprehensive review of the theoretical and empirical literature. The analysis for transit ridership is also intended to evaluate the impact of the application of ITIS along with other important variables to develop and explain the monthly transit ridership in DART area in a comprehensive manner with time series monthly data for the ten years.

6. Data and Analysis

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

$$\text{Log } y = \log\alpha + \beta_1\log x_1 + \beta_2\log x_2 + \beta_3 \log x_3 + e \tag{1}$$

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.

$$\text{Log Transit Ridership} = \log\alpha + \beta_1\log\text{Income} + \beta_2\log\text{ITIS} + \ldots +\beta_{24} \log\text{Fare} + e \tag{2}$$

In order to do the research, the null hypothesis (Ho) is usually constructed to make its rejections possible and get the desired result, which is the alternative hypothesis (Ha). However, the alternative 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, hypotheses for the research question are as follows. As fare, income, temperature, precipitation, freeze, and snow increase, transit ridership will decrease.

On the other hand, as gas prices, car trips (congestion), unemployment, poverty, and the ITIS application usage increase, transit ridership will increase. ITIS increases transit ridership because it reduces negative aspects and the cost of using transit through providing information, saving time and other attributes, and makes transit more competitive with the automobile

In this study, the datasets consist of ridership, socio-economic data, 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 study to capture any seasonal changes over this period or roughly few years before the implementation of ITIS transit applications to a few years after. The required data for this study was obtained from a wide variety of sources. The study uses a time-series perspective to examine changes in transit ridership over ten years period in a monthly base to capture the incremental exposure to ITIS technology. Most of the socioeconomic data were found in the Census and the American Community Survey (ACS). The changes in these socioeconomic data impacting the transit system in the DFW area help to answer the research questions. The North Central Texas Council of Governments (NCTCOG) provides objective data and analysis on the development of the 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 the study area and all geocoded information needed for converting some data from other jurisdictions into the DART operation area. The Dallas Area Rapid Transit (DART) provided the ITIS data.

To explore the effect of a percent increase of an affecting variable on the transit ridership, a double-log model was used. 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. Descriptive statistics for the dependent and independent variables are presented in Table 1. The mean transit ridership in DART area between 2007 and 2017 was estimated to be 211,092. The mean rail ridership was 82,225, and the mean bus ridership was 128,866. The ITIS application usage mean was estimated to be 53,280. The mean Car Trips was 20,959, and the mean per capita income was $44,620. The mean Gas price per gallon was $2.74, and the mean Fare was $1.62.

The average temperature was 65.6 Fahrenheit, 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 438,222, and the mean Unemployment rate was 6.3.

Table 1. Descriptive Statistics.

Selected Variables	N	Mean	Std. Deviation
Transit Riders	132	211,092.22	16,688.655
Rail Riders	132	82,225.91	16,801.411
Bus Riders	132	128,866.31	16,882.794
ITIS	132	53,280.69	31,233.763
Car Trips	132	20,959.54	5377.765
Income	132	44,620.42	5119.189
Gas Price/Gallon	132	2.74229	0.654949
Fare	132	1.615	0.1928
Temperatures (F)	132	65.638	16.0895
Precipitation	132	2.7829	2.52864
Freeze	132	1.78	3.541
Snowfall (ASN)	132	0.11	0.403
Poverty (EPP)	132	438,222.73	33,550.477
Unemployed	132	6.2821	1.62116
Valid N (listwise)	132		

Moreover, the assumption of normality was checked to identify if the data were normally distributed (Thode 2002; Wooldridge 2013). Our test of the normality showed that the initial dependent variable, transit ridership, was 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).

The assumption of normality should be tested to identify if the data are normally distributed. The test of normality was carried out, and the normal Q–Q plots were checked. Also, the Kolmogorov–Smirnov and Shapiro–Wilk test was carried. The null hypothesis for this test is that the data were 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 2 describes the results of the test for normality. It shows the *p* values for all transit ridership (LnTransit) are greater than 0.05, which means the data is normally distributed.

Table 2. Test for Normality.

