ABSTRACT

Title of Document:	IMPACT OF TRANSIT ORIENTED DEVELOPMENT ON MODE CHOICE WITH CONSIDERATION FOR SELF SELECTION AND MULTIMODAL ACCESSIBILITY
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The U.S Department of Transportation allocated $10 million in 2013 to provide funding to advance planning efforts that support Transit Oriented Development (TOD) associated with new fixed guideway and core capacity improvement projects. Transit Oriented Development (TOD) is generally considered to be a type of pedestrian-friendly community development around the major transit station that promotes transit ridership, increases non-motorized travel and encourages local economic development. This thesis is an effort to analyze the effect of TOD on travel mode choice in both Washington, DC, and Baltimore metropolitan areas using the MWCOG 2007 household travel survey. A relatively new method in the transportation field called "Propensity Score Matching" was used to address the self-selection, and statistical models were developed to evaluate the impact of TOD on mode choice. The results indicated that after controlling for self-selection, TOD has a significant impact on boosting transit ridership and increasing active mode of travel.

IMPACT OF TRANSIT ORIENTED DEVELOPMENT ON MODE CHOICE WITH
CONSIDERATION FOR MULTIMODAL ACCESSIBILITY AND SELF
SELECTION

By

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Dedication

To my mother, father and sister; who mean the world to me.

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First, I want to thank Dr. Lei Zhang for his guidance and recommendations from the

first day I entered the transportation engineering program in graduate school.

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Chapter 1: Introduction

1.1 Transit Oriented Development

Transit Oriented Development (TOD) continues to be an interesting and popular area of research because of the unknown and yet-to-be-explored aspects of it in terms of planning, implementation, and success, despite all the research that has been done in this area so far. It has also received a lot of attention during the recent few years after several major government transportation agencies allocated funds and resources to promote and expand transit services and facilities (The most recent attempt by the government toward this goal was the MAP-21 act signed by President Obama on July 6, 2012). Decision-makers in metropolitan planning organizations and local DOTs want to know how and to what extend TOD can help them reduce congestion, increase transit ridership and promote non-motorized modes. Furthermore, planners suggest that these effects could lead to secondary benefits such as reducing air pollution and green gas emission, increasing livability and vitality of the neighborhood.

Transit-oriented development is generally defined as a type of community development that includes a mixture of housing, office, retail and/or other commercial development and amenities integrated into a walkable neighborhood and located within a walkable distance of a major transit station [1]. High employment and population density, mixed land use, proximity to major transit station and walkable neighborhoods are the main components of the TOD definition based on the literature.

In general, TODs are planned and built in order to provide a pedestrian-friendly environment where residents have easy access –usually within a walking distance- to transit network and different amenities and thus are encouraged to make fewer auto trips and use transit more often. Based on the Center for Transit Oriented Development websites, major TOD benefits are as follows:

1- Reduced household driving and thus lowered regional congestion, air pollution and greenhouse gas emissions

2- Walkable communities that accommodate more healthy and active lifestyles

3- Increased transit ridership and fare revenue

4- Potential for added value created through increased and/or sustained property values where transit investments have occurred

5- Improved access to jobs and economic opportunity for low-income people and working families

6- Expanded mobility choices that reduce dependence on the automobile

1.2 TOD and Travel Behavior

There is a large body of literature on how different attributes of built environment affect travel behavior. These findings could help us better understand how living in transit-oriented development would change the pattern of travel of its residents. This research studied the effect of density, design, diversity and accessibility on travel behavior, and the concept of TOD is the integration of all these attributes. A major transit station provides high accessibility to TOD residents and mixed land use with pedestrian-friendly design encourages more people to choose walking and biking as their means of travel for short trips. By developing dense areas around transit stations,

more people would have the choice to use transit as their means of travel. Furthermore, by having high employment density, there are more job opportunities in proximity of residential locations with high accessibility by transit.

The main issue in the research of built environment and travel behavior is self-selection. For example, in the context of this study, is it the effect of TOD that its residents use more non-auto mode shares or people who do not like to use autos move to TODs. Does this pattern of travel behavior caused by living in TOD or by personal preferences and attitudes affect both residential location and travel behavior? Several methods have been proposed (discussed in the literature review section) to address the self-selection, and all the studies have emphasized the role of this issue when evaluating the effect of land-use policies on travel behavior.

1.3 Research Objectives and Approach

The objective of this research is to evaluate the effect of TOD on mode choice with consideration for self-selection and multimodal accessibility. Using MWCOG 2007-2008, a household travel survey used in both Washington, DC, and Baltimore metropolitan areas, a seemingly unrelated regression model was used to estimate the effect of TOD on auto, transit and walk and bike mode share after controlling for socioeconomic variables. In the next section, a propensity score matching method was used to control for self-selection and estimate the net effect of TOD on its residents. Finally, using an SUR model and multimodal accessibility measures at the block level, the mode share of each household was estimated and validated using the American Community Survey as ground truth. In general, this study is an effort to

propose a framework to examine the effect of land-use policies and specifically transit-oriented development on mode of travel.

1.4 Research Contribution

This study tries to give us a better understanding in research related to the association between TOD and travel behavior. First, it proposes a framework for estimating the effect of land development plans and specifically TOD on travel mode choice after controlling for socioeconomic variables. Second, this study incorporates a relatively new method in the transportation field (propensity score matching) to address the self-selection issue using only cross-sectional data and assess if the relationship between TOD and mode choice is correlation or causation. Finally, unlike usual MPOs planning models, the models developed in this thesis are sensitive to walkability and multimodal accessibility and could help planners and decision-makers evaluate the effectiveness of their long-range plan in encouraging non-auto mode share.

1.5. Thesis Organization

In the first chapter of the thesis generally explains transit-oriented development and its association with travel behavior. Chapter 2 is the literature review related to TOD and mode choice and self-selection. Chapters 3 and 4 describe the data and methodology used in this thesis in detail. In chapter 5, model estimation results and discussion is presented and in chapter 6 some of the application and validation of the models are discussed. Finally, in chapter 7, I make some conclusions based on the results and provide some suggestions for future studies.

Chapter 2: Literature Review

2.1 Transit Oriented Development

I reviewed the literature on Transit-oriented Development both in terms of how it has been defined over time and what are the policy requirements in designing the TOD areas. In addition, TOD performance and its impact on travel behavior, congestion relief, and affordable housing in urban areas after implementation were extensively reviewed.

2.1.1 TOD Definition

Research community's present state-of-knowledge on TOD provides various definitions for TOD based on different viewpoints and perspectives. Some define it simply as a high-density area that is within walking distance of a transit station (CTOD) and some highlight the walkability factors as well as high-density and mixed use aspects. By doing so, they define TOD as a high density area where there are shopping, housing and employment opportunities available, designed for pedestrians without excluding the automobiles [2]. Others focus on how well the collaboration of land uses and transit can work [3] and identify TOD as "development with a functional relationship to transit, allowing it to achieve synergies that enhance the value of both.

Peter Calthorpe (1993) defined TOD as a "moderate and high-density housing, along with complementary public uses, jobs, retail and services, concentrated in mixed-use developments at strategic points along the regional transit systems" [4]. More recently, Parker et al. (2002) defined the concept of TOD as: "moderate to higher

density development, located within an easy walk of a major transit stop, generally with a mix of residential, employment and shopping opportunities designed for pedestrians without excluding the auto."[5]

Most of the theoretical definitions proposed for TOD include some common elements such as compact mixed use development, pedestrian-friendly urban areas, and developments which are close to and well -served by transit- mainly a major transit station- as a core and mixed use developments located around it [6]. In practice, there are different approaches proposing different quantitative measurement criteria for TOD. Bernick and Cervero (1997) have specified a half-mile buffer zone around a transit station as TOD. They defined TOD as "a compact, mixed-use community, centered around a transit station that -by design- invites residents, workers, and shoppers to drive their cars less and ride mass transit more. The transit village extends roughly a quarter mile from a transit station, a distance that can be covered in about 5 minutes by foot. The centerpiece of the transit village is the transit station itself and the civic and public spaces that surround it. The transit station is what connects village residents to the rest of the region" [7].

