THE EFFECT OF LIGHT RAIL TRANSIT ON EMPLOYMENT: A CASE STUDY OF DALLAS, TEXAS

A Thesis

by

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ABSTRACT

The decentralization of residents and jobs from central cities has greatly impacted low income residents as they have remained in the central city while employment opportunities are locating further away. This trend has negatively impacted the employment participation of these residents, worsening their economic situation. Public transit may mitigate this issue by providing direct employment connections to residents and creating employment opportunities through the stimulation of development in the area. This can help attract more jobs into the central city, while potentially increasing the employment opportunities for low income residents.

This study aims to investigate whether proximity to light rail transit influence total employment and various types of employment opportunities by comparing longitudinal employment data within ¼ mile of Dallas Area Rapid Transit (DART) light rail stations to those in the control groups identified through the propensity score matching technique. The propensity score matching method was utilized in an attempt to obtain an adequate control group within the analysis and estimate the influence which proximity to transit has on employment. Additionally, multi-linear regression was integrated into the analysis act as a second level of analysis in the estimation of the influence which proximity to transit has on employment. Although differences in employment were found between areas in close proximity to transit versus comparable areas located elsewhere, it was not found that proximity to transit had a positive or negative influence on employment. The results did not support the stated hypotheses as

no significant influence was obtained through this analysis. As seen by these results, the presence of transit does not automatically induce development; certain policies have to be in place in order to encourage it to occur.

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NOMENCLATURE

ATT	Average Treatment on the Treated
CBD	Central Business District
DART	Dallas Area Rapid Transit
GDP	Gross Domestic Product
LODES	Longitudinal Employer-Household Dynamics
MSA	Metropolitan Statistical Area
TANF	Temporary Assistance for Needy Families
WMATA	Washington Metropolitan Area Transit Authority

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1. INTRODUCTION

The decentralization of residents and jobs from central cities has greatly impacted low income residents as they have remained in the central city while employment opportunities are locating elsewhere. This trend has negatively impacted the employment participation of these residents, worsening their already grim economic situation. Policymakers have attempted to mitigate the negative impacts associated with decentralization through the implementation of transit projects (Belzer et al. 2002). Transit may help alleviate this situation by improving the mobility and economic state of this population. This is accomplished as transit serves as an affordable mode of transportation which connects residents to various potential employment opportunities throughout the city. These projects can further improve economic conditions within a city by creating desirable sites for future development. This induced activity needs to be further examined in an attempt to further understand the economic impact associated with transit projects.

Multiple studies have shown that transit does not significantly improve the employment participation of low income residents located within the central city (Cooke, 1996; Ellwood et al. 1986; Thompson et al. 1997; Sanchez, 1999; Sanchez et al. 2004). Although transit can lead to economic development, this development does not seem to positively impact low income residents. Employment opportunities which can arise from this development may not be adequate for low income residents. For this reason, the change in commercial real estate in areas in close proximity of transit lines need to be further studied in an attempt to determine how transit impacts the types of jobs made available in the area (Kahn, 2007).

The purpose of this study is to better comprehend the economic impact which transit can have in a community. This will be done by utilizing the Dallas Area Rapid Transit system (DART) as a case study. Employment change for areas within a ¼ mile of newly constructed transit lines will be measured in order to approximate the influence which transit can have on employment growth. Additionally, employment change by industry and earnings are analyzed in an attempt to investigate how employment opportunities suitable for low income residents have changed. The desired result of this study is to better comprehend the economic impact of transit in regards to development and in terms of opportunities for low income residents.

2. LITERATURE REVIEW

2.1 Sprawl

2.1.1 Evolution of Urban Form

City form has evolved from the once dominant monocentric form to the now prevalent sprawling communities. The advancement of transportation helped spur sprawl as it made it made it possible for certain residents to escape the problems of the city and reside in the periphery. The dependence on horses and walking in the 1800's encouraged a compact city form as the necessities of everyday life were located within walking distance (Hensen et al. 2004). The central node of the city contained the majority of economic activity as it was a hub for employment and commerce (Rodrigue et al. 2006). The desire to be located in close proximity to work led many residents to locate as close to the city center as possible. This was seen as advantageous as it reduced their commute. This decision caused many issues as it exposed low income residents to the hazardous conditions produced by industrial sites in the area (Hensen et al. 2004). Population densities within cities were very high during this period, until the streetcar was introduced in the late 1800's.

Streetcars served as the one of the first modes of mass transit in the United States. They predominantly ran on electricity and had a greater capacity than previous modes of transportation. Streetcar lines extended out from the city center into the country side. This created corridors in which communities sprawled to. This territory was desirable as it provided residents the opportunity to escape the deteriorating conditions of the city while not losing access to the necessities located within. Streetcars provided a more reliable mode of transportation while also increasing speed. This led to the expansion of the once monocentric city form into a longitudinal form as the city expanded along these transit corridors (Hensen et al. 2004). Commercial activity began to spread to these corridors which influenced many more residents to migrate into these sprawling communities. These communities largely consisted of middle to upper class residents as the limited resources of the lower class forced them to stay in the city center.

Decentralization was exacerbated as the invention of the internal combustion engine led to the automobile era. It was during this time in which urban form changed radically. Although only the wealthy, initially, were the only residents who could afford a private automobile, the development of the assembly line system helped produce affordable vehicles which more of the population could afford (Hensen et al. 2004). This increase in mobility by middle and high income residents led to the creation of many low density suburb communities which were located even further away from the city center. The road infrastructure did not allow residents to stray too far from the city as it was not fully developed and dependable at the time. Wooden planks atop dirt roads were utilized in order to travel without the risk of getting stuck in the mud. Issues like these were later addressed as President Dwight E. Eisenhower made it a priority to improve the nation's transportation network (Hensen et al. 2004). Utilizing the autobahn as inspiration, he set out to create a network of highways which reached coast to coast. The construction of a national highway system greatly improved individual mobility and accessibility, and made it possible for residents to live further away from the once vital city core. This led to both residential and employment decentralization as several sub-centers emerged in order to serve these new suburban communities. Again, this evolution of the transportation system predominantly benefited middle to upper class residents as they were most able to relocate further from the city core. Many of the homes constructed in these suburbs were built on large lots which made them unaffordable to low income residents (Ihlanfeldt, 2007). As auto dependency grew within this nation, so did the rate of decentralization. The city core lost some of its influence as economic activity followed the migration of residents into outlying communities, creating a multimodal form.

2.1.2 Current Trends

For many of today's cities the central business district (CBD) is no longer the dominant economic hub it once was. The migration of residents and economic activity has led to the creation of many activity centers outside of the city, leaving the city with vacant land (Gardner et al. 2013; McKenzie 1925). The once dominant retail and commercial activity centers within the city now have to share their distinction with suburban areas (Berechman et al. 1996; Gardner et al. 2013). This move of employment opportunities was influenced by the redistribution of the population caused by sprawl. High and median income residents leaving the central city for the suburbs led to the concentration of low income residents in the urban core. Employment shifted outward as some employers went out of business or moved, while new firms selected the suburbs as their desired location (Bederman et al. 1974). During this time many employment opportunities which were once found in the CBD were dispersed in suburban locations outside of the city. The average distance between a central city resident's home and potential employment opportunities began to increase substantially during this time (Holzer, 1991). Specifically, many employment opportunities which are appropriate for low income residents began to locate in areas unreachable by this population. The location of employment opportunities in the retail industry are influenced by residential location, which is largely occurring in suburban areas (Alsonso, 1960; Ding 2000). An example of this decentralization can be seen in in the City of Chicago. Chicago has experienced employment loss in much of the city while suburbs located 10 to 30 miles from the CBD have experienced substantial growth in employment (Kawamura, 2001).

The extent in which decentralization is occurring can be demonstrated by current commuting patterns. What was once a dominant pattern of commuting from the suburbs into the central city has evolved into a suburb to suburb commuting pattern (Pisarski, 1987; Baldassare, 1992; Gardner et al. 2013). This trend has continued as the 2000 Census showed that suburb to suburb commuting accounted for 46% of journeys to work within metropolitan areas and the traditional suburb to central city commute only accounted for 19% of journeys to work (Pisarski, 2006). This shift in commuting patterns shows the extent in which economic subcenters found in suburban areas can adequately serve residents. It seems as if the economic activity found in the suburbs can compete with that of the central city in certain areas. This shift in economic activity can impact the residents in the central city in many ways. The weakening of the economic base of a city can lead to its deterioration as vacant properties emerge as businesses move to the suburbs. The loss of this economic activity, in addition to the increase in vacant land, can negatively impact the tax revenue produced by a city. Property values suffer due to increased vacancies and the loss of economic activity. This decrease in revenue translates into a decline in public services available to inner city residents (Ding, 2000).

There are several characteristics which many of today's cities share in regards to urban form and decentralization. These characteristics are that 1) job growth is occurring predominantly outside of the central city, 2) low income residents are largely concentrated within the central city, and 3) there are large disparities between the employment and earnings of low income residents and the suburban population (Ihlanfeldt, 2007). The spatial mismatch theory emerged as a way to explain the cause of low employment participation of inner city low income residents. This theory attributes the low employment participation to the fact that there is a mismatch between housing location and location of entry level retail and service jobs (Yi, 2006; Kain, 1968). Many of these employment opportunities are locating in the suburbs while the labor force which can fill them are concentrated in the central city. This highly influences the employment participation of low income residents located in the central city, as they do not have the resources to meet the travel requirements necessary to reach these employment opportunities (Sanchez, 1999). The City of Atlanta can be utilized to illustrate the spatial mismatch between low income residents and potential employment opportunities in the suburbs. According to the 2010 Census, African-Americans compose 32.4% of the total population of the metropolitan area but account for 54.0% of the population within the City of Atlanta. This demonstrates the extent of spatial mismatch which is occurring between disadvantaged populations and employment opportunities in the suburbs. That, coupled with the declining opportunities available within the central city, can greatly impact the employment participation and economic situation of low income residents.

2.1.3 Decentralization

Decentralization can have many negative impacts on a community and its residents as it can lead to increased infrastructure costs, loss of agricultural land and open space, transportation congestion and inflating housing costs (Freilich, et al. 1993). Some of these impacts influence certain populations more than others. The decentralization of employment has greatly influenced the employment participation of low income residents of the central city. Jobs are locating in the suburbs and the lack of accessibility to these opportunities has led to high unemployment rates for low income residents (Giuliano, 2005; Stoll 2005). Low income residents simply cannot reach employment opportunities which are located in outlying areas due to their lack of mobility (Sanchez, 1999; Yi, 2006). A study focusing on 300 metropolitan statistical areas (MSAs) found that employment sprawl is positively and significantly correlated with mismatch conditions for African-American residents (Stoll, 2005). This finding supports the theory that sprawl is characterized by great levels of spatial mismatch between African-Americans and employment opportunities. Decentralization seems to increase the spatial isolation of low income residents as they are not able to access the employment growth occurring in the suburbs (Stoll, 2005). Cervero found similar results as he discovered substantial spatial mismatch between relevant employment opportunities and low income neighborhoods located in the San Francisco bay area

(Cervero et al. 2000). The suburbanization of relevant employment opportunities to the suburbs is not the only factor contributing to the low employment participation of low income residents. The types of employment opportunities remaining in the central city also play a major role. Employment opportunities have remained within the central city, but they largely consist of managerial and information processing services (Sanchez, et al. 2003; Sanchez, 1999). These employment opportunities are in close proximity to low income residents but they do not serve as a viable source of employment. Low income residents do not have the educational attainment or skillset necessary to take advantage of these opportunities (Kasarda, 1983; Wachs & Taylor, 1998). This creates a surplus of low skilled workers in the central city while only a limited amount of jobs adequate for this population are present. Following the supply and demand model, low skill employment opportunities within the central city will decrease their wages due to the surplus in available workforce (Ihlanfeldt, 2007). This situation would worsen the economic conditions of inner city low income residents as the few which have employment would be earning a lower wage than those in comparable positions located in the suburbs. One method to help resolve this issue is to attract employment opportunities back into the central city which could then be potentially filled by low income residents. An alternative strategy is to increase the mobility of low income residents in order to increase the number of employment opportunities available to them, and ultimately improving their economic situation. The implementation of transit projects could do both while mitigating some of the negative impacts produced by decentralization.

2.2 Transit

2.2.1 The Role of Transit

The civil unrest of the 1960's led the Johnson administration to form the McCone Commission. The responsibility of the McCone Commission was to determine the cause of riots which were occurring nationwide within low income neighborhoods of central cities. It was discovered that inadequate public transportation contributed to the high rate of unemployment within these communities (Kain & Meyer, 1970). This finding has spurred discussion about the relationship between employment and mobility. Policymakers have since attempted to address employment within these low income communities by enhancing their mobility through the implementation of transit services (Blumenberg, Ong, and Mondschein 2002; Yi, 2006).

The rate of sprawl within the United States is rapid as metropolitan areas are expanding at twice the rate of population growth (Belzer et al., 2002). This trend can potentially worsen the economic situation of residents of the inner city. One method in which to mitigate any negative impacts of sprawl is to construct a transit system which can increase the mobility of the inner city poor, while also attracting employment opportunities to the central city. The market for transit is strongest in the central city as it has many of the characteristics necessary for such a system to succeed (Giuliano, 2005). The high densities in the central city as well as the high number of transit dependent residents would produce a substantial amount of potential transit users. The high cost of parking and high rates of congestion which are found in the central city can influence the ridership of such a system in a positive way (Giuliano, 2005). Transit does not only make jobs located outside the central city accessible but it can also encourage job growth within the city itself. Light rail transit can stimulate growth, effect land uses, promote redevelopment, and increase property values, as it is seen as a permanent investment in a fixed location (Cervero, 1984; Cervero and Sullivan 2011; Crampton 2003; Filion and McSpurren 2007; Handy 2005; Geller 2003; Marstens 2006; Litman 2011). Transit can be a magnet for economic activity as it improves regional access which often leads to the clustering of new development around stations (Cervero, 1984). This can assist the deteriorating urban core to regenerate as new development and increasing property values return. With this new development comes the infusion of employment opportunities which can be serviced by the inner city work force.

Constructing a transit system can be very costly and the pressure to cut government spending can reduce the probability of such systems being implemented. One method which can alleviate some of the financial burden of constructing and operating a transit system is the possibility of entering into a public-private partnership (Cervero, 1984). The increased property values of land adjacent to transit projects can experience an increase in property values as it becomes more desirable for development. Transit and governmental agencies can take advantage of this situation by entering into partnerships with private entities which would decrease their construction and operating costs. Allowing density bonuses or tax breaks in exchange for financial assistance in the construction, operation, or maintenance of a transit system is a common strategy. The Washington Metropolitan Area Transit Authority (WMATA) demonstrated how the benefits of transit can be utilized to cover large costs. The WMATA began to aggressively purchase land around potential transit nodes. When the transit system was eventually completed the WMATA leased the land which they had previously purchased to private parties. The revenue collected on this strategy amounts to six million dollars a year (Topalovic et al. 2012). Municipalities collect revenue in other ways as well, like in the form of property taxes.

The development which is spurred by transit is desirable by municipalities because it is dense and can help reshape a region. High density development is classified as being "smart growth" and has been advocated for by many communities (Belzer et al. 2002). This type of development is not guaranteed to occur simply by constructing a transit system as there is a need for complimentary factors to be present in order to help stimulate this level of economic development. In many instances, local policies are present in order to stimulate such economic growth. Incentives in the form of land use change, tax breaks, and joint development are important in attracting development to inner cities (Cervero, 1984). The availability of land is also important in attracting development although decentralization has left vacant land in the inner city. These complementary factors can assist in attracting appropriate development in areas serviced by transit. Transit can then be utilized to calm the exodus of employment opportunities from the inner city through the development which it encourages within its service areas. The city of Buffalo, NY did just that as it utilized light rail as a tool to reverse the suburbanization of retail jobs (Cervero, 1984). Transit can be utilized as an effective tool in combating the negative impacts of sprawl. A study investigating the impact of transportation subsidies on urban sprawl found that public transit subsidies reduced sprawl while auto travel subsidies increased it (Su et al. 2008). Transit has a greater impact in encouraging compact development and mitigating the negative impacts of sprawl than other alternatives. The federal government has supported light rail projects during the past decades, in part, due to the benefits which are associated with such projects.

2.2.2 Legislation

Public transit is considered to be an efficient connector between low income households located within the central city and suitable entry level jobs which are located in outlying areas. The Intermodal Surface Transportation Efficiency Act of 1991 was enacted in order to improve the connections between low income residents and potential sources of employment. The majority of previous legislation largely focused on providing funding for road projects, specifically the national highway system, while ignoring other modes of transportation. This strategy did not prove helpful to low income residents as the majority do not own automobiles. This legislative act deviated from the previous by providing significant funding for alternative modes of transportation, in an attempt to create a multi-modal transportation network (U.S Department of Transportation, 1991). This increased the amount of funding made available for transit projects, which better served low income as a feasible mode of transportation. The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 was one of the first legislative pieces which solely focused on improving transit services as a means to address the unemployment problem of the inner city poor (Cervero et al. 2002; Yi, 2006; USDOT, 1998; Willis, 1997). The federal government continued to focus on addressing unemployment through legislation as the Balanced Budget Act of 1997 provided funding for the transportation needs of welfare recipients while the Transportation Equity Act of 2001 improved transit services to low-income individuals for commuting and employment-related travels (Sanchez, et al. 2004). In 2005, the Safe, Affordable, Flexible, Efficient Transportation Equity Act continued this trend and provided authorized a total of $727 million for grants which focused on enhancing employment transportation connections (Sanchez and Schweitzer 2008). These series of legislations have all stressed the importance of transit in improving the employment of low income residents. Transit projects present large expenditures so it is valuable to understand the job-accessibility benefits associated with such projects. This can assist policy makers in making better decisions when it comes to strategies on how to construct an equitable transportation system (Fan et al. 2012).