	Kolmogorov-SMIRNOV [a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
LnRail	0.058	132	0.200 *	0.985	132	0.173

* 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 8 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 9. The P–P Plots should show data points falling very close to the diagonal line, and the histogram should form a bell shape. The results in Figure 9 indicate that residuals are normally distributed.
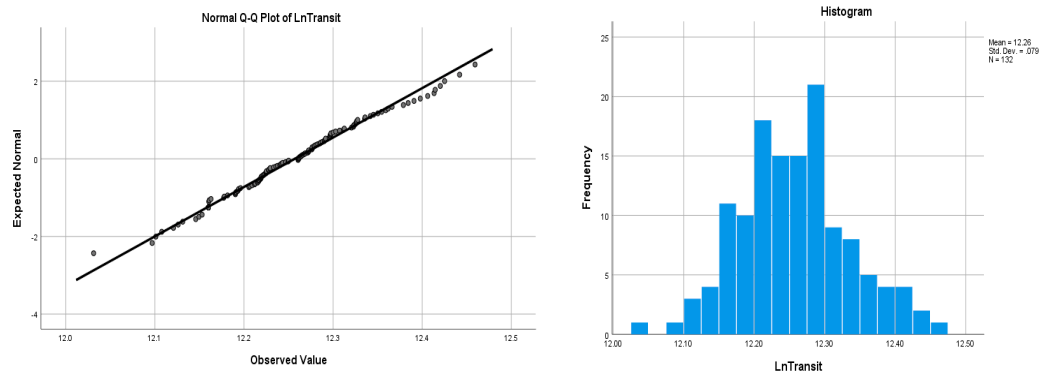
Figure 8. Q–Q Plots (**left**) and Histograms (**right**) of the dependent variable.
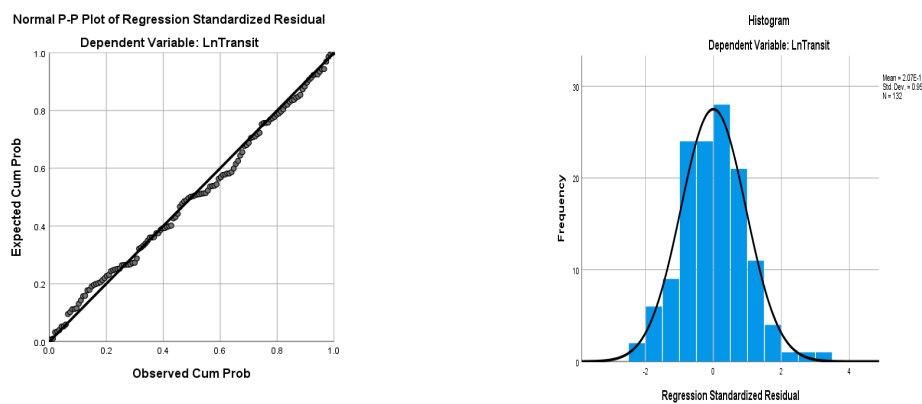

Figure 9. P–P Plots (**left**) and Histograms (**right**) of the dependent variable.