Lund, et al. (2004) also emphasizes on TOD design for both motorized and non-motorized modes and suggests that encouraging pedestrian trips without having to discourage automobile traffic is possible by creating street networks which allow safe and efficient interaction among all these modes [8].

In addition to studies which built theoretical framework for TOD definition, characteristics, design guidelines, and expected benefits, there are research projects focusing on the empirical aspect of TOD analysis. This is done to perceive how effective TODs are in terms of increasing transit ridership, reducing traffic congestion, and encouraging more non-motorized travel.

One of the earliest studies of this kind, by Robert Cervero, shows that TOD residents are around 5 times more likely to take transit to work. Also, those who work in TOD areas are around 3 times more likely to use transit to work compared to all workers in the city [9]. Another more recent study by Cervero and his team considered17 TOD projects of varying sizes in four urbanized areas. Again, they stated that living in TOD areas increases transit trips by 2-5 times more for commuting trips, compared to those who are not living in TOD areas [10]. They claimed that automobile travel is reduced in TOD areas for three main reasons: 1) residential self-selection, 2) the availability of retail stores in neighborhoods and the short distance to the transit stations, and 3) the reduced car ownership rate as a result of residing in transit-served neighborhoods. Lund et al. (2004) also found that transit shares for TOD residents is higher compared to the other surrounding areas by a factor of 4.9. Also within TOD areas transit share is higher for work trips than for non-work travel [8]. In a very interesting piece of research, Renne (2005) found that over the 30-year period from 1970 to 2000, transit mode share for work trips has increased amongst TOD residents from 15.1% to 16.7%, while it has decreased across all regions from 19% to 7.1. Despite regions becoming increasingly auto-dependent for work trips, more than

twice as many TOD residents used transit for commuting, compared to the regional average (16.7% versus 7.1%) in 2000 [11].

There are different views among researchers about the importance of specific land use characteristics such as high density and mixed use in TOD areas. Some claim that presence of a transit station alone can be a very effective factor in encouraging residents to use transit [12]. Cervero (1993) found that for TOD residents, proximity to a transit station is more strongly associated to transit use than land use mix or high-quality walking facilities. He claimed that "as long as one lived near a rail station, other design factors are unlikely to deter them from using transit". Others take the opposite side by saying that all else being equal, the higher the residential and employment densities around transit stations and the higher the mix of land uses, the greater the transit ridership [13]. There is a third viewpoint saying that for non-work trips, shifting to transit is largely dependent on the degree of mixed use, the scale of the development, and the high residential and retail densities [14], while for work trips these factors are not as important. Cervero et al. (2008) also believes that the mixed use nature of built environment in TOD areas allows transit use for a variety of trip purposes and accommodates non-work trips throughout the day and week. Also, their study found that the combination of high densities and small block size significantly increased transit ridership among TOD residents in the San Francisco Bay Area in 2000. However, the land use features of TOD seem to be more effective in shorter distance non-work trips. In other words, having offices, shops, restaurants, and other amenities around a major transit station in high density areas encourages less driving and more non-motorized travel [15].

2.1.3 TOD and Self Selection

As mentioned before, the issue of self-selection is addressed in a few recent TOD studies. They state that a very significant reason for higher transit use in TOD areas is rather because of the prior intention of frequent transit riders or those who are unable to drive to live in areas with higher access to transit. Lund et al. (2004)'s survey in California shows that self-selection is actually among the top three reasons for residence selection by TOD residents [21]. Cervero (2007) indicated that based on studies in California, self-selection accounts for about 40 percent of the mode choice decisions for commute trips [11]. On the other hand, there are researchers who claim that the impact of self-selection is not as important. For instance, Chatman (2005) claimed that self-selection plays a limited role for pro-transit people, but not as much for "auto-oriented" people who move to TOD areas [15].

To capture the effect of self-selection in these kinds of analysis, one should study the travel behavior of TOD residents prior to moving to the TOD area and the previous status of their access to transit. Cervero (1994) studied the ridership among people living near California rail stations and how they commuted at their prior residence. Results of this study show that of those who did not experience change in their work location after moving to TOD, 56% were already transit riders for their commute trips and thus TOD residency did not have much of an effect on changing their travel behavior. Among those who drove to work prior to moving to TOD, 52% switched to transit for commute trips after residing in close proximity to transit [16]. Another survey done in California in 2003 clearly distinguished between mode choice before and after moving to TOD to capture the effect of self-selection. It showed that among

all surveyed TOD residents, around 12% shifted from some form of automobile travel to transit for their main trip purposes, 10% shifted from transit to auto after moving to TOD, and 56% drove as much as when they lived away from TOD [17].

2.2 Self Selection

The residential self selection has become the main issue in the research of relationship between built environment and travel behavior. Numerous researchers have study the correlation between land use and travel behavior [18], however, a strong causal link has not yet been established because of self selection issue. The question in my context of study is do people in transit oriented developments walk more or take transit more because the built environment encourage them to do so or because they have attitudinal preference for not using auto to make trips. If the latter is true, TOD is not the only cause of lower auto mode share and these people would drive less even if they did not live in TOD. If self-selection is not considered when estimating the effect of built environment on travel behavior, we will probably overestimate the success of TOD on encouraging non-auto mode share [19].

Residential self selection is a result of two characteristics: socioeconomic and attitudinal. The example for socioeconomic characteristic is that a household with zero auto have no other choice rather than using transit or walk and bike to get to places. The example for attitudinal self selection is when someone like walking or taking transit just based on attitudinal preferences and that is the reason they moved to a place with high transit accessibility.

Several methods have been used to address self selection in field of transportation research. In this study, I review 5 major methods that have been used to address self selection: 1-Direct Questioning 2- Statistical control 3- Instrumental Variable 4- simultaneous models 5- Longitudinal Designs

2.2.1 Direct Questioning

In this method, researchers ask people how their travel pattern influences their residential location. Handy and Clifton [20] conducted a survey in Austin, TX and examined the effect of local shopping on reducing auto dependency. 1368 respondents from eight neighborhood were asked and eight focus group discussion was conducted after the survey. They concluded that self selection is significant "to some extent" in decision to walk to local stores and walking to store is partly because of the desire to walk to store. In another study, Hammond (2005) [21] asked respondents from Century Wharf, Cardiff about residential location and commuting mode choice. Based on his results, living in city center and closer to work place is correlated with lower auto use. He also asked about the sequence of decision making between commuting mode choice and residential location. 18% of the 90 respondents chose commute mode before making their decisions on residential location, and that 39% chose residence and commute mode simultaneously. Based on his descriptive results, commuting mode choice is significant factor in selecting residential location and sometimes it is the dominant factor.

2.2.2 Statistical Control

In this method, self selection is addressed by including attitudinal variables in the equation for estimating travel behavior. This method requires measuring attitudinal preferences and data on for preference for different mode of travel and residential location. Since this kind of data is lacking from the usual household travel surveys, this method has been used only in research and has not found it ways in practice. Several statistical models such as linear regression, negative binominal regression, seemingly unrelated regression and nested logit are used in literature to control for self selection using statistical control.

Handy et al. (2005, 2006), Cao et al. (2005, 2007a) and Cao, Mokhtarian, et al. (2006) [22,23,24] investigated the effect of built environment on different dimensions of travel behaviour using the data collected from 1682 respondents in Northern California in 2003. They measured for 12 dimensions of residential preference and travel attitude and incorporate these measures in model to predict travel behavior.