2.2.3 Development Stimulation

Aggressive commercial development can occur within areas in proximity of transit and could ultimately influence the employment participation of inner city residents. The Ballston district in Arlington, VA was once a small commercial district but since the opening of a light rail line connecting it to Washington D.C it has evolved into a thriving commercial node (Cervero, 1992). High rise development is dominant as major redevelopment has occurred in this area. Significant transformations like this can occur but is dependents of supporting land use. In many cases land use is changed in order to accommodate the desired development around transit projects. A study focusing on land use around the Bay Area Rapid Transit (BART) system found that lots located within station service areas were more likely to change land use than those located outside of service locations (Landis et al. 1995). This higher likelihood in land use change can expedite and encourage development in these areas and increase employment as a result. The significance of having the appropriate conditions in order to stimulate development can be seen in the case of Portland, OR. The CBD in Portland was experiencing high vacancy rates and declining retail centers. The city then constructed a light rail system which vastly improved economic conditions. Downtown office vacancy rates declined to levels which surpassed those found in the suburbs while rent in the area also began to increase. Growth has occurred so rapidly and aggressively in downtown Portland as areas surrounding downtown stations have experienced over 2 billion dollars in development (HDR, 2005). The level of impact which transit can bring in terms of economic activity can vary but cities which have successfully implemented light rail transit services have reported an increase in economic activity, development, and increased employment nodes (Crampton, 2003; Topalovic et al. 2012).

This growth which is occurring in the central city has mitigated the exodus of employment while experiencing higher growth rates than suburban locations. Areas serviced by transit have been found to develop quicker than areas not in the service area. In Atlanta it was found that areas within the service area of the transit system experienced twice the amount of employment growth in comparison to sites located elsewhere (Bollinger et al. 1997). The same was found in Los Angeles as areas serviced by the BART system accounted for 57% of the total employment growth within the three county area which the system intersects (Cervero et al. 1999). Much of the growth which occurs seems to be concentrated in certain locations. Areas which seem to be most desirable are located near transit stations downtown or in the central business district. This has led to a shift in which employment opportunities are now locating within the central city at a higher rate than anywhere else. Within the past two decades, businesses within the City of Chicago have migrated to areas in close proximity to transit (Kawamura, 2001). This can ultimately assist in the reestablishment of the central business district and improve the employment participation of inner city residents. This could ultimately improve the economic situation of this inner city poor as median neighborhood incomes have been shown to rise in newly transit accessible communities (Heres et al. 2014).

2.2.4 Firm Location Decision

It is evident that the presence of transit can spur development but it is necessary to know what in particular attracts businesses to locate in these areas. Several factors can influence the location decision of a business. It is essential to understand the factors which can influence this decision in order to assure that these factors are taken into consideration when developing a transit system. This is necessary as one of the greatest impacts a transit project can have is the development of new employment opportunities. In many instances, decision makers justify the construction of new transportation infrastructure with the theory that this expenditure will lead to the attraction of employment centers (Kawamura, 2001). It is necessary to note that the presence of transit alone is not enough to induce development. Certain policies need to be in place which complement transit, in order to maximize the benefits associated with such projects.

Classical industrial location theory, developed by Alfred Weber, theorized that firms decided where to locate based on the location which minimized their costs of production at optimal level (Kawamura, 2001). The evolution of this location theory integrated transportation costs and is still is prevalent today. A study which examined the factors influencing business location decisions found that cost is the primary factor considered but accessibility a major influence as well (Wendt, 1972; Karakaya et al. 1998). Transit does increase the accessibility of those entities located within its service area and could be an attractor for many businesses. Many firms which wish to locate within the urban core value access to rail stations while those which locate in the suburbs are more attracted to locations in close proximity to highway ramps (Kawamura, 2001). This demonstrates how much businesses value accessibility, regardless of their location. Proximity to transportation infrastructure can also benefits businesses in other ways. Transportation infrastructure has the ability to enlarge a market and attract many businesses into a location (Karakaya et al. 1998). Businesses named several key benefits which they obtain when locating near transit. These benefits are that they are close to customers, in a growing area, have exposure to potential customers, and that customers and employees can reach their location via transit (McQuaid, 2004).

Transit, especially when located in the urban core, can influence development as it facilitates high density construction (Weisbrod et al. 2009). High density is even more highly concentrated around transit stations as these are the areas are more desirable for development due to their improved accessibility (Kawamura, 2001). This concentration of development can have benefits of its own for many businesses. The concentration of businesses can evolve into an economy of agglomeration. This can benefit certain businesses as they would attract a large and skilled labor market which can adequately fill their necessities. Businesses would also have the advantage of accessing a broader customer base as they, as a collection, can more efficiently arrange for necessary resources (Weisbrod et al. 2009). In general, many of the benefits which are associated with economies of agglomeration would be present for businesses highly concentrated in these locations. The construction of a transit system would not only benefit businesses clustered around its stations but also to those located within the city. Investing in public infrastructure can improve mobility and expand service, which is of benefit for all. The reduction in congestion which could occur can positively influence the productivity of businesses, regardless of their location. Manners in which these benefits can manifest themselves are in the form of greater business revenue, total gross domestic product (GDP), and an increase in total employment (Weisbrod et al. 2009). These benefits can translate over to the general economy and produce major employment and economic centers. Investment in transit can be advantageous as it can produce several diverse benefits. The return of such investments can greatly surpass the initial costs as Weisbrod found that every $1 billion annual investment in public transportation can result in more than $1.7 billion of net annual GDP (Weisbrod et al. 2009). Utilizing transit as a method to not only increase mobility but to encourage development seems to be an efficient strategy. Transit has proven to attract development into an area while creating conditions in which businesses can thrive.

2.3 Employment Impact of Transit

2.3.1 Potential Impact

The integration of transit into the transportation network can influence various aspects of a community and its population. A transit system can enhance the economic situation of residents as it can provide access to employment opportunities located outside of the core while also attracting employment to locate around its corridors. Transit also improves mobility for residents within the city. This can be crucial as there are large concentrations of residents within the urban core which have limited transportation options. When suburbanization was occurring, residents with limited mobility were not able to relocate outside of the city. This population is still concentrated in the urban core and is largely composed of senior citizens, minorities and low income residents (Baum-Snow et al. 2005). This population is less likely to own an automobile as parking and insurance costs can be great. There are also some policies in place which make it more difficult for low income residents to improve their mobility. Welfare recipients are not allowed to own a vehicle which is valued at more than 4,600 dollars. This restriction leads these residents to purchase automobiles at a low cost. Vehicles which meet these criteria are usually older and less reliable. Maintenance for such vehicles can also be costly, which makes it less desirable for this population to acquire an automobile (Yi, 2006). The difficulties associated with getting an automobile for low income residents in reflected in their auto ownership rates. According to the

National Household Transportation Survey, 17% of low-income households and 30% of poor households do not own a private automobile (Fan et al. 2012). This is a disadvantage for this population as sources of employment are limited to areas near their home. The construction of a transit system could provide access to areas of a city once unreachable to populations with limited mobility. Previous employment opportunities which where once located in auto oriented locations become accessible through transit use (Belzer, 2011).

In areas in which transit systems have been implemented, it has been found that the majority of users are composed of residents with limited mobility. Low income and minority residents were found to compose roughly 55 % of transit users in a system (Sanchez et al. 2003). This revelation shows how transit systems can adequately serve populations with limited mobility while also showing how this population could help support transit through ridership. Transit can then not only serve as an additional mode of transportation but also as a means to address poverty, unemployment, and equal opportunity goals (Blumenberg and Manville 2004; Rast 2004). Transit could not only be utilized to attract new development but also to enhance the mobility of residents. This increase in mobility can translate into new economic activity through time savings or the enhanced connection to potential job centers (Baum-Snow et al. 2005; Bederman et al. 1974). This can greatly impact inner city residents as the new opportunities available to this population can ultimately allow them to better their economic situation.

2.3.2 Case Studies

Although the majority of transit users are low income residents, previous studies have shown that proximity to transit does have a positive impact on employment participation for this population. This is surprising given the positive impacts in terms of mobility and accessibility which transit can bring. Transit can also stimulate development along its corridors which can produce employment many opportunities. It has been anticipated that transit could then alleviate the underemployment of inner city residents (Bederman et al. 1974). Regardless of the benefits associated with transit, this has not been the case. Thompson found a weak relationship between employment participation and proximity to transit when analyzing the impact of the transit system in Miami, FL on employment of low income residents (Thompson, 1997). Similar results have been found in a variety of different studies. The role of access to public transit for Temporary Assistance for Needy Families (TANF) recipients in gaining employment or getting off the welfare program in six metropolitan areas was analyzed. What was found was that access to public transit and job accessibility by transit played no significant role in explaining the employment status of TANF recipients (Sanchez et al. 2004). Job access was found to have no significant effect on the labor participation of low income residents in Boston while similar results were found in Chicago (Cooke, 1996; Ellwood et al. 1986). Research studies have not fully explained the impact that transit has on employment outcomes as there have been various conflicting results produced (Yi, 2006). It is difficult to explain how increasing the mobility of low income residents does not increase their employment participation as they now have access to geographic areas that were once unreachable. The development which is occurring in close proximity to transit can potentially influence the impact which transit has on employment opportunities for low income residents. This activity is spurred by changing property values in areas newly serviced by transit and can lead to the movement of employment opportunities which are appropriate for low income residents to other locations. The same consequence can occur in regards to housing opportunities for low income residents as the increasing property values in areas serviced by transit can diminish the affordable housing stock in that area. The impact which increasing property values can have on this analysis is taken into consideration.

2.3.3 Influence on Property Values

One potential negative influence which transit can have on employment participation for low income residents is associated with its effect on property values. The construction of a transit project can have a significant impact on property values of areas located in close proximity. This is due to the many benefits which are associated with such a system. Transit can improve the mobility of residents so many wish to locate within the service area of a transit system. This increases the desirability of properties located in close proximity to transit. Locating in these properties can decrease commuting costs for residents as they can avoid the congestion which is affiliated with automobile use in the central city. This substitution in transportation modes can result in travel time savings as commute time can be reduced (Diaz, 2009; Kahn, 2007). Transit can hypothetically shrink the distance from ones place of residence to their employment location through travel time savings and the reduction of commuting costs (Vessali, 1997). The benefits associated with transit are not only relative to employment but touch on various aspects of resident's lives. Transit can improve the accessibility to retail and recreational activities as well (Vessali, 1997). Impacts associated with the improvement of accessibility are affiliated with the extent of the transit system but they tend to be positive. Generally, transit significantly improves regional accessibility and this improvement is usually reflected by the increase in property values within transit service areas (Cervero, 1992).

Transit is highly valued amongst households, especially when compared to other amenities and services (Gibbons et al. 2004). Properties in close proximity to transit tend to have higher property values than similar properties located in areas not serviced by transit (Voith, 1991). Although there are some nuisances produced by transit, such as noise and traffic, there tends to be a net benefit on property values which surpass the impacts of any nuisance produced (Diaz, 1999). Land value increases can occur before construction begins as the anticipation of the associated benefits which may arise is considered (Hess et al. 2007, Topalovic et al. 2012; McMillen et al. 2004). The desire to locate near transit can spur the development of vacant land near the proposed system. This conversion of vacant land into development has its own impact of increasing the property values of properties in the vicinity of transit (Diaz, 1999). This increase in property values can come in the form of increased rents, sales price, and median home value (Diaz, 1999). There are several examples throughout the United States which demonstrate the impact which transit can have on residential property values. Table 1 summarizes the impact which several transit systems had on property values in their own community. McMillen found that properties in proximity to transit experienced a 6.89 percent appreciation in value when analyzing the impact a newly constructed transit line had on property values in the city of Chicago (McMillen et al. 2004). This study focused on a newly opened line which provided service to the Southside of Chicago which is composed predominantly of low income neighborhoods. Cervero found a similar impact on property values as he found that properties adjacent to the Bay Area Rapid Transit System (BART) in California sold for 38% more than properties in areas not serviced by transit (Cervero, 1996). Median home prices were also found to be greater for properties in proximity of a newly constructed light rail line in both New Jersey and Philadelphia (Voith, 1991). This increase in property values can be great for a city as it will result in higher property tax revenue. This impact on property values could be a negative for some segments of the population as it could limit the opportunities they have.

Table 1 Summary of Impact on Residential Property Value

Author	Location	Impact vs. Comparable Properties
Bajic, 1983	Toronto, ON – Spadina line	$2,237 avg. premium for homes in close proximity of transit
Voith, 1991	PATCO System– New Jersey	Median home price for census tracts immediately served by the rail line were generally 10% higher
Voith, 1991	SEPTA System – Philadelphia	Avg. median home price for census tracts served by SEPTA enjoy a 3.8% premium
Nelson, 1992	Atlanta, GA – MARTA East Line	$1,000 increase in home price per 100 ft. closer to transit
Al-Mosaindt et al. 1993	Portland, OR	10.6% increase in property values for homes located within 500 meters of transit
Gatzlaff et al. 1993	Dade County, FL - Miami Metrorail	5% appreciation rate increase in property values

Table 1 Continued

Author	Location	Impact vs. Comparable Properties
Cervero, 1996	BART system – California	Homes adjacent to BART would sell for close to 38% more
McMillen et al. 2004	Midway Line – Chicago, IL	6.89 appreciation in values for properties in proximity to transit
Duncan, 2008	San Diego, CA	+10% increase in condominium property value
Pan, 2013	Houston, TX - MetroRail	Significant increase in property values for residential properties outside ¼ mile radius of transit stop

As shown in the examples above, increased property values can result in increased rents for areas in close proximity to transit. This can have a negative impact on low income residents as they are less likely to be homeowners and rely on rental properties for residence. The increase in rental prices can force low income residents to relocate further from transit. This can result in pushing the people who depend on transit the most to areas not within the service area of a transit system. This could mitigate the positive impacts of transit on mobility for low income residents as they can no longer afford to live in areas in which they could take advantage of this resource. This change in property values can drastically change the character of a community. This change could result in gentrification as only median to high income residents would be able to afford to live in these areas. An example of how drastically a community can change is found in Fairfax County, Virginia. A transit line which connected this area to Washington D.C was constructed which led to major redevelopment in that area. A developer of a nearby residential neighborhood proposed a plan to demolish 61 single family homes, currently present, in order to construct luxury condo towers which ranged from \$500,000 to \$800,000 in value (Kahn, 2007). The plan was approved by the city council, although it greatly changed the character of the community, and did not offer affordable housing options for low income residents. Developers want to capitalize as much as possible on the increased activity which can result from the implementation of a transit project. This desire to maximize benefits can greatly impact the character of a community, leaving low income residents out of luck. This impact on property values can potentially influence the employment participation of low income residents. This increase can mitigate the increased accessibility produced by the system as they are forced further from service area. Development is attracted to transit, which could serve as employment opportunities for low income residents, but the impacts of transit can push low income residents further from its service area. This phenomenon can mitigate the positive impact of transit for low income residents as they can't reach the system which is attracting all of these opportunities.

2.4 Propensity Score Method

This study uses propensity score matching methods as the analytical technique. In this study, a propensity score is calculated for each census block group. This score measures the probability of receiving a treatment based on observed baseline covariates (Heinze and Juni, 2011; Rosenbaum and Rubin, 1983). This score is determined through a logistic regression in which the treatment variable acts as the dependent variable and the confounding variables act as the independent variables. Once propensity scores are calculated it is then possible to match observations in the treatment group with those in the control group. These matched observations should then theoretically have similar distributions of baseline covariates (Heinze and Juni, 2011). This makes it possible to better measure the treatment effect as similar observations with differing treatment alternatives are compared.

Propensity score matching has been used in many disciplines such as statistics (Rosenbaum, 2002; Rubin, 2006), epidemiology (Brookhart et al., 2006), sociology (Morgan and Harding, 2006), economics (Imbens, 2004), political science (Ho et al., 2007) and more recently in urban planning (Cao and Fan, 2012; Funderburg et al., 2010). This method is ideal in situations when there is a treatment and control group present, making it practical in use across many fields (Caliendo and Kopeinig, 2008). Selection bias is a common issue which is experienced when comparing treatment effects. The utilization of propensity score matching is a manner in which to avoid this issue as it matches observations, which vary in treatment, based on relevant pretreatment characteristics (Caliendo and Kopeinig, 2008). This assures that compared observations share similar characteristics, making for an efficient evaluation. The resulting comparison can thus yield an unbiased estimate of the treatment effect (Dehejia and Wahba, 2002). Utilizing this analytical method for the measurement of treatment effect is beneficial as it assures that the compared treated and control groups are as similar as possible (Heinze and Juni, 2011). It does this by including potential confounding variables in the logit regression which calculates propensity scores (Bollinger and Ihlanfeldt, 1997). Once matches between the treatment and control group are made, it is then possible to compare the outcome variable amongst groups. This outcome can be more accurately attributed to the effect of the treatment.

One of the most common methods utilized in determining a treatment effect is the use of a multiple linear regression (Zanutto, 2006). A multiple linear regression can estimate treatment effects by regressing the outcome variable on covariate variables, which include the indicator variable for treatment. The treatment effect would be determined based on the significance of the coefficient of the treatment indicator variable (Zanutto, 2006). Although multiple linear regression is most commonly used when determining a treatment effect, propensity score matching has been found to produce similar results. In a comparison of 43 studies which were evaluated by both propensity scores and regression models, it was found that the statistical significance did not differ greatly between methods (Shah et al. 2005). This supports the idea that there can be little difference between methods when used appropriately (Glynn et al. 2006). Both methods can yield similar results but each has distinctive strengths and weaknesses which can influence when one method should be used in place of the other.