To determine the factors most heavily affecting the transit ridership, a good number of variables were obtained from the literature review for examining their effects on transit ridership. Many independent variables were tested, and models were revisited by both employing different sets of models and variables combinations to find the best model explaining the ridership variable. All needed statistical procedures such as testing for the absence of high degree of multicollinearity was applied; multicollinearity means that two or more variables are highly correlated with each other which means two or more of the independent variables are not independent of each other (Lewis-Beck 1980; Berenson et al. 2009). As a result, some of the independent variables may be eliminated. After testing the VIF, normality, multicollinearity, and homoscedasticity, a modified approach based on Berenson et al. (2009) was utilized to evaluate all possible variables in consideration for affecting transit ridership and to determine the best selection for this purpose. Berenson et al. (2009) employed two criterions to determine the best selection of variables for analysis. 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 10 summarizes the steps devised for the analysis proses.
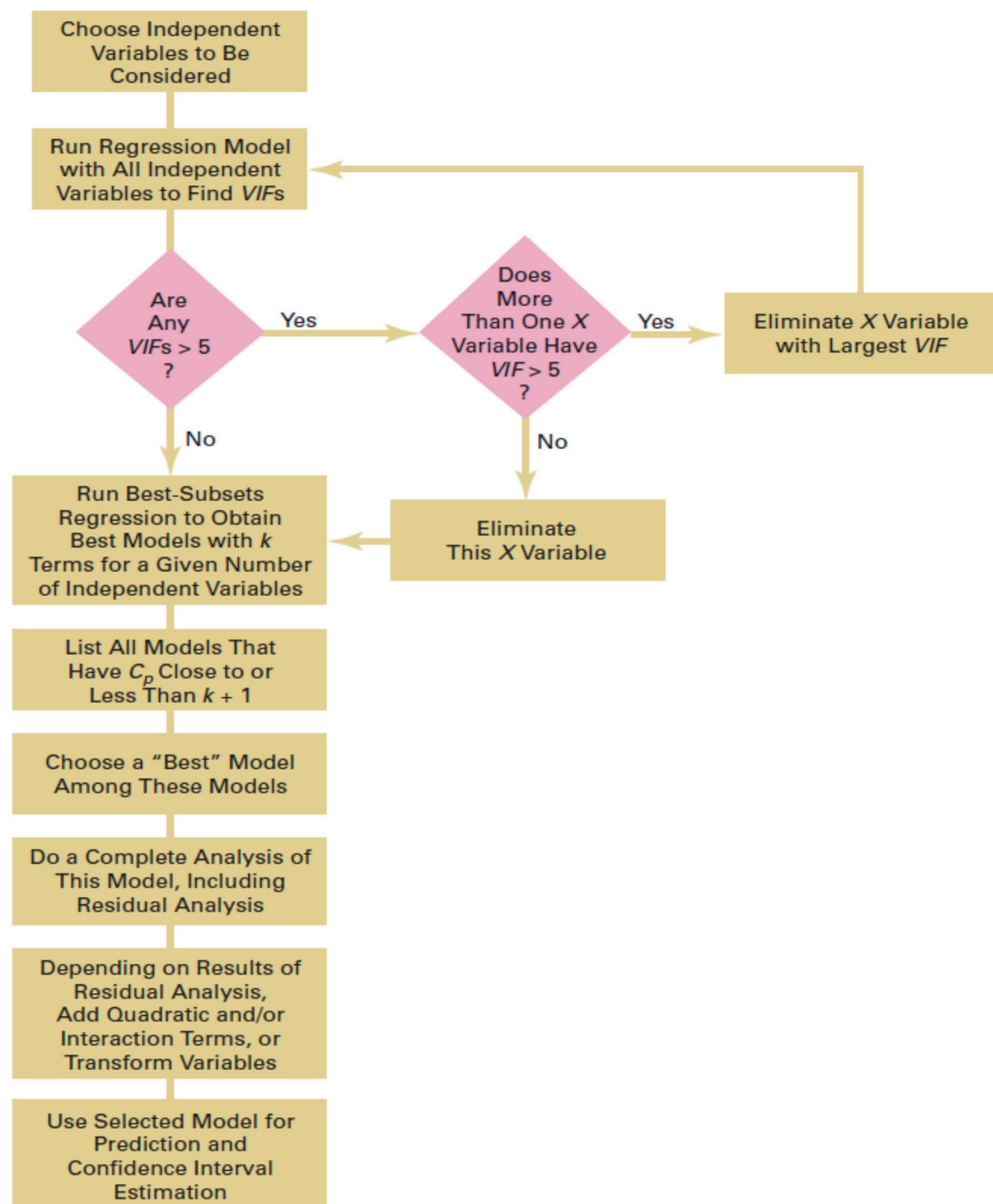
Figure 10. Summary of steps involved in model building. (Adopted from Berenson et al. 2009).

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 3, the model is free of collinearity problems. Also, after running Pearson's correlation tests, the regression model did not have multicollinearity problems.

Table 3. Variance inflation factors (VIF) for the LnTransit.