Handy (2006) included travel attitudes and neighborhood preferences in the model and concluded that built environment has an significant effect on walking behavior even after controlling for self selection. Although they had a quality data on travel attitude and neighborhood preference, the authors mentioned that their results are not definitive since the data is cross sectional and longitudinal data is needed to establish causation between built environment and travel behavior.

Chatman (2005) [25] used data collected from 999 adults in the San Francisco Bay Area and the San Diego metropolitan area in 2003, and studied the effect of modal preference in the relationship of built environment and non-work travel. Based on his results, proximity to heavy rail stations, retail density and distance to downtown had a positive impact on transit mode share for non-work travel after controlling for self selection.

2.2.3 Simultaneous Equation models

Simultaneous equation models (SEM) are used when the dependent variable in one relationship is the explanatory variable in other relationship. This method has the power to estimate both direct and indirect effect of an explanatory variable on outcome variable. In our context, attitude and lifestyle preferences has direct and indirect effect on travel behavior. The direct effect is the influence of travel attitudes and preferences on travel behavior and the indirect one is the effect that attitude has on residential location and built environment which then affect travel behavior. This method gives researchers the ability to estimate all of these relationship and see if these hypothesized effects are significant.

Bagley and Mokhtarian (2002) [26] used this method to investigate the relationship between residential neighborhood type and travel behavior, incorporating attitudinal, lifestyle and demographic variables in their model. This model includes interrelationships among nine key variables in a set of nine equation structural models. Based on the result, considering both direct and indirect effects, attitudinal and lifestyle variables had the greatest impact on travel demand among all the explanatory variables. Their interesting conclusion is that there is no direct causality

between land use and travel patterns and the association observed between these two is the result of correlations of each of those variables with life style preferences and attitude variables.

Bhat and Gue (2007) [27] proposed a methodological formulation to control for residential sorting effects in the analysis of the effect of built environment attributes on travel behavior-related choices. They used joint mixed multinomial logit-ordered response structure to include differential sensitivity to land use and transportation network variables and attiudenal variables to address self selection based on car ownership preferences stemming from both demographic characteristics and unobserved household factors. Based on their empirical analysis, built environment variables have an significant impact on residential location decision as well as car ownership.

Using data from 2691 residents in the region of Cologne, Germany, in 2002 and 2003, Scheiner and Holz-Rau (2007) [28] incorporated simultaneous equation model to examine the complex interrelations between life situation, lifestyle, residential location choice, urban form and travel mode. Based on their result, the effect of lifestyle on travel mode is indirect and through the effect it has on residential location. They concluded that travel mode is more influenced by life situation than by lifestyle. They also discussed that "the variance in travel behavior explained by the models does not considerably exceed traditional multiple regression analysis, despite the complexity of structural equation modelling".

2.2.4 Longitudinal Design

This method is used in situation that we have residential moves or significant change in travel behavior. Longitudinal design requires longitudinal data (before and after) that could answer the question of how built environment affect travel behavior. Under the assumption that attitudinal preferences do not change in time, the difference in travel behavior before and after the change in residential location is based on built environment. Since conducting longitudinal surveys is very expensive, there are few studies in the literature that uses longitudinal design.

Based on retrospective responses from 1244 parents, Boarnet et al (2005) [29] examined the effect of improvement in walking and biking infrastructures on children walking and biking to school. He considered these changes as treatment for children and selected a control group consists of children who did not live where this improvement take place. The results indicated that 15.4% of the 486 children who passed the SR2S projects increased their walking or bicycle travel to school, while only 4.3% of the 376 children who did not pass the projects increased their non-motorized travel.

Meures and Haajijer (2001) [30] examined the effect of built environment on travel patterns using Dutch Time Use Study data from 1990 to 1999. They split their respondents into movers and non-movers and developed a regression model to estimate the changes in number of trips by different modes using changes in built environment and socioeconomic variables as explanatory variables. They concluded that after controlling for self selection, built environment has an significant impact on

travel pattern especially on shopping and recreational trips. On the other hand, commuting trips is mainly determined by personal characteristics.

Using data from Northern California, Handy (2005) [31] studied households who have changed their residential location and examined the built environment impact on driving, walking and biking. They only measured travel behavior at multiple times and the attitude and residential location preference is only for current state. After controlling for current attitudes and changes in socio-demographics, the results indicated that changes in neighborhood characteristics consistently affect changes in travel behavior and it is the most important factor in explaining changes in driving and walking.

2.2.5 Propensity Score

Propensity score matching is a very popular method in sociology. The extensive explanation about this method is available in the methodology section. The propensity score matching is different from the statistical control model since it only controls for observed characteristics and whether the subject is treated or not based on these characteristics. In statistical method, attitudinal variables are controlled for by including them in the equation for travel behavior as the explanatory variable. In transportation field of research, this method is relatively new and the this method has recently gained interest among scholars in this field.

Using 1995 US national personal transportation survey (NPTS), Boer et al (2007) examined the relationship between built environment and walking choice. They used logistic regression model to estimate the propensity scores and households and

individual socioeconomic characteristics as the explanatory variables. After the matching based on propensity score, many variable that were significant before are insignificant. They concluded that self-selection plays an important role in walking behavior [32].

Cao (2010) [33,34] used this method to estimate the effect of neighborhood type on travel behavior. Binary probit model was used to estimate the propensity score based on demographics, residential preferences and travel attitudes as independent variable. The results showed that, on average, the true effect of neighborhood type on driving distance is 18.0 miles per week, which accounts for 12% of individuals' overall vehicle-miles driven. The ATE on walking to store frequency is 1.86 trips per month, which accounts for 61 percent of the observed difference. The ATE of neighborhood type on strolling frequency is 2.05 trips per month, which accounts for 86% of the observed difference. Therefore, neighborhood type has a more important influence than self-selection.

Chapter 3: Data

Multiple data sources have been used for this project. The 2007/2008 DC and Baltimore travel survey data was used to capture travel behavior information. The data includes information on personal socioeconomic and demographic characteristics, activities, and travel information such as travel distance, mode, travel time, purpose of the trip, and origin/ destination information for each surveyed household in the metro area. The households' home location is geocoded at traffic analysis zone (TAZ) level. Nearly 4000 households in Baltimore and 8000 households in DC area reported their travel diary. To calculate the built environment and land use characteristics of the neighborhood of residence for each household, the 2005 DC and Baltimore land use data was used. These datasets include population and employment information in each traffic analysis zone (TAZ). The land use variables we used include residential and employment densities, mixed use development (entropy), average block size, and distance to the city center. These land use variables and their calculation methods have been directly taken from Zhang, et al. 2011 [35]. The land use variables were incorporated into our model as well as several socioeconomic and demographic information of each surveyed household in the area.

Also, GIS shapefiles of census blocks and TAZs were used for spatially processing the datasets and also for data integration needed prior to statistical modeling. The

TAZ location information has been used to link built environment measures to travel behavior using GIS.

To define TOD boundaries based on criteria explained in next chapter, we used the Baltimore and DC major transit station data obtained from the National TOD database website. This dataset includes geocoded information about all rail transit stations in Baltimore and DC metropolitan areas. For analyzing conditions around the transit stations, a half mile buffer was created around each transit station to represent the transit zone (TOD). This was used as the basis for identifying whether the TAZ can be considered as a TOD area or not. Figure 4 below indicates the location of transit stations and the half-mile buffer around them, for both D.C. and Baltimore, as well as the places where the buffer areas for different stations overlap, which indicates better transit service and coverage.

Three sets of variables have been used in this model: 1) the socioeconomic and demographic variables of each household, including household's size, annual income, number of workers in the household, and number of vehicles available in the household, 2) the neighborhood level build environment variables for each TAZ, and 3) the binary variable for whether or not the household is located in a TOD area.