Benefits associated with propensity score methods can make it an ideal alternative in analysis. One of the largest benefits of utilizing propensity score methods is associated with its matching technique and it being non-parametric. During the matching process this method checks for balance between the distributions of covariates. This highlights areas in which there is little overlap between treatment and control groups and would require for there to be extrapolation in the estimation of treatment effects (Stuart, 2010; Zanutto, 2006). This can be beneficial for the researcher as it can provide a range in which comparisons can be made with greater confidence. It has been shown that regression models have performed poorly in situations in which there is minimal overlap between covariate distributions (Dehejia and Wahba, 1998, 2002; Glazerman et al., 2003). Propensity score methods measure this overlap while this diagnosis is not incorporated in regression models. The inclusion of this procedure in propensity score methods can provide awareness on the quality of the results. These aspects of propensity score methods help make the diagnostics more direct in the assessment of the results (Stuart, 2010). The benefits associated with propensity score methods have influenced its increasing use in the field of urban planning. This method can provide an efficient manner in which to analyze treatment effects which, as described previously, bring new elements not found in previous methods.

There are also several limitations which are associated with the use of propensity score matching which should be considered when selecting an appropriate analytical method. One assumption which is made under propensity score matching is that all covariates are observed. This is not the case in many instances as it is common to have missing data within the covariate variables (Stuart, 2010; Stuart and Rubin, 2007). The utilization of boosted models can assist with this issue as they do not require fully observed covariates in order to estimate propensity scores (Stuart, 2010). Another issue which can arise when utilizing propensity score matching concerns unobserved variables. The possibility of omitted covariates within the model could violate the assumption of unconfounded treatment assignment (Stuart and Rubin, 2007). The possibility of unobserved variables being correlated with those included in the model can mitigate this issue as they would be accounted for to some extent. During the matching process, observations which are not matched are excluded from analysis. This results in the loss of information, potentially reducing the power and accuracy of the model. This is a limitation which is associated with propensity score matching but it is estimated that the reduction of power is often minimal. The accuracy in a two sample comparison of means is most influenced by the smaller group size so it is estimated that if the control group remains the same the power of the model might not be greatly reduced (Ho et al., 2007). The matching technique also assists in maintaining the power of the model high as it assures that the groups being compared as very similar.

2.4.1 Propensity Score Methods in Urban Planning

The use of propensity score methods in the field of urban planning has been steadily increasing over time. These methods are more commonly applied in quasi experimental research designs in which a control group is needed in order to adequately measure a treatment effect. Propensity score methods are deemed adequate for these situations as they account for confounding variables in the selection of the control group. This assists in the reduction of selection bias and produces a result which more accurately represents the treatment effect. The use of this method in the field of planning is recent and has spread to various specializations within the field. As seen in Table 2 below, propensity score matching methods have been applied to studies which focus on policy, housing, health, economic development and transportation. This method could be applied to analyzing varying situations in urban planning due to its associated benefits and capabilities. This study utilized this analytical method as it proved to be ideal for this research design. This study is comparable to those listed in Table 2 as the intent is to adequately measure treatment effect. This method was then utilized in similar capacities as previous studies in the field of urban planning.

Table 2 Summary of Urban and Regional Studies Using the Propensity Score Matching Method

Author	Study	Propensity Score Use
Diaz and Handa, 2004	An Assessment of Propensity Score Matching as a Non-Experimental Impact Estimator: Evidence from a Mexican Poverty Program	Utilized to find a match for families selected to receive benefits from poverty program. PSM was used to find comparable households and evaluate impacts of the program.
Boer et al., 2007	Neighborhood Design and Walking Trips in Ten U.S. Metropolitan Areas	Utilized in order account for confounding variables when comparing household walking behavior specific to neighborhood design characteristics.
Cao, 2010	Exploring causal effects of neighborhood type on walking behavior	Matched individuals from suburbs to those residing in traditional neighborhoods and measured differences in travel behavior.
Funderburg et al., 2010	New highways and land use change: Results from a quasi-experimental research design	Utilized to select a control for each spatial unit that received access to new highway infrastructure. Measured difference in growth indicator variables.
MacDonald, et al. 2010	The Effect of Light Rail Transit on Body Mass Index and Physical Activity	Utilized to match and compare individuals before and after the construction of a LRT system. Measured change in physical activity of LRT users and non-users.
Billings, 2011	Estimating the value of a new transit option	Utilized to match neighborhoods in close proximity to transit with similar neighborhoods located elsewhere to compare housing prices.
Artz and Stone, 2012	Revisiting WalMart's Impact on Iowa Small-Town Retail: 25 Years Later	Utilized to find a match for each host town that represents what would have happened in the host town had WalMart not located there.
Deng, et al., 2012	Private residential price indices in Singapore: A matching approach	Houses sold at the baseline time were matched with those sold at a later time. Sale index was constructed from difference.
Cao and Fan, 2012	Exploring the influences of density on travel behavior using propensity score matching	Matched individuals in low density communities with those in high density communities, Compares travel behavior.

2.5 Motivation of Study

The construction of transit systems can greatly increase the mobility of a population in addition to acting as a stimulant for economic development. This can be crucial as the decentralization of residents and jobs from central cities has been occurring within the United States for some time (Holzer, 1991 Kawamura, 2001). Policymakers have attempted to mitigate the negative impacts associated with decentralization through the implementation of transit projects (Belzer et al. 2002). These projects can attract economic activity into the city by creating desirable sites for future development. This induced activity needs to be further examined in an attempt to further understand the economic impact associated with transit projects. Specifically, employment change needs to be analyzed in order to measure the effectiveness in which transit is attracting development.

The characteristics of the development which is constructing near transit needs to be further analyzed as well (Kahn, 2007). This analysis is necessary in order to further understand the reason why the employment participation rate for low income residents does not improve given the presence of transit (Cooke, 1996; Ellwood et al. 1986; Thompson et al. 1997; Sanchez, 1999; Sanchez et al. 2004). The economic impact which transit has on low income residents has primarily been examined through the analysis of the unemployment rates of this population. These studies have found weak or no significant relationship between employment participation and proximity to transit. There have been minimal studies conducted which attempt to determine the cause of this weak relationship. Although transit can lead to economic development, this development may not provide adequate employment opportunities for low income residents. This could be a contributing factor to the minimal influence which transit can have on low income residents. This study addresses these gaps in the literature while differentiating itself from previous studies by utilizing propensity score as the analytical method.

This study focusses on further comprehending issues identified by previous studies. There are two research questions which have evolved from these issues and remain central within this study. These questions are: 1) Do new transit service areas experience a positive trend in employment growth when compared to areas not serviced by transit? and, 2) Do employment opportunities pertinent to low income residents experience a negative trend in new transit service areas? It is hypothesized that transit service areas will experience a greater positive trend in employment growth than comparable areas not serviced by transit. There are many benefits of transit which make adjacent land desirable for development. It is believed that this will induce growth which will concentrate employment opportunities around transit stations. It is also hypothesized that transit service areas will experience a negative trend in employment opportunities pertinent to low income residents when compared to non-service areas. Although a positive influence between proximity to transit and total employment is anticipated, it is hypothesized that a negative influence will occur between the same and employment opportunities for low income residents. This is anticipated as previous literature has shown that transit does not have a positive impact on the employment participation of low income residents. It is believed that this may be due to the substitution of relevant employment opportunities with those with a specialized workforce.

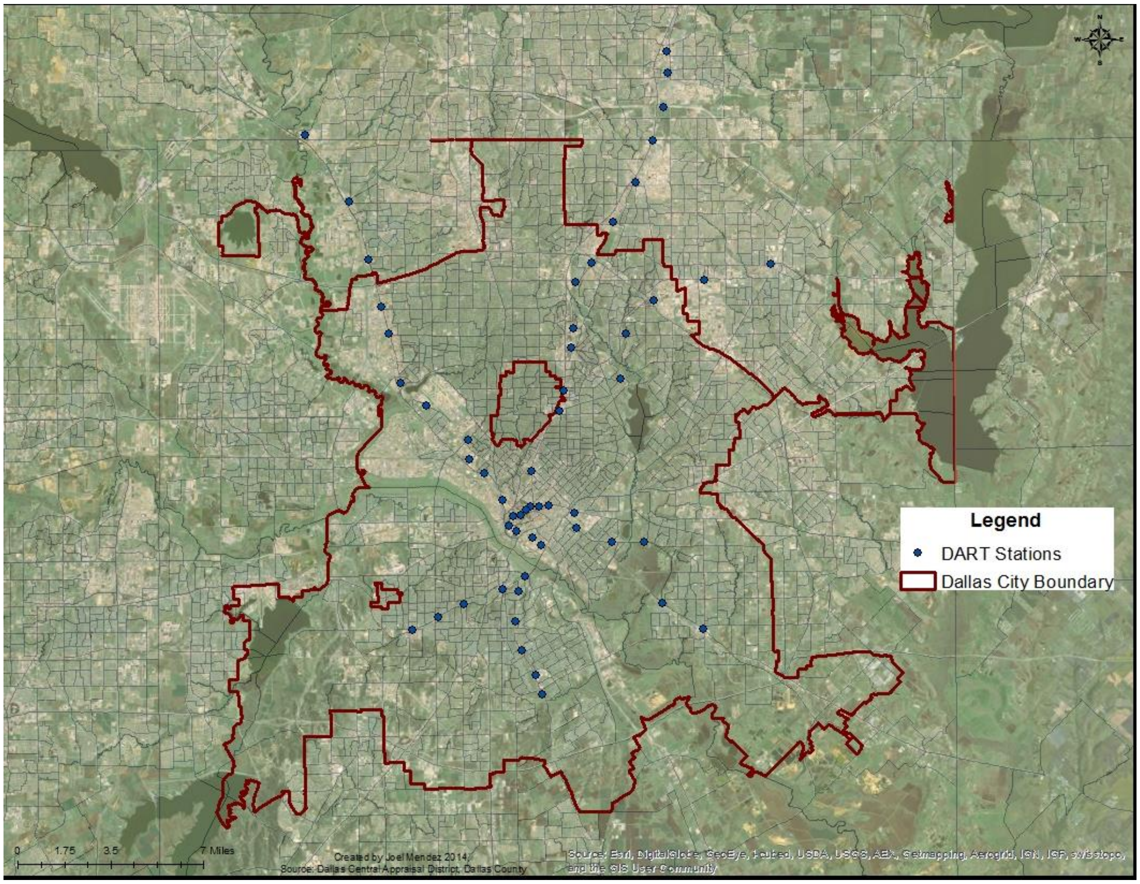
3. METHODOLOGY

3.1 Study Area

The City of Dallas, Texas is home to 1.197 million residents, with an MSA population of 6.371 million (U.S Census). Dallas is home to a diverse population. Though half the population identifies as White, African Americans make up 25% of the population, Asians make up 3%, and 42% identify as Hispanic. With 24% of Dallas's population currently living under the poverty line, retaining and attracting employment opportunities should become a priority to addressing this concern. Transit Oriented Development can produce an economic impact which can assist the city of Dallas in stimulating economic growth. The DART system is the transit system currently in place in Dallas, and the focus of this study. This transit system serves a diverse population as it is in close proximity to both low income and high income communities. It serves as a viable connection between labor force and employment opportunities. This system could also attract new development which can shrink the gap between residents and employers.

The thought of a light rail system in Dallas emerged in the late 1980' as the possibility of a system was included in the regional transit system plan. DART began to acquire railroad right of way in order to prepare itself for the implementation of such a system. Funding from the federal government later arrived and assisted in construction of the initial components of what is now the current light rail system. The initial 11 miles of light rail system opened in 1996 and has continued to expand ever since. DART rail is now composed of 85 miles of track which traverse Dallas and Collin counties. The system in its entirety can be seen in Figure 1 below.

Figure 1 DART Rail System



This study will solely focus on the light rail component of the DART system. Light rail is seen as being permanent fixture, thus encouraging more development than other forms of transit (Cervero, 1984). For this reason, the bus component of the DART system will not be included in this analysis. This study focuses on the impact which transit can have on economic development. Only certain transit stations will be included in this analysis. A complete description of the stations which compose the light rail system is seen in Table 3. Only stations constructed in 2001 and 2002 will be considered as they overlap the time period which the necessary data is available for analysis.

Table 3 DART Corridor Information

Corridor	Line	Miles	Number of Stations	Opening Year
CBD	All	1	4	1996
Oak Cliff	Red/Blue	3.8	4	1996
S. Oak Cliff	Blue	4.6	5	1996-1997
W. Oak Cliff	Red	4.6	4	1996
North Central	Red	6	4	1997
North Central	Red	12.3	9	2002
Northeast	Blue	11.2	5	2001-2002
Northeast	Blue	4.6	1	2012
Northwest	Green	1.2	1	2004
Northwest	Green	16.2	11	2010
Southeast	Green	2.7	4	2009
Southeast	Green	7.4	4	2010
NW-Irving	Orange	9	5	2012

Source: Dallas Area Rapid System, Reference Book.

3.2 Research Design

A quasi-experimental design was utilized in order to conduct this analysis. Specifically, the nonequivalent comparison group post-test only design was utilized and is shown below. This design is composed of a non-randomly assigned treatment and control group. There is a treatment administered to the treatment group and observations are made afterwards in an attempt to measure the impact of the treatment. In order to more accurately measure the effect of the treatment, the treatment group is compared to a non-random control group. The control group is composed of observations which share similar characteristics to observations in the treatment group, before the treatment is administered. These characteristics on which the treatment and control group are matched are identified as confounding variables. In this study, the treatment is classified as being the opening of the DART rail stations identified earlier.

NR x O1
NR   O1

The equation above represents the quasi-experimental design of this analysis. The "NR" represents the non-random selection of observations while "x" represents the treatment. The "O1" variable represents the observations after the treatment for both the control and treatment group. These observations are taken at the exact same time and on a yearly basis from 2002 to 2011 after the treatment. As stated previously, both control and treatment groups are not randomly assigned as the treatment group consists of census block groups in close proximity to transit, while the control group consists of census block groups located further away. The composition of the treatment group is based on a ¼ mile threshold from rail stations. All census block groups whose centroid fell within a ¼ mile radius of rail stations were included in the treatment group. A ¼ mile distance from transit stations was utilized because it is considered that the majority of benefits associated with rail transit fall within this threshold (Diaz, 1999). This threshold is largely influenced by the fact that ¼ mile is identified as being a reasonable walk to transit (Curtis, 2011; Bressi, 1994; Calthorpe, 1993; Gehl, 1987). There is some discussion in the identification of an adequate distance which constitutes a reasonable walk to transit. It has been argued that a reasonable walk is longer than ¼ mile (Dickens, 1975; Ker and Ginn. 2003). In order to control for this possibility and not compare census block groups which are both being influenced by transit, the control group is composed of areas outside of a ½ mile radius of rail stations within Dallas County. In order to account for additional influences in our analysis, census block groups located within a ½ mile distance from rail stations constructed in the future were not included in the control group. Census block groups located within a 1 mile distance from highway off and on ramps were also omitted from the control group as these areas could experience growth not representative of the conditions found in the city. This selection criterion resulted in a treatment group composed of 40 census block groups. There were 929 census block groups which formulated the pool in which the control group would be selected from.

3.3 Variables

The variables utilized for this analysis are shown in Table 4. This table is composed of the independent, confounding, and dependent variables. The independent variable is a measure of proximity to transit and includes all census block groups within a ¼ mile radius of selected DART rail stations. Confounding variables are incorporated into this analysis in order to account for potential outside influences. Variables utilized include per capita income, population density, labor force, educational attainment, land area, employment density, and vacancy rates. These variables were identified as being significant in influencing employment growth (Lucas, 1988; Rauch, 1993; Simon; 1998; Abraham and Hunt, 1999). These confounding variables are all available through the U.S Census and correspond to the year 2000 in order to match on pretreatment conditions. The dependent variable of this study is a measure of employment opportunities. The longitudinal employment employer-household dynamics dataset (LODES), obtained through the US Census, was utilized to obtain the dependent variables of this study. This dataset provided the number of employment opportunities in census blocks while also sorting them by earnings and industry. The variables utilized from this dataset measure total employment, employment by earnings, and employment by industry.

Employment by earnings is analyzed as the category representing earnings under $1,250 a month is linked to opportunities for low income residents, earnings ranging from $1,250 to $3,333 a month being associated to median income and earnings above $3,333 a month being associated with opportunities for high income residents. Only certain industries were considered when analyzing employment opportunities. Employment in the industries of retail, accommodation and food services, and other services were utilized for this analysis. These industries were selected because, based on their annual median earnings, they are most likely to employ low income employees. These industries also require a lower skilled workforce which can be largely composed of minority and low income residents (Stoll, 2005). Employment within the industries of Information, finance, technology, and management were included when representing employment opportunities for high income residents. These were selected as median incomes for employment opportunities were representative of a highly skilled labor force. Lastly, total employment was also analyzed as a dependent variable as total employment change, regardless of type, was measured.