Model		Collinearity Statistics	
		Tolerance	VIF
	(Constant)		
	LnITIS	0.384	2.521
	LnCarTrips	0.547	1.829
	LnIncome	0.237	3.214
	LnGas	0.534	1.872
1	LnFare	0.636	1.573
	LnTemp	0.470	2.129
	LnPrecipitation	0.930	1.075
	LnFreeze	0.435	2.298
	LnSnow	0.733	1.365
	LnPoverty	0.397	2.519
	LnUnemp	0.635	1.576
	Dependent Variable: LnTransit.		

The results of the analysis were used in a multiple regression model to examine the impact of the independent variables on the dependent variables in the study area. The model was 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, which will lead to a percent increase for the coefficient in the dependent variable (Transit Ridership) between 2007 and 2017.

7. Summary Results

The study as a preliminary study explored the factors impacting transit ridership in the Dallas Area Rapid Transit (DART), and how transit ridership can be increased to determine if policy and/or actions can be taken to improve ridership in the study area. The study examined factors that influence transit usage in the presence of intelligent transit information systems (ITIS). Multiple regression models were formulated to examine the impact of the independent variables mentioned above on the transit ridership as the dependent variable. Results of the model were in accordance with the hypothesis; the statistical analysis found that several of the variables, as well as ITIS, have a significant impact on transit ridership. It worth mentioning that ITIS had a very high effect, which indicated it is an important variable contributing to the increase of transit ridership. The regression model estimates transit ridership between 2007 and 2017 as a function of weather, socioeconomic factors, and ITIS in the study area. The findings below show the significant independent variables which have an impact on transit ridership within the study area.

The results showed a significant positive correlation between car trips, gas price, and poverty with the transit ridership. Several variables had a significant negative correlation with transit ridership, including income, unemployment, and weather-related variables. ITIS app usage in the study area shows a positive correlation with transit ridership. This is supported by some of the available literature that suggests that ITIS reduces the negative aspects and costs of using transit through providing information, saving time and other attributes, which makes transit more competitive with the automobile.

8. Conclusions and Policy Implications

The purpose of this study is to examine the effect of socioeconomic factors on transit ridership to identify variables that could positively affect ridership to help with policy planning and action to increase it in the car-oriented cites of the United States. The study explored the factors influencing

transit ridership in Dallas Area Rapid Transit (DART) as a case in car-oriented cities, and also examined the effect of intelligent transportation information systems (ITIS). The study identified major factors through a comprehensive review of literature, use of an innovative process which assisted the selection of the most significant variable, and a time series regression mode to study the effects of variables in the study area between 2007 and 2017 through use of monthly data.

Some of the significant variables through the findings have major policy implications. For example, the study showed that poverty has a positive correlation with transit ridership. This correlation means that as poverty increases, ridership increases. This finding suggests that poor individuals are most likely to choose public transportation for access to employment and other household necessities in an urban setting like the study area. Since the demand for transit is higher for the low-income population who also had to cut from their other living expenses to afford transportation, it behooves that transit should be subsidized for the low-income population. This is also supported by the findings that, as expected, fare price has a negative correlation with ridership and was statistically significant, which conforms to existing literature and suggests that as fare increases, ridership decreases within the study area. It also is in line with findings that 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 necessities, a further justification for the subsidy.

Finally, the ITIS app usage in the study area shows a positive correlation with transit ridership; as the ITIS app usage increases, transit ridership also increases. This is supported by some of the available literature that suggests that ITIS reduces the negative aspects and costs of using transit through providing information, saving time, and other attributes, that makes transit more competitive with the automobile. The results showed that ITIS has been affecting transit ridership, and it showed that ITIS contributed to a significant increase in transit ridership; as people got to know about the availability of the service and used it more, the ridership increased. The implication is that transit organizations investments in intelligent transportation information systems and furthering its capabilities is warranted and should be encouraged. It reduces the negative aspects of using transit for consumers.

As was mentioned, this study was a preliminary exploration of the determinants of transit ridership, and further study need to overcome the limitations of this study. Future research needs to further detail the ridership study and improve the findings. More importantly, the breakdown of the ridership by transit modes could shed light on the effect of important identified factors on different transit modes.

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