Chapter 4: Methodology

4.1 TOD Definition

Researchers have defined the concept of TOD in various ways. In general, it has been defined as a high-density, mixed-use neighborhood with easy access to transit for age and income groups such that people can easily reach various destinations by transit and/or non-motorized modes in a timely manner ([20], [14], and [21]).

Many TOD definitions have similar criteria aiming to produce a walkable environment for people to access the transit stations. As a result, TODs are transit centers with specific urban design characteristics such as high densities and mixed use neighborhoods. In our proposed framework for TOD identification, we have considered several land use factors as well as proximity to transit services.

To identify TOD areas, we used the method proposed by Nasri and Zhang as our base [35]. They quantitatively measured TODs using factors such as population and employment densities, level of mixed-use development, and pedestrian-friendliness in a half-mile buffer zone (straight line) around major rail transit stations. We revised their method by accounting for housing affordability criteria in addition to other factors in their TOD definition. Each Traffic Analysis Zone (TAZ) is marked as a TOD if it meets the following conditions:

$$TAZ \in TOD \; iff$$

$$\left(D_R^{TAZ} \geq D_R^{Avg} \; OR \; D_E^{TAZ} \geq D_E^{Avg} \right)$$

$$B_{TAZ} \leq BAvg$$

$$Rank_{TAZ}^{Entropy}/n \geq 0.30$$

$$X_{HT} \leq 0.45$$

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$$TAZ \in U_{1 \le i \le n} Ball_{0.5}^{T_i}$$

Where:

D_R^{TAZ} = Residential density of *TAZ* = residential population / area (acre)

D_E^{TAZ} = Employment density of *TAZ* = employment population / area (acre)

D_R^{Avg} = Average residential density for the entire metropolitan area

D_E^{Avg} = Average employment density for the entire metropolitan area

B_{TAZ} = Average block size for each TAZ, sq. mile

B_{Avg} = Average block size for the entire metropolitan area, sq. mile

X_{HT} = Housing & transportation affordability; % of housing + transportation cost of HH income

$Rank_{TAZ}^{Entropy}$ = The rank of *Entropy (TAZ)*[1] when sorted decreasingly according to entropy

$Ball_R^C$ = The circle of radius r (mile) around point *C*

$T_i, 1 \le i \le n$ = The point where the transit station is located

Using this novel method, we identified 44 TOD sites in Washington, D.C. and 10 TOD sites in Baltimore metro areas. The red highlighted areas in Figure 1 illustrate the TOD zones in our two cities and their position with respect to the major arterials and roadways. Most of the TOD zones are concentrated either in downtown areas where higher employment opportunities and better transit service are provided or in

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[1] The entropy formula has been widely used in several land-use and transportation related articles ([23] and [24])

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close proximity to the major roads and arterials where there is easy access to various destinations.
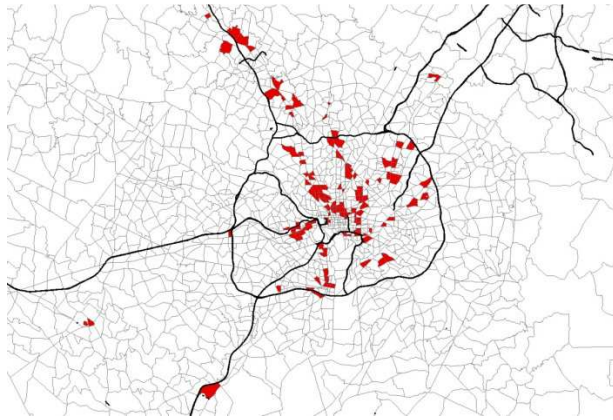
Washington, D.C.   Baltimore, MD
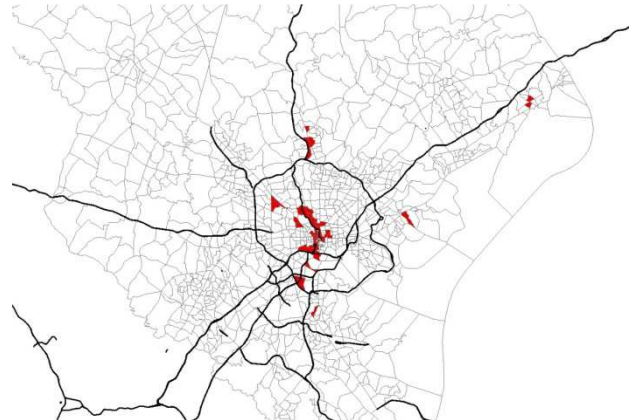
Figure1_ Location of TOD zones

However, the methodology presented above is an arbitrary one we decided to apply in this research based on our knowledge and experience. Various other definitions and quantitative methods can be definitely applied in the future to test the sensitivity of the results to those other types of methodologies and definitions for TOD.

4.2 Mode Share Model

The Seemingly Unrelated Regression (SUR) method is incorporated into the model mode share using three primary modes of auto, transit, and walk/bike. The percent of the mode share of all trips originating from each TAZ is our dependent variable and the independent variables that include land use variables and household characteristics. Since our model is at zone level, all the households' characteristics

used have been averaged from individual households to the entire households living in a specific zone (equation 2).

$$Auto = \alpha_1 \left(SES_j \right) + \beta_1 \left(BE_j \right) + \epsilon_1 \tag{2}$$

$$Transit = \alpha_2 \left(SES_j \right) + \beta_2 \left(BE_j \right) + \epsilon_2$$

$$Walk\,\&\,Bike = \alpha_3 \left(SES_j \right) + \beta_3 \left(BE_j \right) + \epsilon_3$$

$$S.t: \begin{cases} \alpha_1 + \alpha_2 + \alpha_3 = 0 \\ \beta_1 + \beta_2 + \beta_3 = 0 \end{cases}$$

Where:

$Auto = Percent\ of\ auto\ mode\ share\ originating\ from\ zone\ j$

$Transit = Percent\ of\ transit\ mode\ share\ originating\ from\ zone\ j$

$Walk\,\&\,Bike = Percent\ of\ walk\,\&\,bike\ mode\ share\ originating\ from\ zone\ j$

$SES_j = Socioeconomic\ attributes\ of\ HH\ living\ in\ zone\ j$

$BE_j = Built\ environment\ attributes\ of\ zone\ j\ including\ residential\ density,$

$employment\ density,\ entropy,\ and\ TOD\ binary\ variable$

This modeling approach allows us to perform the analysis with a set of simultaneous equations and preset constraints. The main constraint used in our model is that the coefficients for each variable in each row should sum up to zero. This constraint was added to capture the changes in different modes simultaneously. Furthermore, this approach has the capacity to consider different sets of variables for each mode share, thus more mode-specific variables could be used to model the share of each mode in the future.

Mode share modeling has been done in two steps: (1) we only controlled for household characteristics, so that the TOD variable captures all the effects of built environment and transit proximity at the same time, and (2) we add land use variables to the model to distinguish between the effect of built environment from other factors in TOD such as transit proximity.

4.3. Propensity Score Matching

Propensity Score Matching (PSM) is a method for estimating the treatment effect in observational studies. In observational studies (in contrast to controlled studies), the treatment is not assigned randomly and there is a possibility of error in estimating the treatment effect due to issues like self-selection or some systematic errors in selecting treated units. Rosenbaum and Rubin (1983) [36] proposed this method to address sample selection bias due to observable differences between the treatment and control groups. PSM is widely used in social sciences and economics in evaluating social programs like labor market policies [37]. In the transportation field, this method is relatively new and few studies have used this method to evaluate the effect of transportation policies. (reference needed)

In the travel behavior and built environment contexts, the treatment is land-use policies like transit-oriented development and the outcome of interest is the success measure of a policy like non-auto mode share. In an ideal situation, for evaluating the effect of TOD on travel behavior, the researcher would randomly assign households with diverse socioeconomic and attitudinal characteristics to live in the TOD and Non-TOD areas and then study their travel behaviors. The average treatment effect (in this case TOD) would be the difference observed in non-auto mode share between

TOD and non-TOD residents. Since transportation researchers generally use cross-sectional data like travel surveys and cannot perform ideal experiments with treatment and control groups, propensity score matching is a proposed method to somehow address the self-election issue with only observed cross-sectional data. This method would match TOD and non-TOD residents based on their socioeconomic and attitudinal characteristics and compare travel behaviors between the matched households. The matching is based on a scalar that integrates all the households' characteristics called the propensity score. The propensity score is the probability of a household living in the TOD (treatment group) given their observed characteristics. This probability can be estimated using discrete choice models. The propensity score is the probability that a household would choose to live in a TOD based on its characteristics. Therefore, comparing the matched households, one from TOD and one from non-TOD, could roughly translate to having an ideal experiment where the assignment of households to TOD is random. In this setting, the average treatment effect, (in our case the effect of TOD on auto mode share), is the average difference in an auto mode share between the matched TOD and non-TOD households.