Table 4 Variables

Variable	Concept	Variable	Unit	Source
Independent Variables	Proximity to transit	Census block groups ¼ mile from transit	CBG	ArcGIS Analysis, US Census
Confounding Variables	Matching Characteristics	Education Attainment	% with H.S	US Census
		Employment Density	Jobs/sq. mi	LODES
		Total Employment	Jobs/CBG	US Census
		Labor Force	Pop age 16-64/CBG	US Census
		Land Area	sq. miles	US Census
		Per Capita Income	Avg. Income	US Census
		Vacancy Rate	% vacant	US Census
		Total Population	Pop/CBG	US Census
Dependent Variables	Employment Opportunities	Employment by earnings	Jobs/CBG	LODES
		Employment by Industry	Jobs/CBG	LODES
		Total Employment	Jobs/CBG	LODES

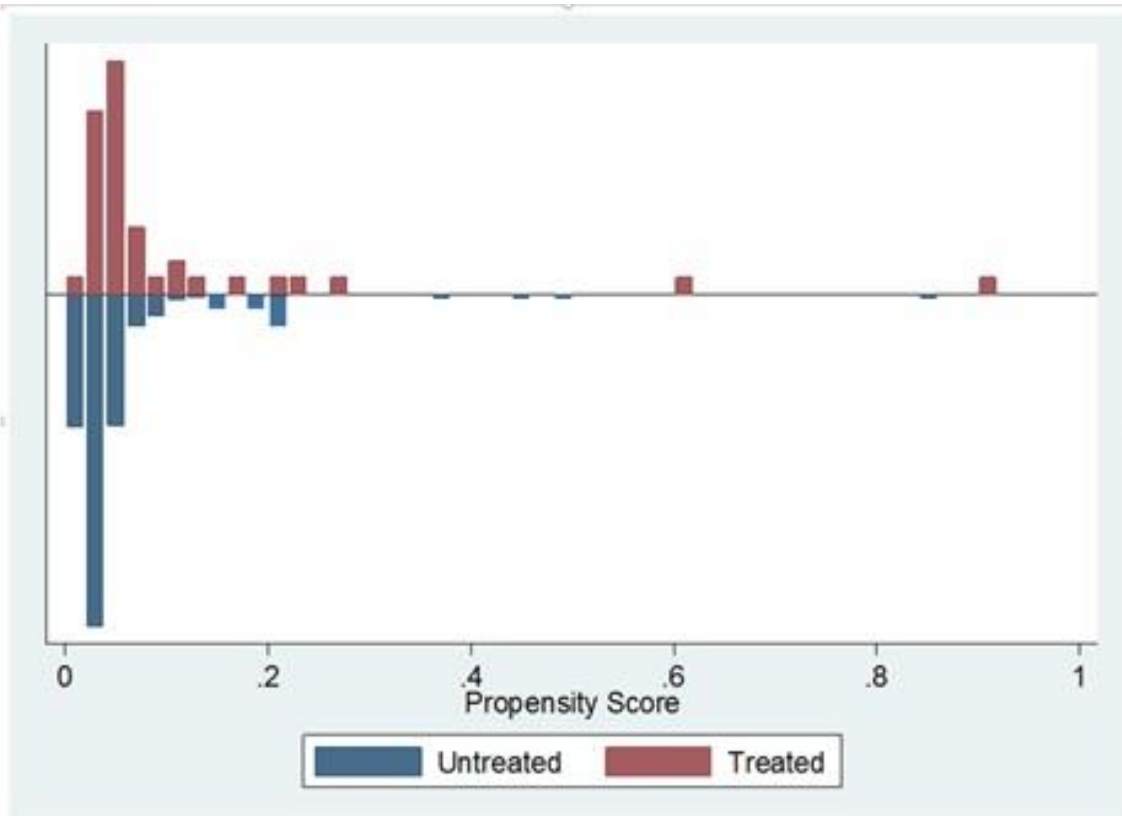
Notes: CBG-Census Block Group, LODES- Longitudinal Employer Household Dynamics
Summary statistics of confounding variables are found in Table 5 and Table 6
Histograms of Employment Densities on Matched CBG's are found in Appendix B

3.4 Procedure

The initial step within this analysis is to calculate propensity scores for each census block group in the study area. The software STATA is utilized throughout this analysis to accomplish the necessary calculations. The propensity score represents the probability of being treated as based on observed baseline covariates (Stuart, 2010; Heinze and Juni, 2011). The propensity score is calculated by running a logit regression while treating the binary treatment variable as the dependent variable and the confounding variable listed in Table 4 as the independent variables. The output for the logit regression can be found in Appendix A. The logit regression holds similar assumptions which are made by the ordinary least squares regression models. The necessary diagnostic analysis were conducted to assure the conformity to these assumptions and their results can be found in Appendix A. The resulting propensity scores summarize all confounding variables into one scalar measurement (Stuart, 2010). This analysis is done at a micro-level as a propensity score are calculated for each census block group based on its baseline confounding variables. Propensity scores can be interpreted as balancing scores as census block groups with similar scores are believed to have similar distributions of baseline confounding variables (Heinze and Juni, 2010). The focus of the resulting propensity scores is not the estimates themselves but the resulting balance of covariates (Stuart, 2010).

In order to match propensity scores it is necessary that there be overlap between the scores of the treatment and control group. The ability to identify this overlap is an advantage which this method has over regression analysis (Heinze and Juni, 2011). Randomness is needed in propensity scores for both treatment and control groups as that guarantees that census block groups with similar characteristics are found in both treatment strategies (Heckman, 1998; Bryson et al. 2002; Caliendo and Kopeinig, 2008). Having this overlap is key as observations which have no similar comparison in the opposite treatment alternative cannot be used in this analysis. Histograms of the propensity scores of the treatment and control groups should be analyzed in order to determine the quality of the overlap. This is portrayed in Figure 2 below. The X and Y axis in Figure 2 are proportional to the each respective group, thus not on the same scale. As seen, there seems to be adequate overlap between treatment groups, making it possible to find adequate matches for each treatment observation. It is also a positive that there are only 40 treatment observations while there are 929 control observations, making it more likely to find an adequate match for each treatment observation. There are other methods in which to check the overlap of propensity scores apart from visually checking the histogram. STATA has a built in function in which propensity scores cannot be matched if there is not sufficient overlap between distributions of treatment and control groups. In this case, there was sufficient overlap and propensity scores were able to be suitably matched.

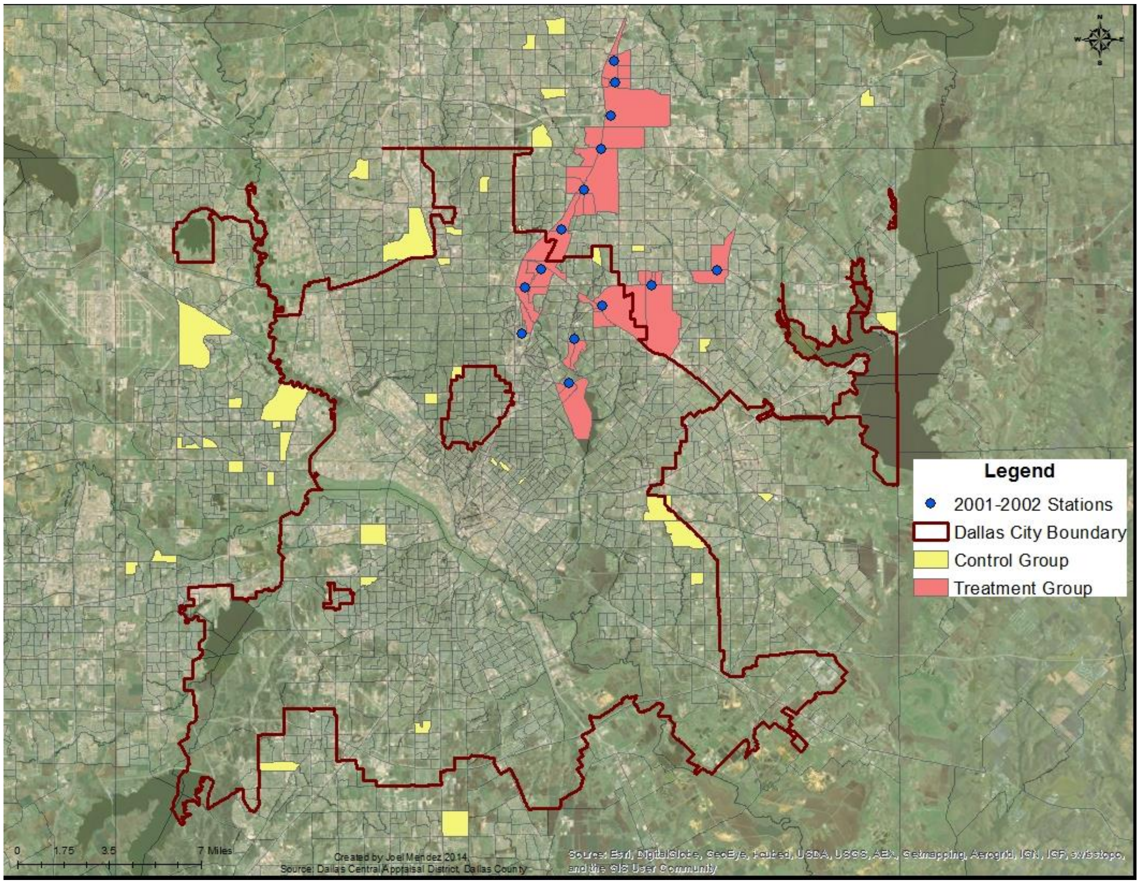
Figure 2 Propensity Score Distribution



There are several methods in which to match propensity scores between treatment and control groups. The most direct method is the nearest-neighbor matching method. This method simply matches an observation from the treatment group to one on the control group which is closest in propensity score (Caliendo and Kopeinig, 2008). The observations in the control group which are not matched with the treatment group are not considered in this analysis, which is ideal for estimating the treatment effect (Stuart, 2010). For this reason, in addition for there being adequate overlap in propensity scores, the nearest neighbor method was selected for this study. Other matching variables can potentially be utilized, depending on the study. There is caliper matching in which a maximum and minimum tolerance can be specified on the corresponding match for each treatment group. This assures that matches have propensity scores within a certain threshold of each other. Kernel matching can also be utilized which weighted averages can be incorporated in the calculation of propensity scores by placing greater influence on certain confounding variables (Caliendo and Kopeinig, 2008).

In this instance, the nearest neighbor matching method was determined to be ideal for the study at hand. Each block group in the treatment groups is then matched with a block group in the control group based on their respective propensity score. The result is the matching of block groups in the treatment group with block groups in the control group which are as similar as possible in terms of employment and demographic characteristics. This method attempts to control for confounding variables by selecting sites which are as similar as possible, except for their proximity to transit (Vessali, 1997; Bollinger and Ihlanfeldt, 1997). The resulting treatment group and matched control group are displayed below in Figure 3.

Figure 3 Treatment and Control Groups



The treatment and control group were matched based on similarities in confounding variables which are referenced in Table 4. Theoretically, matched census block groups would have comparable values in confounding variables. Summary statistics for these confounding variables are shown below in Table 5 for the treatment group and Table 6 for the control group. When comparing these results it is evident that confounding variables in the control group are indeed similar to those from the matched treatment group. This is supported by the results found in Table 7, as the difference between variables was found to not be significantly different from zero. These results support the quality of the matches made, as they describe similar outcomes. The distribution of employment densities corresponding to the matched control and treatment group, for every year of analysis, is shown in Appendix B.

Table 5 Treatment Group Summary Statistics

Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
AlandSqmi	40	0.88	1.56	0.05	0.22	0.34	0.67	7.61
TotPop	40	1,478.05	702.86	462.00	949.50	1,269.00	1,997.50	3,259.00
PopDens	40	5,568.17	5,582.80	169.41	1,498.02	4,100.10	6,929.32	24,672.15
EmpDens	40	3,603.81	4,700.46	32.74	1,082.61	2,462.29	3,860.38	22,280.86
LbForceDen	40	2,896.87	2,992.65	92.85	909.54	1,941.84	3,473.11	12,491.57
PCInc	40	23,432.75	13,836.45	7,538.00	13,960.00	20,019.00	27,895.50	78,512.00
PerVac	40	4.40	4.43	1.10	1.85	3.00	5.40	26.40
PerHS	40	20.01	8.48	6.17	14.14	18.54	25.94	36.03

Table 6 Control Group Summary Statistics

Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
AlandSqmi	40	0.62	0.95	0.03	0.18	0.26	0.5	4.56
TotPop	40	1,380.35	665.79	502.00	1,022.00	1,266.50	1,583.50	4,234.00
PopDens	40	6,775.10	7,155.21	266.17	2,289.88	5,052.08	7,956.18	36,866.60
EmpDens	40	3,289.79	5,414.17	2.18	508.56	1,474.67	5,132.17	30,931.30
LbForceDen	40	3,444.12	3,753.75	160.10	1,331.00	2,605.00	4,125.30	18,885.03
PCInc	40	20,359.75	11,216.24	8,424.00	12,612.50	16,569.50	27,568.50	57,866.00
PerVac	40	3.40	2.96	0.40	1.4	2.75	4.55	15.90
PerHS	40	20.24	10.60	6.94	11.37	20.99	28.07	48.39

Table 7 Treatment-Control Group T-Test

Variable	Variable Definition	Diff	P value
AlandSqmi	Land Area (Square Miles)	.258	0.375
TotPop	Total Population	97.7	0.525
EmpDens	Employment Density	314.48	0.78
LbForceDen	Labor Force Density	547.64	0.473
PCInc	Per Capita Income	3,073.48	0.279
PerVac	Percent Vacant	1.0	0.239
PerHS	Percent with High School Diploma	0.23	0.917

It is then possible to compare similar census block groups which differ in treatment to better measure the impact of transit. This is done by estimating the difference between the mean outcomes of the treated census block groups with the mean outcome of the matched control census block groups (Rosenbaum and Ruben, 1983). This method is known as determining the average treatment effect on the treated (ATT) as it focuses specifically on the treatment effect on those which the treatment was intended for (Caliendo and Kopeinig, 2008). This method is expressed as

$$\tau ATT = E(\tau \mid D = 1) = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1]$$

where the ATT (Average Treatment Effect on the Treated) is the average of estimated differences between the mean of the treated group, expressed as Y(1), and the control group, expressed by Y(0). This difference is considered only under the distribution of the treatment group, noted as D=1. The outcome variables investigated in this study include total employment, total employment density, low earning employment, low earning employment density, median income employment, median income employment density, high income employment, high income employment density, service oriented employment, service oriented employment density, professional employment, and professional employment density. The difference between treated and matched control census block groups were taken and utilized to measure treatment effect. This difference in means acts as an unbiased estimate of the treatment effect on each outcome (Stuart, 2010; Heinze and Juni, 2011). This process in its entirety is completed utilizing STATA using the *teffects nnmatch* command (StataCorp, 2013).

A multi-linear regression model was incorporated into the study in an attempt to further comprehend the influence which transit has on employment and verify the integrity of the propensity score model utilized. The multi linear regression model consists of the following independent variables: log(per capita income), total population, census block size, log(labor force), percent of population with high school degree, percent of vacant properties, treatment dummy variable, dummy variables indicating the year, and interaction terms between the year and treatment. The treatment variable is a binary dummy variable in which a value of 1 represents census blocks located within ¼ mile from the light rail stations identified in this study area. A value of 0 represents census block groups not located within ½ mile from light rail transit stations and 1 mile from highway off and on ramps. The year dummy variables have an assigned value of 1 when a census block group observation corresponds to that year. The interaction variables with values of 1 represent census block groups within a ¼ mile from transit stations particular to a year. The dependent variables utilized in this regression consist of the same employment variables utilized in the propensity score method. These variables are total employment, low, medium, high earning employment, service oriented employment and professional oriented employment. A regression was conducted for these employment variables for each year through the 2003-2011 time span of this study. The year 2002 was omitted from the regression in order to eliminate issues with multi-collinearity which arise when incorporating an interaction variable in the regression. The coefficient which pertained to the interaction variable between treatment and year was then interpreted, as it served as a measure of the influence of transit on each employment variable. The regression model is further explained bellow as Y represents the employment dependent variables, "β" represents the coefficient of each independent variable, and "u" represent the error.

$$Y = \beta_0 + \beta_1 LandArea_1 + \beta_2 Percent\ Vacanct_2 + \beta_3 Per\ Capita\ Income_3 + \beta_4 Total\ Population_4 + \beta_5 Labor\ Force_5 + \beta_6 Per.HS\ Grad_6 + \beta_7 Treatment_7 + \beta_8 \text{year 2003} + \beta_9 \text{year2004} \ldots + \beta_n \text{Treatment*year2003} + \beta_n \text{Treatment*year2004} \ldots + u$$

4. RESULTS AND DISCUSSION

4.1 Total Employment

The ATT for each outcome variable is calculated utilizing propensity score method. The initial variable in which treatment effect was determined was for total employment and total employment density. The ATT for these variables were determined through the 2002-2011 time span in order to measure the longitudinal impact of the newly opened DART line.

Table 8 ATT Total Employment

Tot Emp	Coef	Std. Err	Z	P> IzI	95% CI	
2002	805.87	597.54	1.35	0.177	-365.28	1977.03
2003	725.82	634.89	1.14	0.253	-518.54	1970.19
2004	660.27	632.63	1.04	0.297	-579.67	1900.22
2005	670.82	648.97	1.03	0.301	-601.14	1942.79
2006	628.05	640.34	0.98	0.327	-627.01	1883.11
2007	605.27	624.86	0.97	0.333	-619.44	1829.99
2008	683.85	604.91	1.13	0.258	-501.76	1869.46
2009	674.87	580.15	1.16	0.245	-462.21	1811.96
2010	720.02	561.29	1.28	0.200	-380.09	1820.14
2011	749.10	733.10	1.02	0.307	-687.75	2185.95

Table 9 ATT Total Employment Density

TEmp Dens	Coef	Std. Err	Z	P> IzI	95% CI	
2002	1076.21	1687.91	0.64	0.524	-2232.03	4384.47
2003	1305.18	1790.27	0.73	0.466	-2203.69	4814.05
2004	1269.32	1737.43	0.73	0.465	-2135.98	4674.62
2005	1385.61	1690.75	0.82	0.412	-1928.20	4699.44
2006	1272.03	1649.27	0.77	0.441	-1960.47	4504.55
2007	1370.85	908.302	1.51	0.131	-409.389	3151.09
2008	1475.64	918.866	1.61	0.108	-325.304	3276.58
2009	1643.29**	807.392	2.04	0.042	60.83805	3225.76
2010	1682.33*	911.996	1.84	0.065	-105.140	3469.82
2011	1711.48*	926.421	1.85	0.065	-104.264	3527.24

As seen by the ATT analysis found in Table 8, proximity to transit does have an influence on total employment. Analyzing the coefficient from the year 2002 to 2011 we see that employment in areas within ¼ of the DART line is greater than employment in similar areas outside of the treatment area. When analyzing the impact which the transit line had on total employment we look at the trend in employment from 2002 to 2011. When doing so we can see that this difference in employment has remained fairly similar throughout these years, not experiencing a clear positive or negative trend. This would support the statement that, during this time span, the opening of the transit line has had no positive or negative influence on total employment. This is presumed as the difference in employment have remained fairly constant throughout this time span as transit service areas have maintained around 600 to 700 more employment opportunities than matched counterparts. If a positive impact was present the results would have shown a steady increase in the coefficient during this time frame, supporting the stated hypothesis. It should be noted that although greater total employment was found in transit service areas none of the findings produced significant results. Similar results were found when conducting this analysis in terms of total employment densities. As shown in Table 9, not many significant differences were found but areas serviced by transit were found to be more likely to contain higher concentrations of total employment than comparable areas not serviced by transit. There does seem to be a positive influence present in total employment densities within transit service areas as values increase throughout the 2002-2011 time span, producing significant values in the latter years. Transit corridors can take several years to develop, which may be a reason why significant values are found seven years after the opening of the stations.

4.2 Employment by Earnings

The ATT for employment opportunities by earnings was also calculated in order to determine the treatment effect on various employment types. The results are shown below for low earning employment opportunities, median earning employment opportunities and high earning employment opportunities. The ATT for employment density was also determined for each earning classification.

Table 10 ATT Low Earning Employment Opportunities

Low Earn	Coef	Std. Err	Z	P> IzI	95% CI	
2002	160.10	156.53	1.02	0.306	-146.70	466.90
2003	167.35	152.28	1.10	0.272	-131.11	465.81
2004	145.30	156.15	0.93	0.352	-160.75	451.35
2005	96.82	171.52	0.56	0.572	-239.34	432.99
2006	79.30	162.30	0.49	0.625	-238.81	397.41
2007	59.35	147.98	0.40	0.688	-230.68	349.38
2008	86.37	121.69	0.71	0.478	-152.13	324.88
2009	105.32	121.18	0.87	0.385	-132.19	342.84
2010	90.75	116.64	0.78	0.437	-137.87	319.37
2011	16.90	153.23	0.11	0.912	-283.43	317.23

Table 11 ATT Low Earning Employment Opportunity Density

LEarn dens	Coef	Std. Err	Z	P> IzI	95% CI	
2002	310.37	450.98	0.69	0.491	-573.54	1194.28
2003	283.28	457.80	0.62	0.536	-613.98	1180.56
2004	309.79	472.36	0.66	0.512	-616.03	1235.61
2005	297.88	456.06	0.65	0.514	-595.99	1191.75
2006	241.13	408.03	0.59	0.555	-558.60	1040.87
2007	266.67	210.95	1.26	0.206	-146.79	680.14
2008	280.11	193.41	1.45	0.148	-98.963	659.19
2009	366.97**	184.05	1.99	0.046	6.24522	727.71
2010	320.10*	192.44	1.66	0.096	-57.092	697.29

Table 11 Continued

LEarn dens	Coef	Std. Err	Z	P> IzI	95% CI	
2011	283.43	204.59	1.39	0.166	-117.55	684.42

Focusing on Table 10 we can determine the influence which proximity to transit has on low earning employment opportunities. Transit service areas seem to have greater numbers of low earning employment opportunities than non-service areas, although no results proved to be significant. The overall trend shows that this difference is declining over time, meaning that the number of low earning employment opportunities in transit service and non-service areas are becoming similar. This can be due to greater employment growth, specific to these types of employment opportunities, occurring in non-service areas. As seen in Table 11, densities for low earning employment opportunities seem to remain fairly stable with transit service areas experiencing around 300 more opportunities per census block group than comparable areas not serviced by transit. The only significant values obtained in the analysis of low earning employment densities were found in the years 2009 and 2010.

Table 12 ATT Median Earning Employment Opportunities

Med Earn	Coef	Std. Err	Z	P> IzI	95% CI	
2002	281.85	237.33	1.19	0.235	-183.31	747.01
2003	264.47	253.78	1.04	0.297	-232.93	761.88
2004	245.22	248.28	0.99	0.323	-241.40	731.85
2005	251.10	247.03	1.02	0.309	-233.08	735.28
2006	265.65	234.55	1.13	0.257	-194.07	725.37
2007	242.42	225.91	1.07	0.283	-200.35	685.20
2008	258.22	215.71	1.20	0.231	-164.57	681.02
2009	266.67	192.93	1.38	0.167	-111.47	644.82
2010	256.70	181.02	1.42	0.156	-98.101	611.50
2011	153.17	213.92	0.72	0.474	-266.10	572.45

Table 13 ATT Median Earning Employment Opportunity Density

MEarn Dens	Coef	Std. Err	Z	P> IzI	95% CI	
2002	456.52	672.54	0.68	0.497	-861.64	1774.69
2003	531.00	653.30	0.81	0.416	-749.44	1811.46
2004	496.87	636.11	0.78	0.435	-749.88	1743.63
2005	498.15	548.36	0.91	0.364	-576.60	1572.92
2006	466.48	510.44	0.91	0.361	-533.97	1466.94
2007	490.08*	292.47	1.68	0.094	-83.15	1063.33
2008	491.89*	280.58	1.75	0.080	-58.04	1041.83
2009	522.48**	248.98	2.10	0.036	34.47	1010.49
2010	581.42**	279.59	2.08	0.038	33.41	1129.42
2011	503.16*	271.79	1.85	0.064	-29.531	1035.86

The influence which proximity to the DART line has on median earning employment opportunities can be seen in Table 12. It is evident that census block groups located within ¼ from transit stops are more likely to have a greater number of medium earning employment opportunities than comparable sites not serviced by transit. None of the analysis produced significant values but there seems to be a constant difference between matched groups. Looking at the trend through this time span we cannot say whether proximity to transit has a positive or negative effect on median earning employment opportunities as the coefficient values have remained fairly constant throughout. As shown in Table 13, higher values within transit service areas remain when focusing on employment densities of median earning employment opportunities. Significant values are obtained in the latter years of the analysis, supporting the idea that development takes time to mature.

Table 14 ATT High Earning Employment Opportunities

High Earn	Coef	Std. Err	Z	P> IzI	95% CI	
2002	363.92	324.93	1.12	0.263	-272.94	1000.79
2003	294.00	309.38	0.95	0.342	-312.37	900.37
2004	269.75	307.94	0.88	0.381	-333.81	873.31
2005	322.90	314.78	1.03	0.305	-294.06	939.86
2006	283.10	325.30	0.87	0.384	-354.49	920.69
2007	303.50	345.69	0.88	0.380	-374.04	981.04
2008	339.25	354.65	0.96	0.339	-355.86	1034.36
2009	302.87	323.10	0.94	0.349	-330.40	936.15
2010	372.57	336.13	1.11	0.268	-286.22	1031.37
2011	579.02	489.35	1.18	0.237	-380.09	1538.14

Table 15 ATT High Earning Employment Opportunity Density

HEarn Dens	Coef	Std. Err	Z	P> IzI	95% CI	
2002	309.32	604.19	0.51	0.609	-874.88	1493.53
2003	490.88	707.34	0.69	0.488	-895.48	1877.25
2004	462.65	656.29	0.70	0.481	-823.66	1748.97
2005	589.57	720.51	0.82	0.413	-822.60	2001.75
2006	564.41	767.79	0.74	0.462	-940.42	2069.26
2007	614.09	450.08	1.36	0.172	-268.05	1496.23
2008	703.62	474.00	1.48	0.138	-225.40	1632.65
2009	753.83*	415.17	1.82	0.069	-59.88	1567.56
2010	780.81*	475.24	1.64	0.100	-150.65	1712.28
2011	924.88*	502.03	1.84	0.065	-59.08	1908.85

The effect which proximity to the DART rail line has on high earning employment opportunities was then analyzed and shown in Table 14. This table shows that there is a positive difference between census block groups within ¼ of the DART line and comparable census block groups located elsewhere. These census block groups within close proximity of transit generally had an additional 300 to 400 high earning employment opportunities when compared to the control group. When analyzing this trend since the opening of the transit stations we see no clear direction of influence.

Table 15 shows the influence which transit has on high earning employment opportunities. What is seen is an increase in employment density occurring within service areas since the opening of the DART light rail stations. This analysis produces significant values at the tail end of the given time frame. This shows that the opening of these light rail stations have indeed had a positive impact on the density of high earning employment opportunities within service areas.

4.3 Employment by Type

The ATT for employment opportunities by type was calculated in order to determine the treatment effect on both service and professional oriented employment. Employment opportunities in the retail, accommodation and food services, and other services were utilized to represent service oriented employment while employment opportunities in the industries of information, finance, technology, and management are utilized to represent professional oriented employment opportunities. Employment densities for each employment type were also determined and shown in the tables below.

Table 16 ATT Service Employment Opportunities

Serv Emp	Coef	Std. Err	Z	P> IzI	95% CI	
2002	26.27	142.32	0.18	0.854	-252.67	305.22
2003	-30.85	144.65	-0.21	0.831	-314.37	252.67
2004	-25.27	140.21	-0.18	0.857	-300.08	249.53
2005	-43.22	148.09	-0.29	0.770	-333.49	247.04
2006	-35.35	143.22	-0.25	0.805	-316.06	245.36
2007	-13.40	148.99	-0.09	0.928	-305.43	278.63
2008	12.10	147.40	0.08	0.935	-276.81	301.01
2009	-4.10	156.74	-0.03	0.979	-311.31	303.11
2010	9.42	132.05	0.07	0.943	-249.39	268.24
2011	-64.87	160.05	-0.41	0.685	-378.58	248.83

Table 17 ATT Service Employment Opportunity Density

SrvEmp_Dens	Coef	Std. Err	Z	P> IzI	95% CI	
2002	-79.33	260.02	-0.31	0.760	-588.98	430.31
2003	-149.70	285.17	-0.52	0.600	-708.63	409.23
2004	-149.39	277.17	-0.54	0.590	-692.65	393.86
2005	-192.63	306.15	-0.63	0.529	-792.68	407.41
2006	-176.31	299.26	-0.59	0.556	-762.86	410.23
2007	41.59	202.29	0.21	0.837	-354.90	438.09
2008	16.96	203.76	0.08	0.934	-382.41	416.34
2009	85.46	168.90	0.51	0.613	-245.57	416.50
2010	96.24	161.98	0.59	0.552	-221.24	413.73
2011	76.59	174.53	0.44	0.661	-265.47	418.67

In order to further determine the effect which proximity to transit can have on employment opportunities the ATT analysis was conducted for service oriented employment opportunities and professional oriented employment opportunities. As seen in Table 16, no significant differences were found and no clear trend is present as positive and negative values are found throughout the given time span. Densities vary from being greater in transit service areas and non-service areas throughout this time span. The same can be said when focusing on employment densities of service oriented employment opportunities. As Table 17 shows, there are no significant values obtained through this analysis although densities remain negative in the former years of the analysis and become positive thereafter. This can speak to the impact which transit might have on employment densities within these industries as they seemed to surpass those found in areas not serviced by transit.

Table 18 ATT Professional Employment Opportunities

Prof Emp	Coef	Std. Err	Z	P> IzI	95% CI	
2002	68.37	244.81	0.28	0.780	-411.46	548.21
2003	55.52	263.71	0.21	0.833	-461.34	572.39
2004	58.12	264.48	0.22	0.826	-460.25	576.50
2005	79.47	277.76	0.29	0.775	-464.92	623.87
2006	91.00	268.32	0.34	0.735	-434.91	616.91
2007	110.02	288.90	0.38	0.703	-456.22	676.27
2008	73.75	308.15	0.24	0.811	-530.23	677.73
2009	-3.60	313.47	-0.01	0.991	-618.00	610.80
2010	56.80	302.60	0.19	0.851	-536.29	649.89
2011	-46.82	335.85	-0.14	0.889	-705.09	611.44

Table 19 ATT Professional Employment Opportunity Density

Prof Dens	Coef	Std. Err	Z	P> IzI	95% CI	
2002	178.74	291.80	0.61	0.540	-393.18	750.67
2003	377.06*	226.39	1.67	0.096	-66.658	820.79
2004	363.23**	183.02	1.98	0.047	4.50	721.96
2005	395.66**	180.47	2.19	0.028	41.92	749.39
2006	371.09**	175.91	2.11	0.035	26.30	715.88
2007	325.62*	191.70	1.70	0.089	-50.11	701.37
2008	362.03*	207.45	1.75	0.081	-44.55	768.63
2009	304.21	190.09	1.60	0.110	-68.35	676.78
2010	401.55**	188.12	2.13	0.033	32.82	770.27
2011	377.02*	203.31	1.85	0.064	-21.46	775.51

Notes: * Indicate the value is significant at $p < 0.10$.
** Indicate the value is significant at $p < 0.05$ levels of significance.
*** Indicate the value is significant at $p < 0.01$ levels of significance.

When analyzing the effect which proximity to transit has on professional oriented employment opportunities we see in Table 18 that no significant difference was found. No trend is seen as coefficients are positive and increasing in the beginning of the time frame before suddenly become negative, showing greater number of professional oriented employment opportunities in non-service areas. Table 19 focuses on densities for professional oriented employment opportunities. The strong majority of the results obtained in this analysis are significant and show that higher densities of professional oriented employment opportunities are found in transit service areas. These densities increase initially before remaining fairly constant, not making it possible to identify a trend in the effect of transit on employment densities within these industries.

4.4 Comparison with Multi-linear Regression Method

In an attempt to further examine the influence which transit can have on employment the use of multi linear regressions was incorporated into this analysis. As previously stated, the employment variables were regressed against log(per capita income), total population, census block size, log(labor force), percent of population with high school degree, percent of vacant properties, year dummy variables, the treatment variable, and treatment*year interaction variables. This was done for each employment variable for every year within the 2003-2011 time span. The coefficients specific to the treatment*year interaction variables are found in Appendix C, along with the results of the multi-linear regression for both total employment and employment density variables. These coefficients could then be interpreted to estimate the influence which transit can have on each respective employment variable. When analyzing the results found in Appendix C it is seen that the area of the census block group and total population are consistently influential and significant when analyzing total employment variables, regardless of employment type. When focusing on the interaction terms which specify the treatment per year of analysis, none were found to be significant for each employment variable. This is consistent with the findings of the propensity score analysis as the treatment was found to not be significant and no trends were observed within the designated study time period.

When examining the influence of transit on employment densities it is found that total population is the only variable which is consistently significant amongst all employment density variables. When estimating the influence of transit on employment throughout the specified time span the treatment*year interaction variables are analyzed for each employment density variable. These variables were found to not be significant amongst any of the employment variables analyzed. Again, these results coincide with those produced when determining ATT as similar conclusions are made when interpreting the findings. Multi-linear regression and ATT analysis each have their own distinct benefits and limitations. These models should not be utilized in substitution of each other but utilized in a complementary manner.

4.5 Implication

Overall, no clear trends were found regarding employment opportunities in transit service areas when compared to areas not serviced by transit and no indicators of this influence proved to be significant. Areas which were located within ¼ mile from the DART stations were found to contain higher amounts total employment, low earning, medium earning, high earning and professional oriented employment opportunities. This was not the case when focusing on service oriented employment opportunities since, in some instances, it was found that employment opportunities were greater in transit non-service areas. Although this is observed in the results, no clear trend was discovered. Since these findings are not significant it is not possible to state that the opening of the rail line has had a negative influence on these types of employment opportunities within the service area.

Total employment and high earning employment densities seemed to increase every year while producing significant values in the latter years of ATT analysis. This seemed to show that total employment densities increased in transit service areas since the opening of the applicable DART stations. Greater densities in low and medium earning employment opportunities were found to be greater in transit service areas than in comparable sites not serviced by transit. Results became significant in the latter years of the ATT analysis but remained fairly constant throughout. When examining service oriented employment densities it was found that these types of jobs were most likely to be located in transit non-service area in years closest to the opening of the DART stations but more so in transit service areas in the latter years of analysis, although the none of the results are significant. Greater density in professional oriented development was found to be located in transit service area with the majority of the years of analysis producing significant values. No clear trend was identified in regards to this employment type as coefficients remained fairly constant.

The opening and proximity to the DART line was found to have no positive or negative effects on employment, as no clear trends were observed within the analysis and significant results were limited. These results do not support the hypothesis made which state that proximity to the DART lines would positively influence total employment while having a negative influence on the number of low earning employment opportunities. There was a positive difference between total employment in areas within close proximity to the DART line and comparable sites elsewhere. This difference was insignificant and remained fairly constant, not allowing us to support the stated hypothesis which anticipated the presence of a positive influence. When focusing on the secondary hypothesis which expected proximity to transit to have a negative influence on low income residents we focus on the analysis which was conducted on service oriented and low earning employment opportunities. These results did show a decline in low earning employment opportunities in transit areas and greater numbers of service oriented employment being located in non-service areas but none of these findings were significant. This, again, does not allow for the support of the hypothesis which states that proximity to transit would result in a negative influence on low income employment opportunities. The lack of influence which the opening of this DART line had on employment can be attributed to many possibilities. Policies which encourage employment growth might not have been implemented in this study area as employment remained stable, relative to comparable locations. The presence of transit alone is not sufficient to induce development and that may be the case in this scenario. The focus of development may have been placed on increasing residential opportunities as opposed to employment opportunities in this study area. This strategy would designate the majority of space for residential uses, limiting the possibility of economic development.