When a treatment group differs in many characteristics from a control group, the matching should be based on a scalar that can integrate all of these characteristics. The propensity score encapsulates all the characteristics (both socioeconomic and attitudinal).

The purpose of this study is to evaluate the effect of TOD on non-auto mode share using propensity score matching. In the first step, I assigned the observations into two groups: the treated group, which is the household who lives in TOD, and the control

group, which includes the households that live in non-TOD. Treatment variable D is a binary variable that determines if the household lives in TOD or not: D=1 for treated observations and D=0 for controlled observation. The outcome of interest is the non-auto mode share for each household based on the travel survey.

The second step is estimating the propensity score for each household using the probit regression. Probit regression is used when the dependent variable can only take two values (binary variable). In my study, the probit regression is used to estimate the probability of each household living in TOD. Socioeconomic variables used for estimation are household size, number of workers in the household, auto ownership and income. Probit model D is the independent variable (whether the household lives in TOD or not) and x is the vector of independent variables:

$$p(x) = prob\ (D = 1|x) = E\ (D|x)$$

The estimated Y in the probit regression always takes the value between 0 to 1 since it is a cumulative normal distribution.

For this study, I used STATA software for propensity score matching. After estimating the propensity score for each household, the software determined the optimal number of blocks for categorizations of the households based on propensity score. After classifying the households, observations are matched between the treatment and control group. Several methods are available for matching: nearest neighborhood, kernel, radius and stratification. In this study, nearest neighborhood is used.
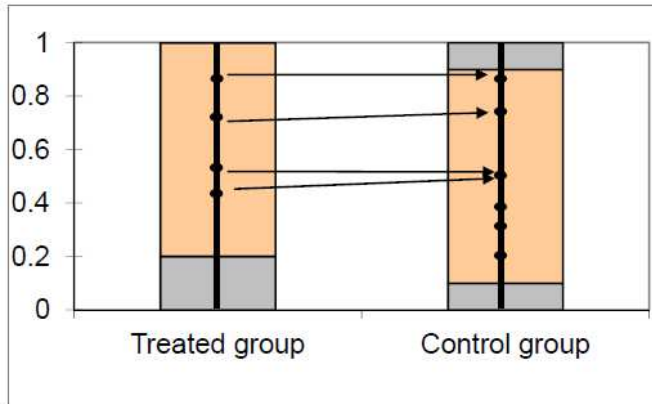
Nearest neighbor matching

Figure 1- Nearest Neighborhood Matching- Source: Econometrics Academy

In the matching process, for each observation i, we need to find a match of control observation j with similar characteristics. In the nearest neighborhood method, for each observation i, a control observation j is selected that has the closest x.

After matching on propensity score, we can compare the outcomes of treated and control observations:

$$ATET = E\left(\Delta|p(x), D = 1\right) = E\left(y_1|p(x), D = 1\right) - E\left(y_0|p(x), D = 0\right)$$

P(x): propensity score

D: binary treatment variable

Y: outcome variable

 Average Treatment Effect in Treated (ATET) is the difference between the outcomes of treated and the outcome of treated if they had not been treated.

$$ATET = E\left(\Delta|D = 1\right) = E\left(y_1 \mid x, D = 1\right) - E\left(y_0|x, D = 1\right)$$

The second term in the equation is counterfactual so it is not observable and needs to be estimated.

4.3. Multimodal Accessibility

In this study, I used walk accessibility developed by the Renaissance Planning Group as a part of the NCHRP 07-78 project [38]. The first step for calculating walk accessibility is developing a detailed pedestrian network based on the facilities and sidewalks using GIS methods. Figure 3 below illustrates a sample pedestrian and bicycle network in Arlington County.

Figure 3- Bicycle and pedestrian Networks in Arlington County

Accessibility is defined as number of destinations reachable in a certain period of time by a specific mode. Therefore, to calculate accessibility for each block, a

detailed travel network should be used to model travel times from a given origin to all accessible destinations (by mode).

This method relies extensively on GIS methods and data to quantify both the characteristics of land use and the connectivity of the transportation network to provide access to the available opportunities. Through relational overlay procedures, it is possible to quantify the accessibility for any mode for any activity at any point in the travel environment.

For transit accessibility, I used travel time and cost from the skim matrix, generated from the MWCOG planning model. The model considers vehicle time, access time and transit cost for each couple of zones.

Chapter 5: Results and Discussion

5.1. Descriptive Statistics

Descriptive statistics of trip generation rates for total and mode-specific trips of households living in Washington, D.C. and Baltimore is presented in Figure 2 below. In both case study areas, as expected, TOD zones on average have a lower number of auto trips compared to non-TOD areas. These statistics show that in general, TOD promotes non-auto mode choices such as transit and walk/bike modes.
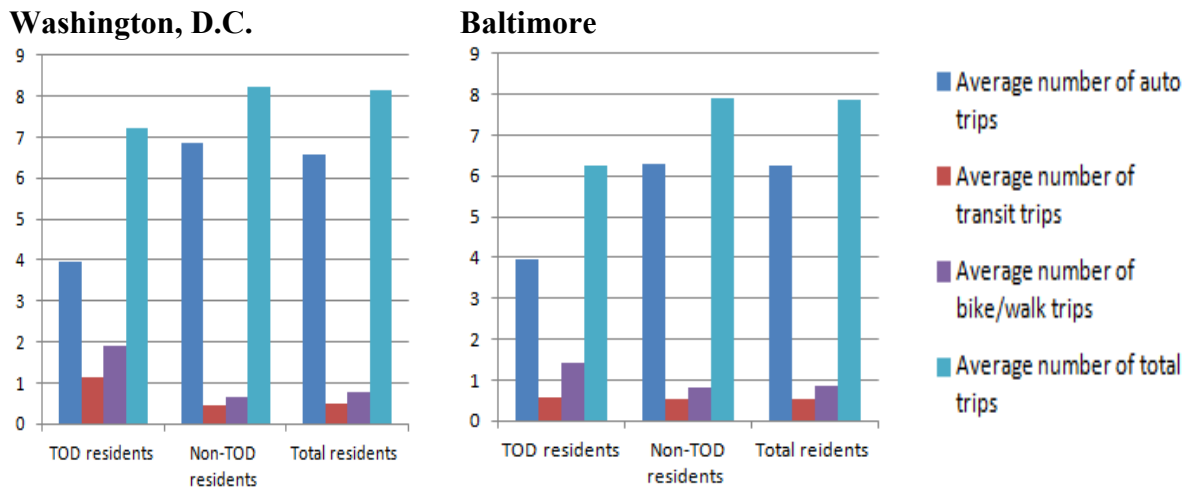
Figure 4- Descriptive Statistics for Number of Trips by Mode

The mode share of auto, transit and walk/bike are compared in figure 3 for TOD and non-TOD areas at the zone level. Non-TOD residents have a 17% higher auto mode share in Washington, DC, and a 14% higher in Baltimore. Baltimore is shown to be a more auto-oriented city than Washington, DC, probably due to the existence of a more efficient subway system in DC. The summary statistics also confirm our hypothesis that proximity to transit stations and living in a mixed and high-density neighborhood results in higher transit use. In addition, Washington, DC, has about a 5% higher transit mode share in both TOD and non-TOD areas than Baltimore.