5. CONCLUSION

Transit has been utilized by policy makers to address the high unemployment of low income residents. This high unemployment rate of low income residents was discovered to be associated with the low mobility of this population and the increased decentralization of employment opportunities. Transit was seen as being a tool which could address this issue as it can improve the mobility of this population while also connecting them to more employment opportunities. This is a reason why policymakers have continued to increase the amount of funding for transit projects. Previous studies have shown that there is no clear connection between proximity to transit and the level of employment participation for low income residents. This needs to be further addressed in order to determine the best strategy to deal with this situation. Identifying the impacts of redevelopment induced by transit can allow municipalities to better plan for it and assure that no one population is being un-proportionally impacted by these affects. Solutions which could be undertaken by municipalities include the implementation of a more comprehensive transit system equipped with various forms of transportation. If it is know that employment opportunities are moving further away from light rail lines, cities can then provide bus routes which connect the light rail line to pockets of low income employment opportunities located further out. This would result in a more feasible commute for low income residents and narrow the gap between their home and employment opportunities. Cities could also take part in public-private partnerships in order to help mitigate any negative impacts associated with redevelopment is having on low income residents. It is common practice for municipalities to give developers density bonuses or tax breaks in exchange for modifying their development in a manner which would benefit the municipality in some manner. These benefits can be given to developers of adjacent land in exchange for providing a certain number of affordable housing units or provide a certain amount of square footage specifically for industries which are most likely to hire low income residents like. The opening of transit projects alone will not encourage development as certain policies need to be in place in order it to occur. This may have been a case in this study area as transit had little to no impact on employment growth in treatment areas. The development of transit corridors do take time to mature and gain ridership (Houston et al. 2014). As corridors mature they have the capability to increase their ridership substantially. This increase in activity could attract development in areas adjacent to transit as they take advantage of this premium location. It may be possible that, with time, the effect which the presence of the DART line has will increase as this corridor matures. Future studies should focus on further analyzing these possibilities while addressing some of the limitations of this study.

5.1 Limitations and Future Research

The economic recession which occurred in the year 2008 might influence the analysis conducted, placing a limitation on this study since it focuses on the 2002-2011 time span. The impact of the recession might have influenced the final four years of the analysis period. This has the potential of showing a false trend in which transit oriented development lowers job growth in certain areas. With the service and retail sectors being some of the hardest hit industries, a disproportionate number of lost jobs could be those of low income workers analyzed by the study. Another limitation of the study is the lack of available data in regards to firm characteristics. Analyzing business birth and death years can assist in the process of determining the impact redevelopment has on employment migration and growth. It would be beneficial to determine if the change in employment in the certain areas is due to current business growth or business migration. This could have provided more of a holistic analysis detailing the influence of transit on employment.

Future studies could address the limitations of this study or build from its conclusion. This study measures the influence which transit has on employment growth, solely focusing on one potential form of development. Focusing not on employment but residential development could be incorporated in a study like this if the data is accessible. This would analyze development not only in the form of employment change but with housing change as well. This could serve as a better measure in how transit can influence development, not only employment growth. Future studies can also focus on diverse study areas while also including policy change into the analysis. This would be beneficial as it would address the question if this trend is occurring in differing environments while also measuring the influence which certain policies have on encouraging or discouraging development in these areas. The presence of transit does not alone encourage development. Certain policies may be influential in the presence of employment opportunities and for this reason they should be further analyzed.

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APPENDIX A

Appendix A: Logit Model Diagnostics and Results

1. Correlation between independent variables

	Percent HS	Percent Vac	PC Income	Labor Force	Land Area	Tot. Population	Employment Density
Percent HS	1.00						
Percent Vac	0.13	1.00					
PC Income	-0.60	-0.08	1.00				
Labor Force	-0.11	-0.06	-0.13	1.00			
Land Area	0.00	0.10	0.03	-0.17	1.00		
Tot. Population	-0.01	0.04	-0.10	-0.02	0.27	1.00	
Employment Density	-0.10	0.03	0.02	0.07	-0.06	-0.09	1.00

2. Multi-Collinearity test

Variable	VIF
Percent HS	1.42
Percent Vac	1.04
PC Income	1.46
Labor Force	1.39
Land Area	1.23
Tot. Population	1.13
Employment Density	1.05

3. **Logit Regression**

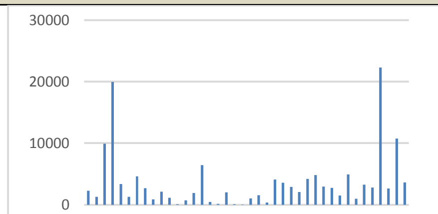
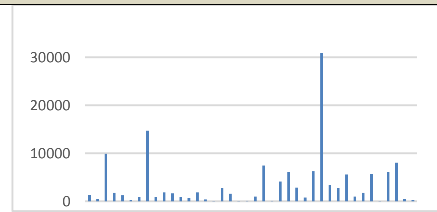
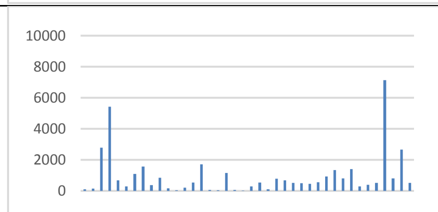
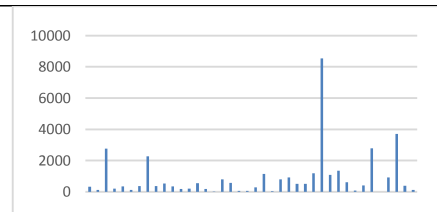
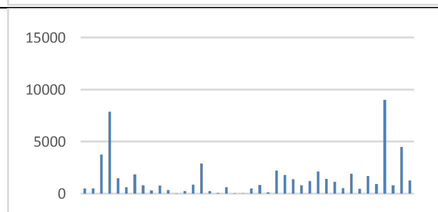
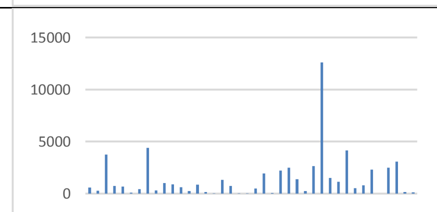
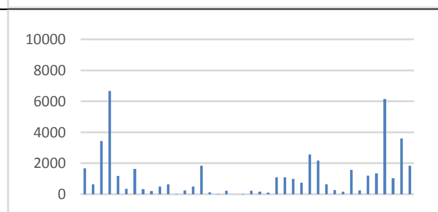
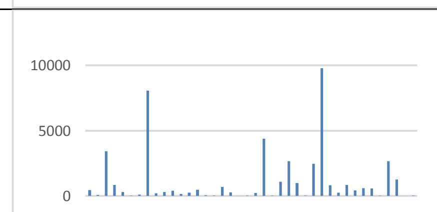
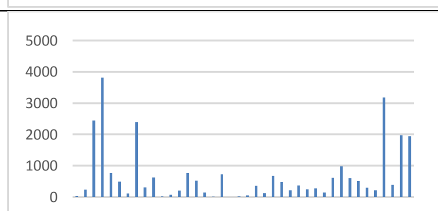
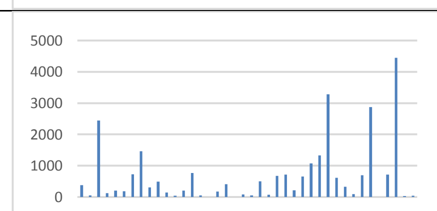
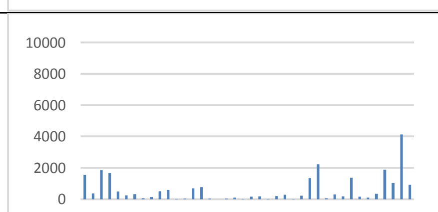
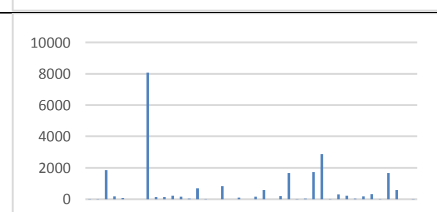
Treat	Coef.	S.E	Z	P> IzI
Land Area	-0.0241588	0.0490781	-0.49	0.623
Tot Pop	0.0000347	0.0001982	0.17	0.861
Emp. Density	0.0000796	0.0000266	2.99	0.003
Labor Force	-0.0000117	0.0000675	-0.17	0.862
PC Inc	-0.0000250	0.0000141	-1.77	0.076
Per Vacant	-0.0109837	0.0446946	-0.25	0.806
Per HS	-0.0475026	-0.0475026	-2.13	0.033
Constant	-1.6118610	0.8691325	-1.85	0.064

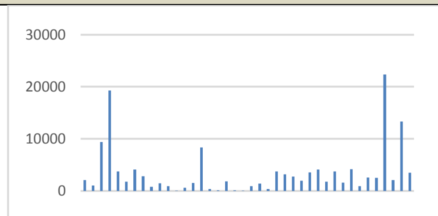
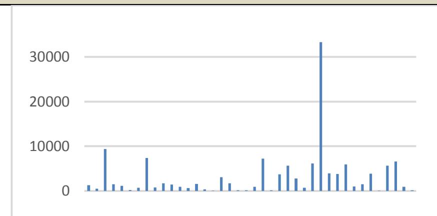
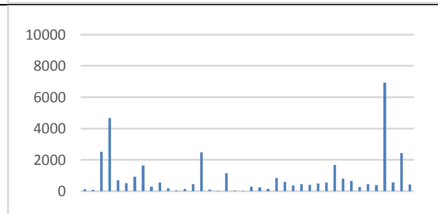
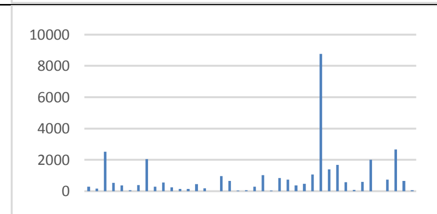
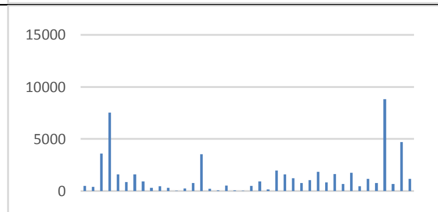
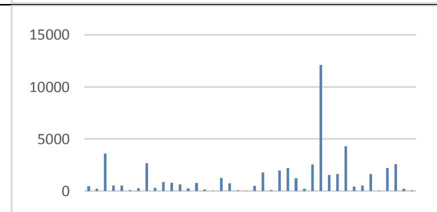
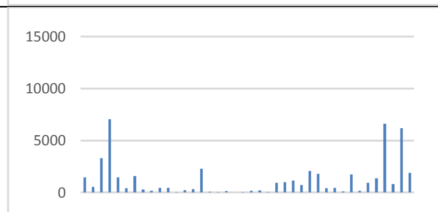
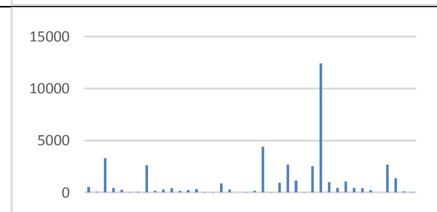
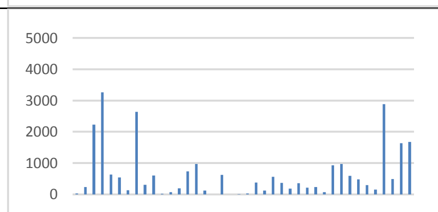
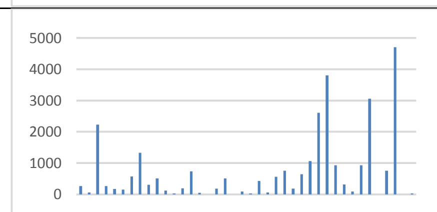
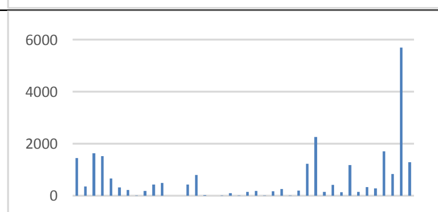
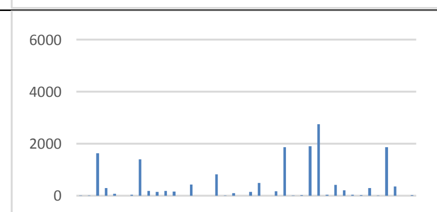
n= 969
r^2= 0.023
pseudo r^2= 0.049

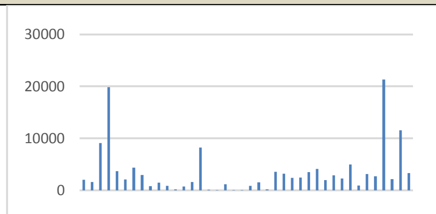
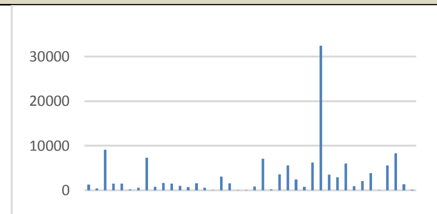
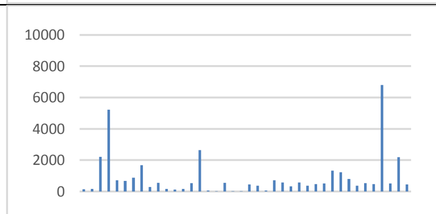
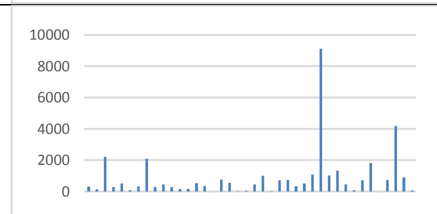
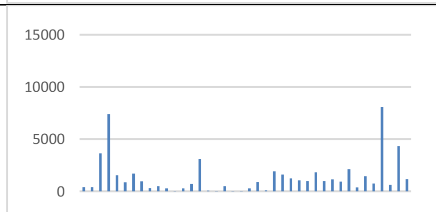
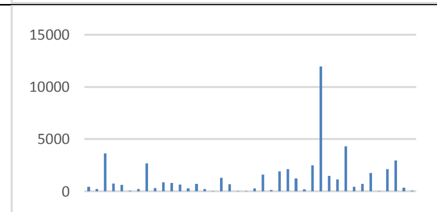
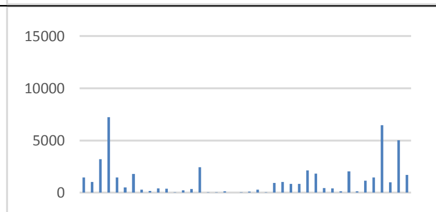
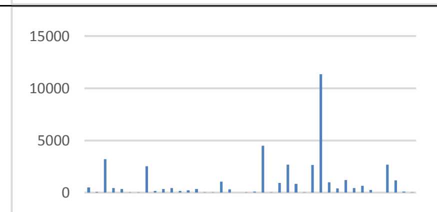
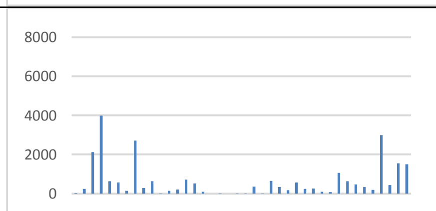
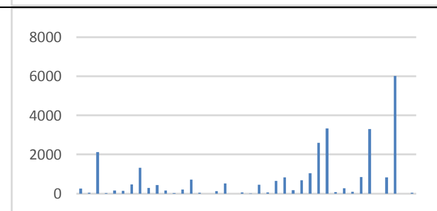
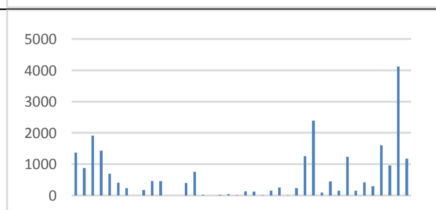
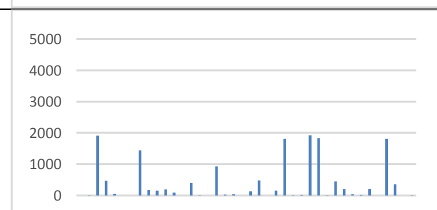
APPENDIX B

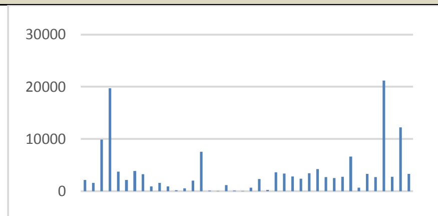
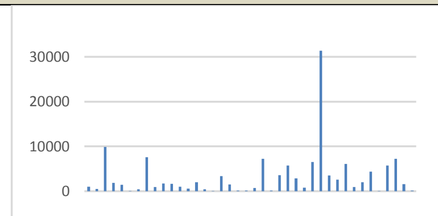
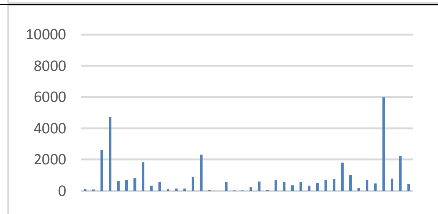
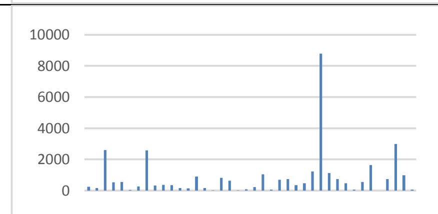
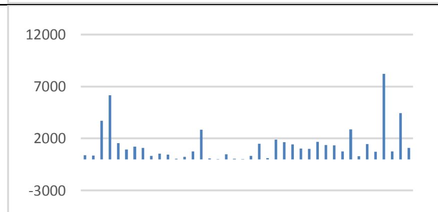
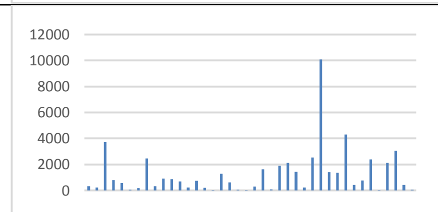
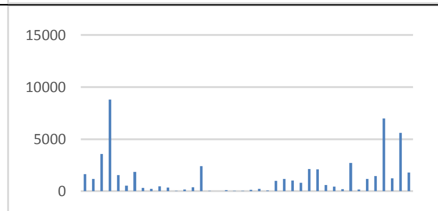
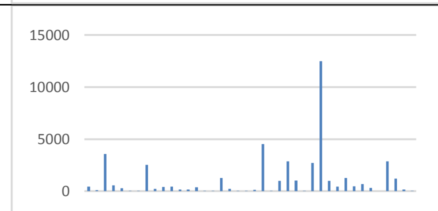
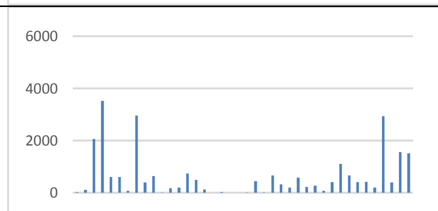
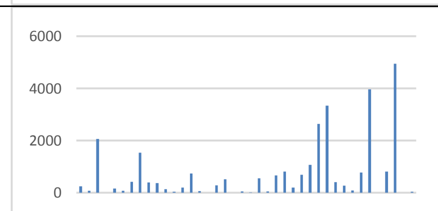
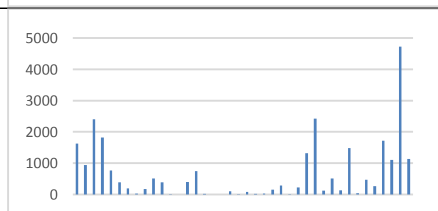
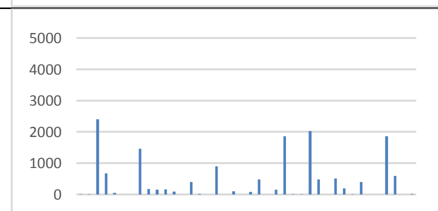
Appendix B: Histograms of Employment Density

The following histograms display employment densities by various categories since the opening of the DART stations identified in this study.

2002	Control Group	Treatment Group
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

2003	**Control Group**	**Treatment Group**
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

2004	Control Group	Treatment Group
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

2005	Control Group	Treatment Group
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

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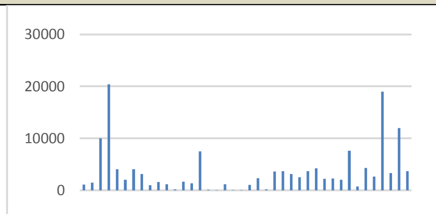
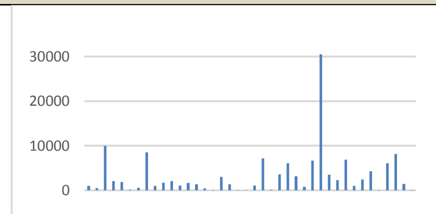
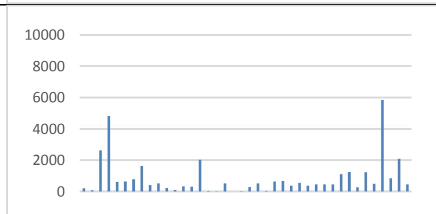
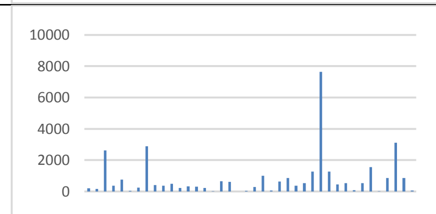
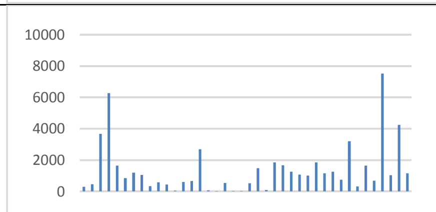
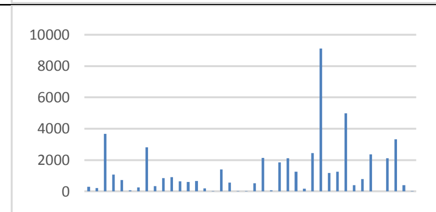
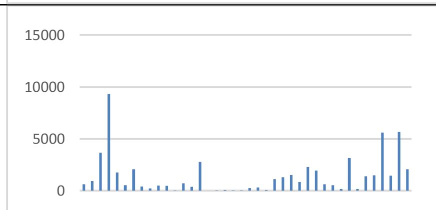
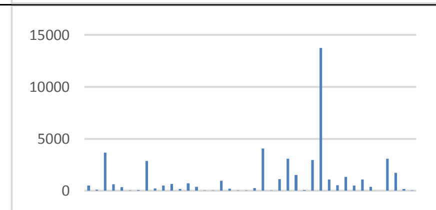
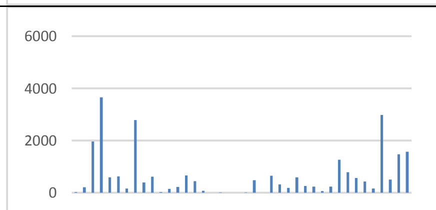
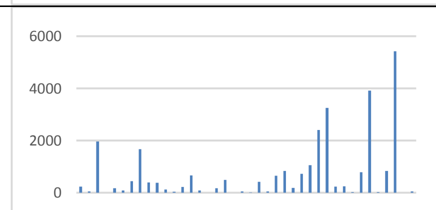
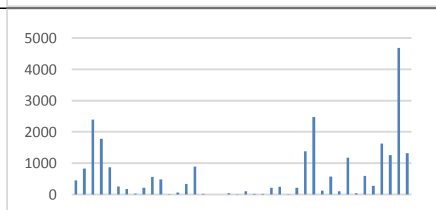
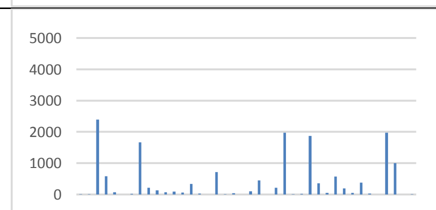
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

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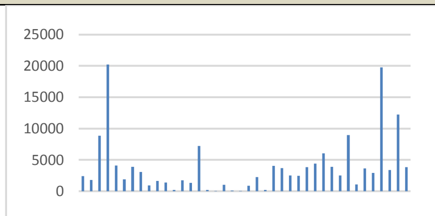
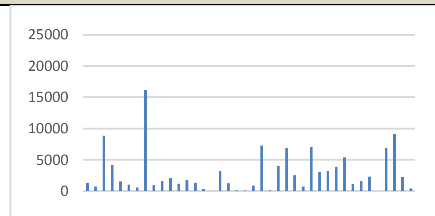
<tr><td>Total Employment</td><td>
</td><td>
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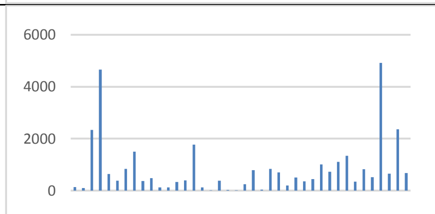
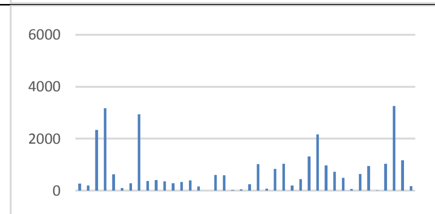
<tr><td>Low Earning Employment</td><td>
</td><td>
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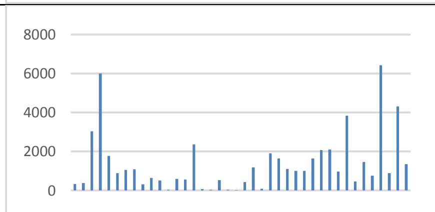
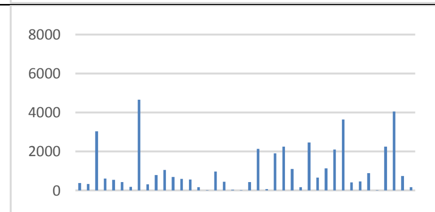
<tr><td>Median Earning Employment</td><td>
</td><td>
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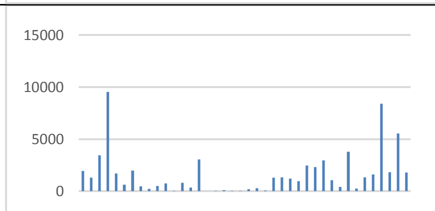
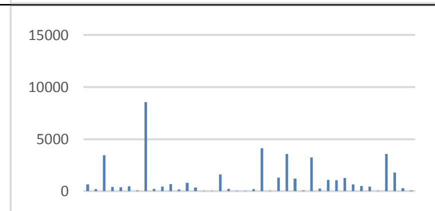
<tr><td>High Earning Employment</td><td>
</td><td>
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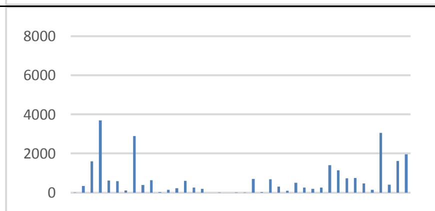
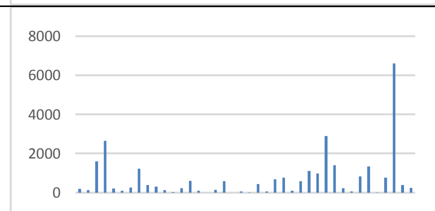
<tr><td>Service Oriented Employment</td><td>
</td><td>
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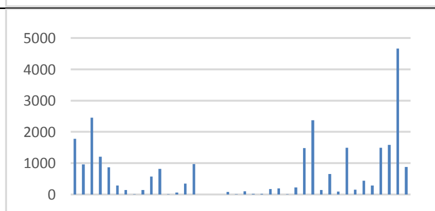
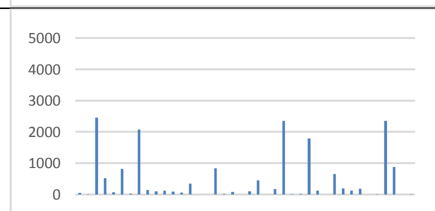
<tr><td>Professional Oriented Employment</td><td>
</td><td>
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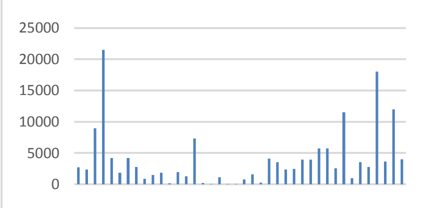
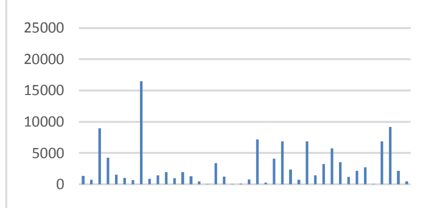
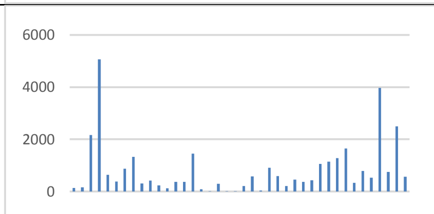
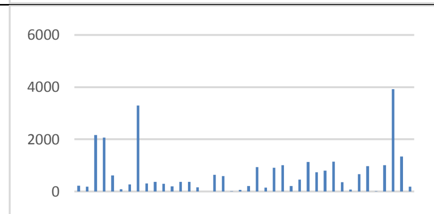
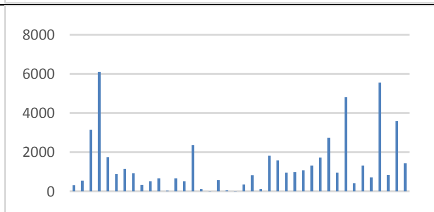
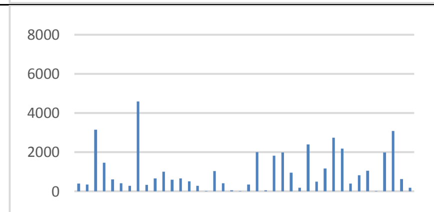
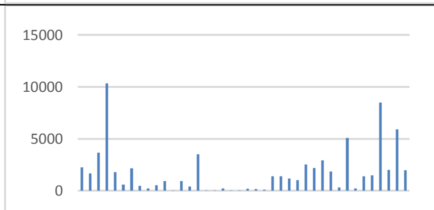
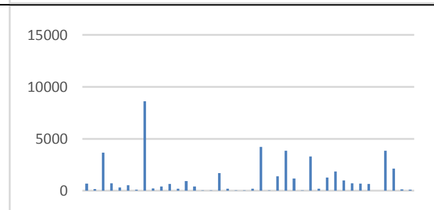
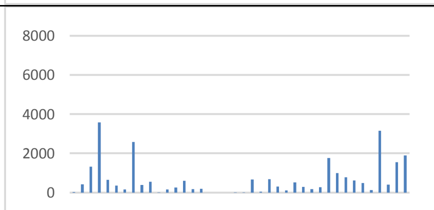
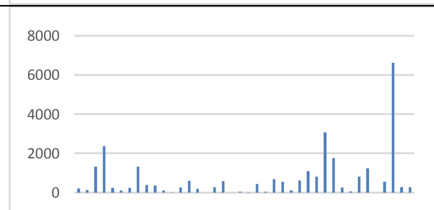
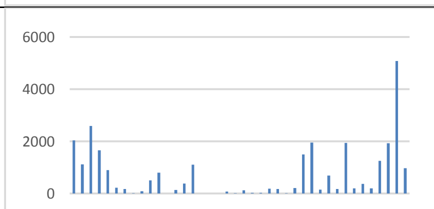
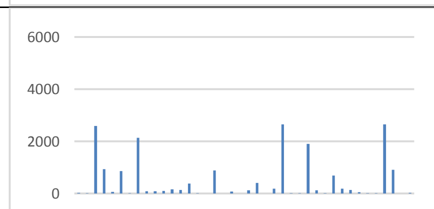
2008	Control Group	Treatment Group
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

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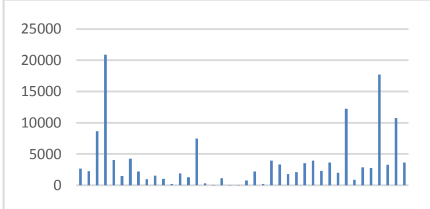
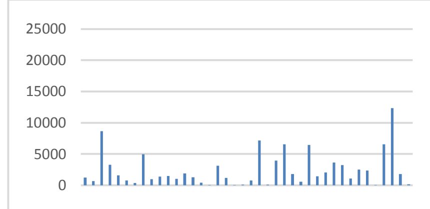
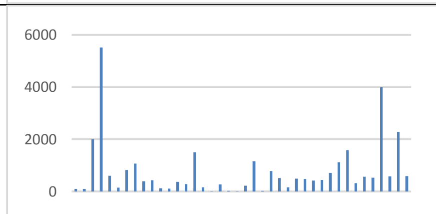
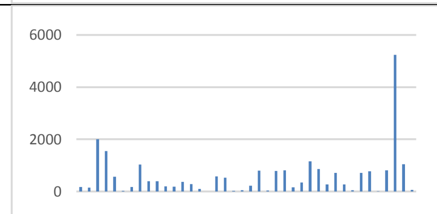
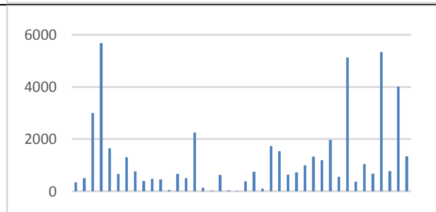
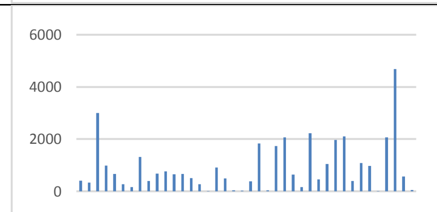
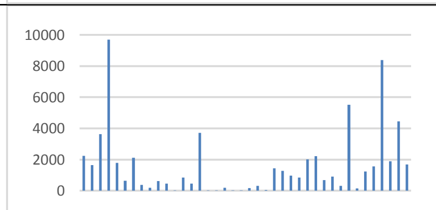
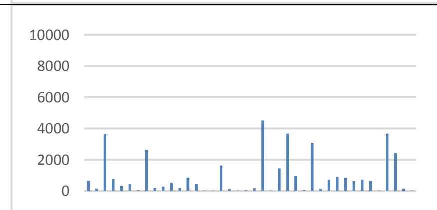
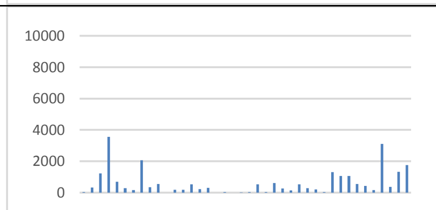
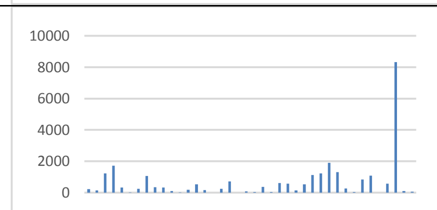
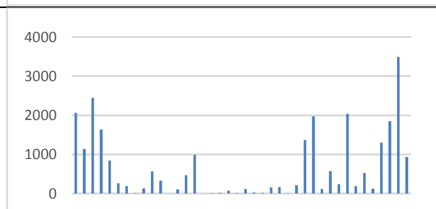
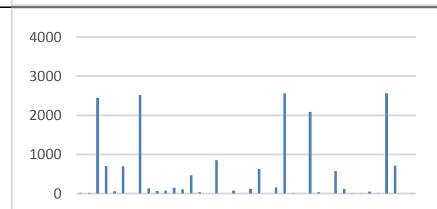
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