Descriptive statistics also indicate that among three modes, walk/bike is most influenced by the TOD designation. In both Washington, DC, and Baltimore, living in transit-oriented neighborhoods results in about 9% higher walk/bike mode share. However, these results only show the aggregate comparison between TOD and non-TOD and do not distinguish the effect of different land use and household characteristics.

Auto Mode Share in Washington, DC, and Baltimore
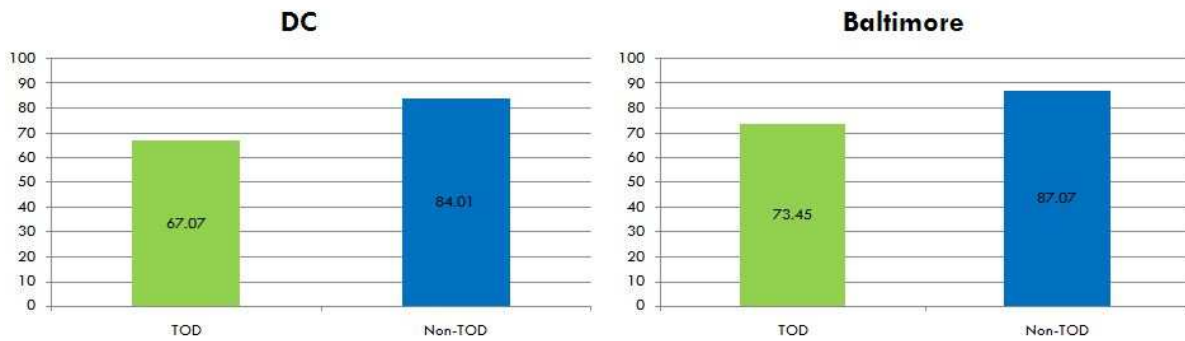
Transit Mode Share in Washington, DC, and Baltimore
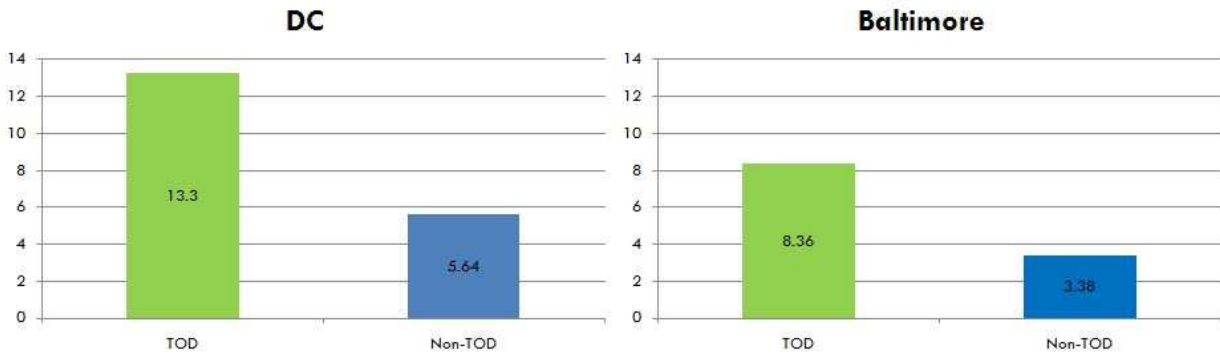
Walk/Bike Mode Share in Washington, DC, and Baltimore
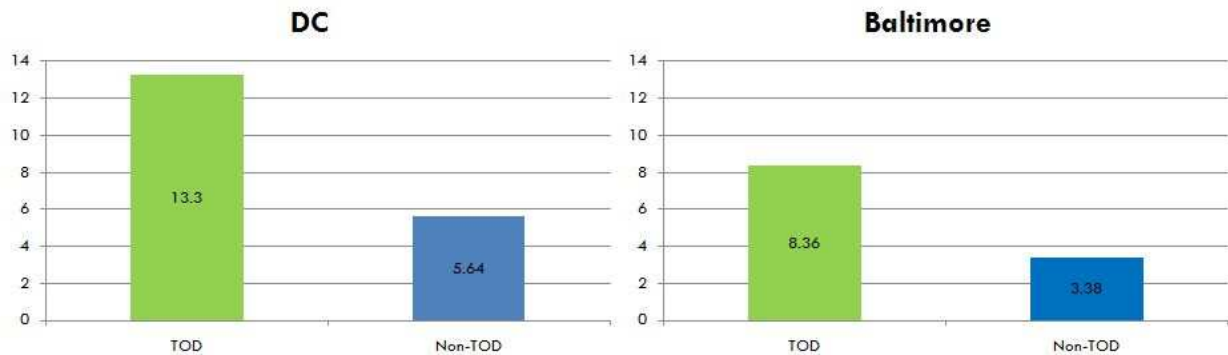
Figure 5- Mode Share Distribution

5.2. Mode Share Model Results

Results of mode share in table 1 indicate that trips originating from TOD in Washington, DC, have significantly higher transit and walk/bike mode shares. In the first step, after controlling for socio-demographic factors, the results indicate that living in TODs is correlated with a 12.13% decrease in auto transit and 4.72% and 7.4% increase in transit and walk/bike mode shares, respectively. Household size does not significantly affect the mode share of trips, while number of workers in the household has a positive effect on transit mode share. This is due to the convenience of using transit among commuters in the Washington, D.C. area. Modeling results also confirm the hypothesis that higher car ownership increases auto dependency and lowers transit ridership.

	Auto	Transit	Walk & Bike
Dependent Variable	**Mode Share Percentage**		
HH Size	-0.54	**-0.70**	**1.24**
Income	-0.29	-0.48	**0.77**
Car Ownership	**10.37**	**-5.08**	**-5.29**
Avg # of Workers	**-3.30**	**2.52**	0.78
Constant	**72.11**	**17.32**	**10.57**
HH Living in TOD	**-12.13**	**4.72**	**7.41**

Table 1- Mode Share Model in DC, Step 1

In the second step of modeling mode share for Washington, DC, residents, after land use variables are separated from TOD, the TOD coefficient shows that living in TODs results in a 7.3% reduction in auto mode share and 3.75% and 3.55% increase in transit and walk/bike mode share, respectively. The coefficients for our land use variables show that as expected, in high-density mixed-use urban areas, more sustainable and environmentally friendly modes of transit and walk/bike are encouraged while automobile use is discouraged. A one-unit increase in residential density would result in 0.24% and 0.12% increases in walk/bike mode and transit mode share, respectively.

	Auto	Transit	Walk & Bike
Dependent Variable	**Mode Share Percentage**		
Residential Density	**-0.36**	**0.12**	**0.24**
Employment Density	**-0.10**	**0.02**	**0.08**

	Auto	Transit	Walk & Bike
Mixture-Entropy	1.78	-2.10	0.34
HH Size	**-1.14**	-0.55	**1.69**
Income	-0.08	**-0.54**	**0.62**
Car Ownership	**7.91**	**-4.26**	**-3.65**
Avg # of Workers	-2.24	**2.23**	0.01
Constant	77.46	16.45	6.09
HH Living in TOD	**-7.30**	**3.75**	**3.55**

Table 2- DC mode share results, Step 2

In Baltimore, the results indicate that trips originating from TOD have 8.95% less auto mode share and 2.46% and 6.49% higher transit and walk/bike mode shares, respectively. The average number of workers has a positive influence on transit mode share, and if average car ownership increases by 1 unit, auto mode share would increase by 7.52% and transit and walk/bike mode share would decrease by 3.39% and 4.14%, respectively.