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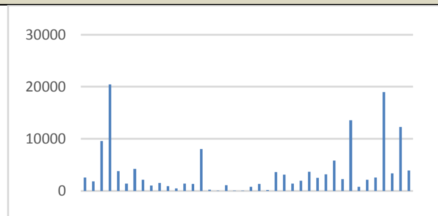
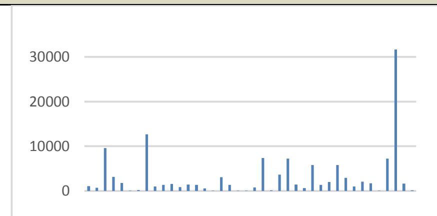
<tr><td>Total Employment</td><td>
</td><td>
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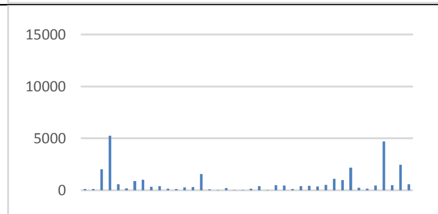
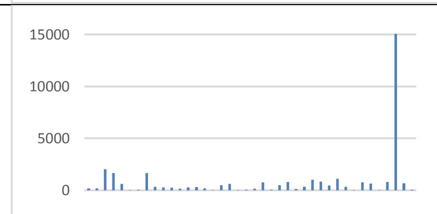
<tr><td>Low Earning Employment</td><td>
</td><td>
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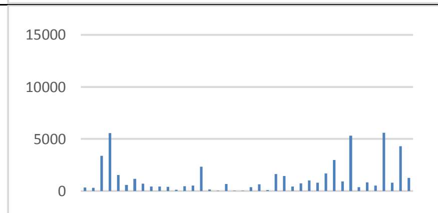
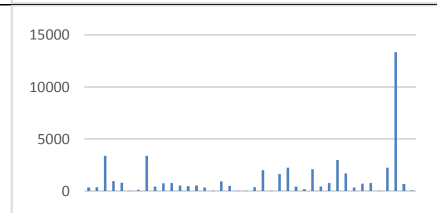
<tr><td>Median Earning Employment</td><td>
</td><td>
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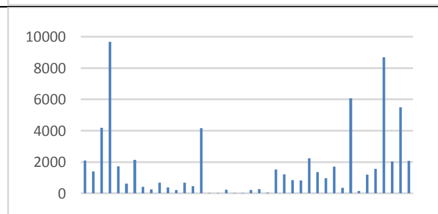
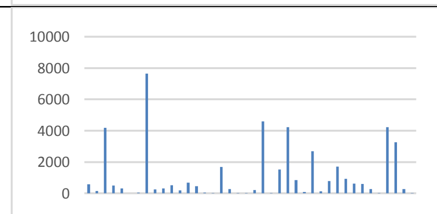
<tr><td>High Earning Employment</td><td>
</td><td>
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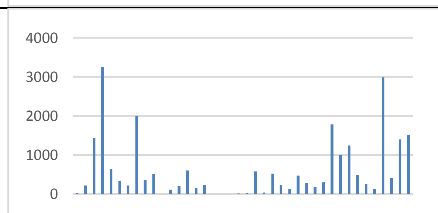
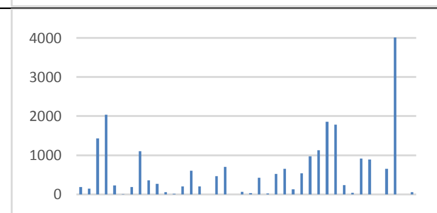
<tr><td>Service Oriented Employment</td><td>
</td><td>
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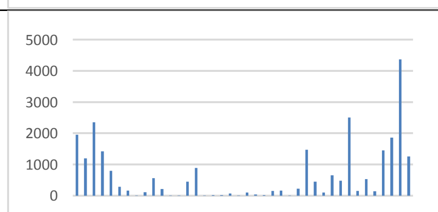
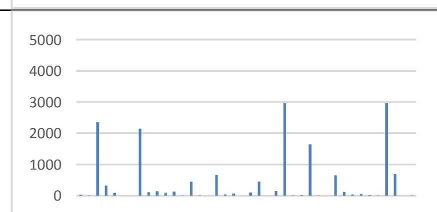
<tr><td>Professional Oriented Employment</td><td>
</td><td>
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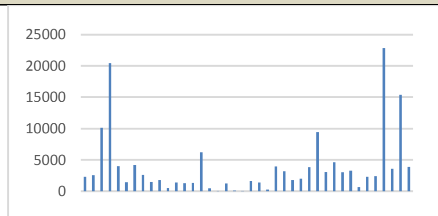
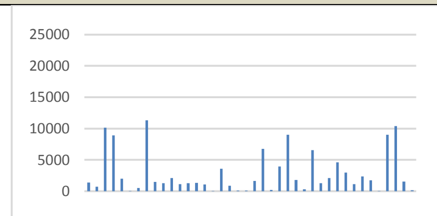
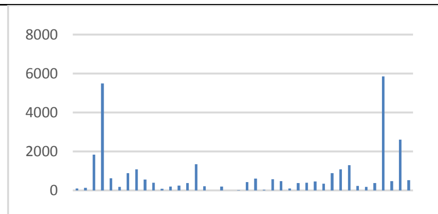
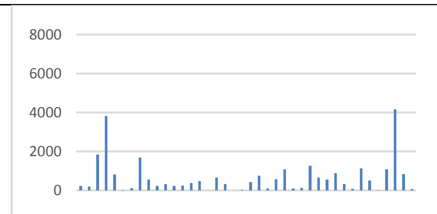
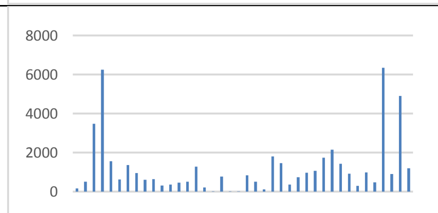
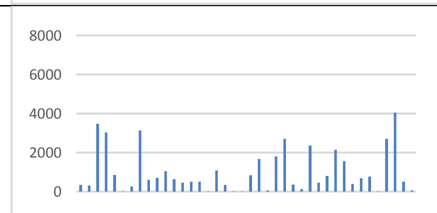
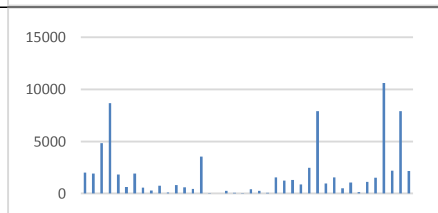
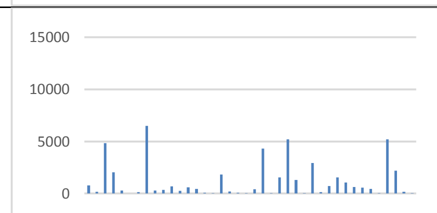
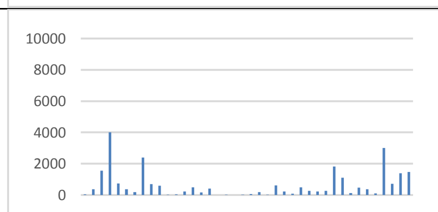
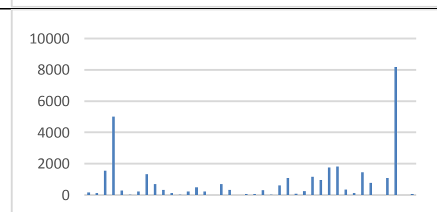
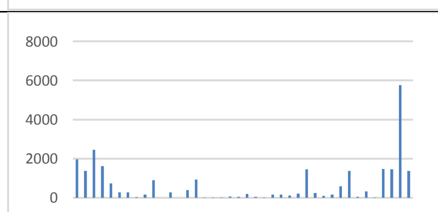
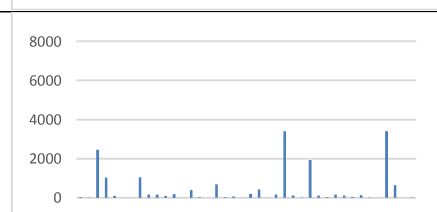
Total Employment		
Low Earning Employment		
Median Earning Employment		
High Earning Employment		
Service Oriented Employment		
Professional Oriented Employment		

APPENDIX C

Appendix C: Multi-Linear Regression Results

1. MLR Results for Total Employment, Low/Median/High Earning Employment

	Model 1 Employment		Model 2 Low Earning Employment		Model 3 Median Earning Employment		Model 4 High Earning Employment	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Area_SqMi	4395.75***	0.000	584.71***	0.000	1551.28***	0.000	2255.15***	0.000
Tot_Pop	-1.59***	0.000	-.20***	0.000	-.406 ***	0.000	-0.96***	0.000
Per_Vacant	34.26	0.148	19.67	0.844	23.99 *	0.010	-9.41	0.466
Per_HS	-2.29	0.824	-2.43	0.244	.4854594	0.904	-0.11	0.984
L_PCInc	-483.58**	0.018	-109.83	0.064	-164.85**	0.039	-234.90**	0.034
L_LbrForce	124.09	0.339	-40.51	0.256	-6.014	0.906	162.86**	0.022
Treat	-34.42	0.950	45.71***	0.000	-40.24	0.851	-18.21	0.951
Yr2003	-110.28	0.840	-78.88	0.643	-64.825	0.762	10.88	0.971
Yr2004	-95.80	0.863	-77.80	0.649	-75.55	0.724	35.00	0.907
Yr2005	-37.65	0.944	-58.63	0.767	-86.32	0.687	84.75	0.776
Yr2006	77.80	0.895	-30.18	0.950	-83.37	0.697	168.80	0.571
Yr2007	172.28	0.756	-20.30	0.643	-99.27	0.643	269.30	0.367
Yr2008	99.20	0.867	-71.50	0.649	-171.05	0.425	319.20	0.285
Yr2009	-42.95	0.944	-107.68	0.767	-196.27	0.360	238.45	0.424
Yr2010	43.90	0.942	-109.25	0.950	-186.07	0.385	316.68	0.288
Yr2011	462.93	0.402	-21.18	0.985	-63.15	0.768	524.70*	0.079
Treat2003	-111.55	0.891	54.96	0.954	-25.02	0.934	-96.38	0.819
Treat2004	-162.60	0.833	35.51	0.955	-48.77	0.872	-104.23	0.805
Treat2005	-135.93	0.862	1.94	0.802	-25.77	0.932	-66.98	0.874
Treat2006	-175.40	0.821	-16.85	0.718	-18.07	0.952	-95.35	0.821
Treat2007	-139.58	0.865	-35.65	0.638	-18.92	0.950	-39.88	0.925
Treat2008	-49.35	0.954	-8.05	0.757	16.87	0.956	-13.05	0.975
Treat2009	-128.38	0.873	10.51	0.840	-14.02	0.963	-79.75	0.850
Treat2010	-261.48	0.742	-24.98	0.683	-63.35	0.834	-128.03	0.761
Treat2011	-315.98	0.681	-97.95	0.405	-181.45	0.549	8.55	0.984
Cons	5568.21**	0.031	1893.37**	0.01	2168.26**	0.032	1926.70	0.170

Notes: * Indicate the value is significant at $p < 0.10$; ** Indicate the value is significant at $p < 0.05$ levels of significance; *** Indicate the value is significant at $p < 0.01$ levels of significance.

2. MLR Results for Total Service Employment, Professional Employment

	Model 5 Service Employment		Model 6 Professional Employment	
	Coef	p-value	Coef	p-value
Area_SqMi	460.18***	0.000	1252.74***	0.000
Tot_Pop	-0.20***	0.000	-0.57***	0.000
Per_Vacant	23.29***	0.000	-2.42	0.822
Per_HS	4.66**	0.022	7.57	0.105
L_PCInc	48.55	0.229	103.11	0.265
L_LbrForce	6.23	0.809	109.82*	0.063
Treat	8.08	0.941	-126.85	0.610
Yr2003	8.98	0.934	8.03	0.974
Yr2004	16.20	0.881	-1.88	0.994
Yr2005	19.50	0.857	9.93	0.968
Yr2006	18.48	0.865	16.18	0.948
Yr2007	1.78	0.987	67.93	0.784
Yr2008	-34.83	0.748	125.65	0.613
Yr2009	-26.98	0.803	124.95	0.615
Yr2010	-32.63	0.763	127.13	0.609
Yr2011	57.18	0.598	225.53	0.364
Treat2003	-63.73	0.678	-12.10	0.973
Treat2004	-65.70	0.668	-0.20	1.000
Treat2005	-76.85	0.616	39.88	0.910
Treat2006	-72.40	0.637	17.05	0.961
Treat2007	-51.83	0.735	17.05	0.961
Treat2008	-12.15	0.937	-31.33	0.929
Treat2009	-42.10	0.784	-81.08	0.817
Treat2010	-53.03	0.729	-111.98	0.750
Treat2011	-131.00	0.393	-214.08	0.542
Cons	-381.90	0.454	-1447.51	0.216

Notes: * Indicate the value is significant at $p < 0.10$; ** Indicate the value is significant at $p < 0.05$ levels of significance; *** Indicate the value is significant at $p < 0.01$ levels of significance.

3. MLR Results for Total Employment Density, Low/Median/High Earning Employment Densities

	Model 7 Employment		Model 8 Low Earning Employment		Model 9 Median Earning Employment		Model 10 High Earning Employment	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Area_SqMi	511.16**	0.011	178.34***	0.001	204.40***	0.004	128.41	0.130
Tot_Pop	-1.80***	0.000	-0.58***	0.000	-0.64***	0.000	-0.58***	0.000
Per_Vacant	56.18	0.194	42.18***	0.000	28.81*	0.060	-14.81	0.420
Per_HS	-82.75***	0.000	-18.33***	0.000	-24.84***	0.000	-39.57***	0.000
L_PCInc	-1290.12***	0.001	-155.54	0.127	-414.21***	0.002	-720.37***	0.000
L_LbrForce	238.51	0.315	314.87***	0.000	109.68	0.192	-186.03*	0.065
Treat	500.40	0.618	128.90	0.639	196.05	0.581	175.45	0.680
Yr2003	-200.55	0.841	-47.44	0.863	-110.55	0.755	-42.55	0.920
Yr2004	-153.07	0.878	-22.08	0.936	-95.08	0.788	-35.90	0.933
Yr2005	-161.61	0.872	-37.85	0.890	-147.24	0.677	23.48	0.956
Yr2006	-33.02	0.974	-42.45	0.877	-114.86	0.746	124.28	0.770
Yr2007	-436.85	0.662	-115.08	0.675	-328.00	0.354	6.23	0.988
Yr2008	-542.79	0.587	-193.77	0.480	-390.17	0.270	41.16	0.923
Yr2009	-831.72	0.406	-257.99	0.347	-454.60	0.199	-119.13	0.779
Yr2010	-152.25	0.879	2.00	0.994	-217.67	0.539	63.42	0.881
Yr2011	-303.41	0.762	-148.80	0.587	-329.32	0.352	174.71	0.681
Treat2003	122.09	0.931	-24.96	0.949	61.47	0.902	85.58	0.887
Treat2004	43.97	0.975	-42.91	0.912	1.17	0.998	85.71	0.886
Treat2005	195.04	0.890	-36.42	0.925	66.53	0.894	164.92	0.783
Treat2006	79.49	0.955	-63.15	0.871	32.36	0.948	110.28	0.854
Treat2007	690.15	0.626	-14.82	0.969	239.53	0.632	465.44	0.438
Treat2008	891.66	0.528	49.44	0.899	272.74	0.586	569.48	0.343
Treat2009	877.66	0.535	69.39	0.858	248.19	0.620	560.07	0.351
Treat2010	298.79	0.833	-202.51	0.601	37.89	0.940	463.41	0.440
Treat2011	595.70	0.674	-33.80	0.931	103.38	0.836	526.12	0.381
Cons	17755.36***	0.000	923.16	0.474	5689.99***	0.001	11142.21***	0.000

Notes: * Indicate the value is significant at $p < 0.10$; ** Indicate the value is significant at $p < 0.05$ levels of significance; *** Indicate the value is significant at $p < 0.01$ levels of significance.

4. MLR Results for Total Service Employment Density, Professional Employment Density

	Model 11 Service Employment		Model 12 Professional Employment	
	Coef	p-value	Coef	p-value
Area_SqMi	310.17***	0.000	122.30***	0.001
Tot_Pop	-0.63***	0.000	-0.18***	0.000
Per_Vacant	65.87***	0.000	5.81	0.460
Per_HS	-5.46	0.172	-7.37**	0.031
L_PCInc	271.77***	0.001	115.74*	0.087
L_LbrForce	534.15***	0.000	-76.39*	0.077
Treat	66.91	0.754	44.55	0.807
Yr2003	51.58	0.808	-169.05	0.352
Yr2004	66.37	0.755	-187.06	0.303
Yr2005	65.16	0.759	-202.79	0.264
Yr2006	67.10	0.752	-181.56	0.318
Yr2007	46.10	0.828	-153.73	0.398
Yr2008	29.71	0.889	-130.78	0.472
Yr2009	33.78	0.874	-142.41	0.433
Yr2010	105.10	0.621	-175.86	0.333
Yr2011	128.80	0.545	-140.70	0.439
Treat2003	-84.35	0.779	188.37	0.463
Treat2004	-124.38	0.679	185.19	0.471
Treat2005	-120.16	0.690	258.30	0.315
Treat2006	-117.03	0.697	213.50	0.406
Treat2007	-50.50	0.867	219.47	0.393
Treat2008	-54.12	0.857	239.68	0.351
Treat2009	-106.05	0.724	196.00	0.446
Treat2010	-177.66	0.555	229.06	0.373
Treat2011	-183.63	0.542	195.52	0.447
Cons	-5582.71***	0.000	273.77	0.749

Notes: * Indicate the value is significant at $p < 0.10$; ** Indicate the value is significant at $p < 0.05$ levels of significance; *** Indicate the value is significant at $p < 0.01$ levels of significance.