	Auto	Transit	Walk & Bike
Dependent Variable	**Mode Share Percentage**		
HH Size	**-1.16**	**-0.41**	**0.75**
Income	**-0.23**	**-0.32**	**0.086**
Car Ownership	**7.61**	**-3.43**	**-4.18**
Avg # of Workers	**-1.08**	**1.27**	**0.19**
Constant	**77.92**	**10.25**	**11.83**
HH Living in TOD	**-8.95**	**2.46**	**6.49**

Table 3- Baltimore mode share results, step 1

In the second step of modeling the mode share for Baltimore residents, the results have different trends than that in Washington, DC. The effect of TOD on mode share is not statistically significant in Baltimore. This may be due to weak performance of transit systems in Baltimore and their relative inefficiency compared to the systems in Washington DC. In the second step, household size has a significant impact on mode share. An increase in household size will result in a higher use of non-auto modes.

The effect of socioeconomic and demographic variables is the same in terms of direction but not in magnitude in both metropolitan areas. The income factor has a significant positive effect on walk/bike mode share. A justification for this result may be that high-income groups use the non-auto mode share for recreational purposes. After controlling for auto ownership, income does not have a significant effect on auto mode share in neither Baltimore nor Washington, DC. As expected, car ownership is the most influential factor in determining the mode of travel in both Washington, DC, and Baltimore.

Looking at land use coefficients, the results are inconsistent, and to some extent, unexpected for the effect of entropy. In Washington, DC, the level of mixed-use (entropy) has a positive but statistically insignificant influence on auto mode share. In contrast, in Baltimore, entropy has a significant and negative influence on auto mode share.

	Auto	Transit	Walk & Bike
Dependent Variable	Mode Share Percentage		
Residential Density	-0.75	0.24	0.51
Employment Density	-0.12	0.05	0.07
Mixture-Entropy	-4.1	-0.83	4.88
HH Size	-1.80	0.52	1.28
Income	-0.05	-0.24	0.29
Car Ownership	3.08	-1.91	-1.17
Avg # of Workers	0.92	0.60	-1.52
Constant	96.19	5.37	0.58
HH Living in TOD	-0.86	0.28	0.58

Table 4- Baltimore mode share results, step 2

To check the reliability of the model, we assume a TAZ with 100 people/acre residential density and employment density as the extreme case. Putting these numbers into the model for Washington, DC, and using average for other variables, the result shows a 35% auto mode share, a 28% transit mode share and a 37% walk/bike mode share. These results show that even in extreme cases, the model would generate reasonable outputs.

Based on the modeling results, residential and employment density both have a significant effect in increasing non-auto mode share. Furthermore, by only controlling for household characteristics, trips originating from TOD have about 10% less auto mode share.

5.3 Propensity Score matching

5.3.1 Propensity Score matching In Washington DC

Table 5 shows the results of a regression model estimating the effect of TOD on non-auto mode share in the DC metropolitan area (transit plus walk and bike) without addressing self-selection. In this model, I controlled for these socioeconomic variables in this model: auto ownership, household size, number of workers in the household and income. The model is at household level and the dependent variable is the percent of non-auto mode share for each household. The results indicate that after controlling for socioeconomic variables households living in TOD have 24.3% higher non-auto mode share. Among other variables, auto ownership has the most significant effect at auto mode share with -13.28 as the coefficient. This number means a one number increase in number of autos in the household leads to a 13.28% decrease in non-auto mode share. Household size and household workers both have significant positive effect on non-auto mode share. As the number of workers in the family increases, the number of commuting trips increases and based on the previous studies, commuting trips have higher transit mode share due to its fixed schedule and destination. The number of observations is 10719 and R-Squared is 0.21.

	Coef	P>t
TOD	24.28	0.00
HHsize	1.79	0.00
HHworker	5.67	0.00
HHvehicle	-13.28	0.00
Income	-0.27	0.02
Constant	34.43	0.00

Table 5- Non-auto mode share regression model results

the probit regression model, estimating the probability of each household living in TOD that is the propensity score. The results show that households with a higher number of workers are more likely to live in a transit-oriented development. This effect is expected, as TODs have high employment accessibility and living in TOD provides households with better job accessibility. Auto ownership has a negative effect, which means as the auto ownership increases, the probability of living in TOD decreases. Household size also has a negative coefficient. This may be explained by the fact that households with children tend to move to suburban areas and away from major transit stations.

TOD	Coef	Std. Err	P>Z
HHSize	-0.064	0.019	0.001
HHWorker	0.18	0.029	0.000
HHVeh	-0.56	0.027	0.000
Income	0.055	0.007	0.000
Cons	-0.98	0.056	0.000

Table 6- Probit Regression model 1

Table 7 shows the classification of households based on their propensity scores. The region of common support is between 0.00001035 and 0.4428.

As it is shown, as the propensity scores increase, the ration of number of households living in TOD to non-TOD increases.

	Percentiles	Smallest
1%	0.0010500	0.0000104
5%	0.0070982	0.0000106
10%	0.0167195	0.0000168
25%	0.0376509	0.0000168
50%	0.0755127	
		Largest
75%	0.1361158	0.4211460
90%	0.1767684	0.4428262

95%	**0.2217830**	**0.4428262**
99%	**0.3359757**	**0.4428262**

Table 7- Propensity Score Percentiles

Average treatment effect is 16.65%. This means that after controlling for self-selection, the effect of TOD on non-auto mode share decreases from 24.3% to 16.65%.

5.3.2 Propensity Score matching In Baltimore

Table 8 illustrates the result of the regression model evaluating the effect of TOD on non-auto mode share after controlling for socioeconomic variables. The results indicate that after controlling for socioeconomic variables, residents of TOD in Baltimore have an 11.1% higher non-auto mode share. Just as in the DC area, auto ownership is the dominant variable in predicting the trip mode share. Household size has a positive effect on increasing non-auto mode share, which may be due to the fact that as the number of people in household increases, the possibility of having access to a car decreases and this may lead to more non-auto trips. The Household worker has the same effect on mode share as in DC, which can be explained with same reasons. Income is the only insignificant variable with the p-value of 0.26.

	Coef	**P>t**
tod	**11.07**	**0.00**
HHsize	**1.72**	**0.00**

HHworker	**6.06**	**0.00**
HHvehicle	**-16.77**	**0.00**
Income	**-0.15**	**0.26**
Constant	**41.44**	**0.00**

Table 8- Non auto mode share regression model

The next step is estimating the propensity score for all the households. From our travel survey, 212 households live in TOD and 8817 live in non-TOD. Table 9 shows the result of the probit regression model for estimating propensity score. The sign of the variables is consistent with the DC model. Auto ownership, household size and income have a negative effect and number of worker has a positive impact on the probability of living in TOD. The range of propensity score for the Baltimore area is from 0.0032 to 0.12. Based on the distribution of the propensity score, the optimal number of blocks is 5. The number of blocks insures that the mean propensity score is not different between the treatment group and control group.

This table shows the inferior bound, number of treated and the number of control for each block.

After classifying households into five blocks, the households are from treatment and control group are matched using nearest neighbor method.

TOD	Coef	Std. Err	P>Z
HHSize	**-0.12**	**0.035**	**0.00**
HHWorker	**0.21**	**0.049**	**0.00**
HHVeh	**-0.16**	**0.041**	**0.00**

Income	-0.07	0.013	0.00
Cons	-1.28	0.079	0.00

Table 9- Probit regression model 1

	Percentiles	Smallest
0.01	0.00105	1.04E-05
0.05	0.007098	1.06E-05
0.1	0.01672	1.68E-05
0.25	0.037651	1.68E-05
0.5	0.075513	
		Largest
0.75	0.136116	0.421146
0.9	0.176768	0.442826
0.95	0.221783	0.442826
0.99	0.335976	0.442826

Table 10- propensity Score Percentiles 1

Here, the average treatment effect is 6.02%, which means after controlling for self-selection, the effect of TOD is decreased from 11.07% to 6.02%.

Chapter 6: Application

Transit accessibility and walk accessibility are the main components of a successful TOD. The center of every TOD is a major transit station with high frequency that would provide high transit accessibility to many destinations. Mixed land use, pedestrian friendly environment and high density encourage people to use non-motorized mode for travel and make more destinations reachable by walk. Using the walk accessibility data from the Renaissance Planning Group, we tried to evaluate the effect of multimodal accessibility on mode choice using the mode share model developed previously (See section 4.2).

6.1. Study Area

The study area is MD-355 corridor in Montgomery County between Friendship Heights and Clarksburg. The section of the corridor is about 22 miles long, beginning in Friendship Heights as Wisconsin Avenue at the DC/MD state line to a northern terminus at Clarksburg. Shown in Map 1, the corridor includes both MD 355 and I-270, which run roughly parallel and provide complementary functions. As defined, the corridor presents a rich array of transportation and land use conditions ranging from highly urban and stable at the southern end to exurban/rural and evolving at the northern end.
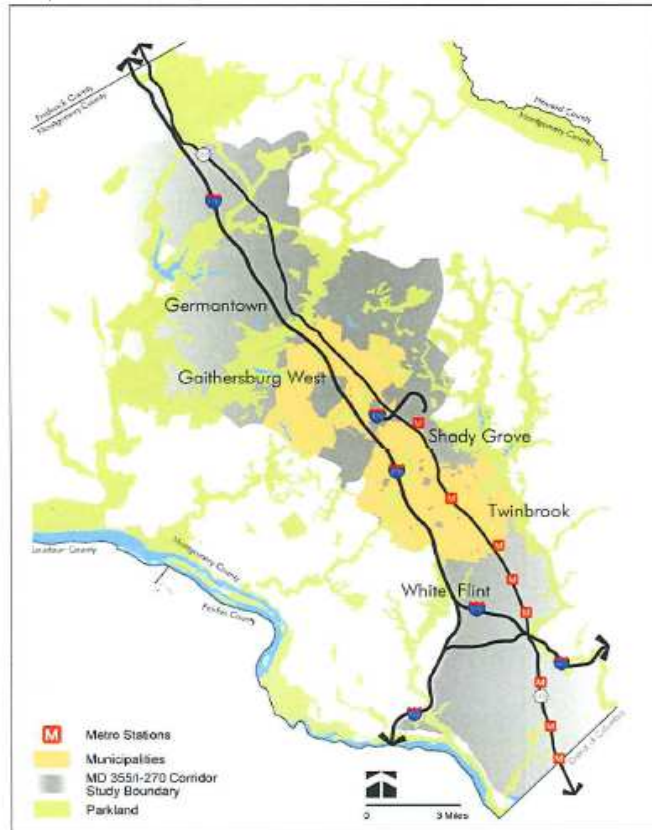
Figure 6- Study Area

6.2. Model Estimation Results

Using the travel survey of 1375 households in the study area from the 2007/2008
MWCOG travel survey, I developed a model to estimate the effect of multimodal
accessibility on mode share. The model is developed at household level; therefore, the
dependent variable is the percentage of each mode share for a household and the
explanatory variables are socioeconomic variables and accessibility variables. The
model is developed separately for work and non-work trips since they could have
different travel patterns.

In the following tables, the results of the model estimation for work and non-work
trips are shown.

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	Auto		Transit		Walk & Bike	
Variable	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value
HH SIZE	-2.78	0.12	0.71	0.66	2.07	0.11
HH Veh	22.64	0.00	-18.2	0.00	-4.43	0.00
HH Worker	-13.73	0.00	9.60	0.00	4.13	0.06
Walk Acc	0.87	0.71	-0.22	0.91	-0.65	0.70
Transit Acc	-8.16	0.01	4.67	0.03	3.49	0.04
Constant	50.68	0.00	38.75	0.00	10.56	0.00

Table 11- Mode Share Model for Work Trips 1

	Auto		Transit		Walk & Bike	
Variable	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value
HH SIZE	-0.70	0.45	-0.51	0.46	1.21	0.08
HH Veh	9.15	0.00	-5.90	0.00	-3.25	0.00
HH Worker	-6.96	0.00	5.73	0.00	1.23	0.19
Walk Acc	-5.66	0.00	0.84	0.45	4.82	0.00
Transit Acc	-6.35	0.00	3.26	0.00	3.09	0.00
Constant	68.80	0.00	15.10	0.00	16.09	0.00

Table 12-Mode Share Model for Non-Work Trips

The interesting finding based on these two models is that walk accessibility is not significant in predicting work trips and it is only significant for non-work trips with signs as expected. This may be due to the dominance of auto and transit mode for commuting trips which leads to the insignificance of walkability in predicting work trips.

In this model, the accessibility measure is normalized, therefore, increasing walk accessibility by 1 standard deviation would result in 5.66% reduction in auto mode share. Transit accessibility has significant effect on both work and non-work trips with the higher effect on work trips. The socioeconomic variables have the similar effect as they had in TOD model.

6.3. Validation

The result of the mode share model is validated using American Community Survey (ACS) data as the ground truth. The average mode share for trips generating from each of the block groups is calculated and compared to the one from ACS. The average difference for auto mode share between model results and ACS is 12%. Figure below shows the validation for different TAZs in the study area:
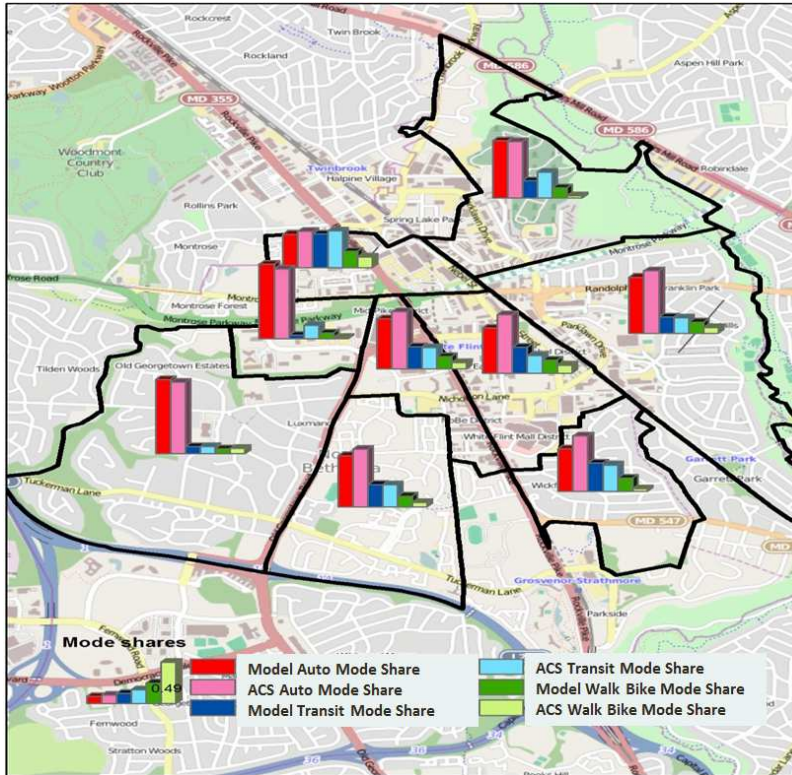
Figure 7- Mode share model validation

6.4. Sensitivity Analysis

In the last section of this chapter, a sensitivity analysis is conducted for White Flint area. Two scenarios are evaluated: first, 10% increase in the walking accessibility and second, increasing the walking accessibility to the maximum of the whole study area:

Figure 8- Sensitivity Analysis 1

These graphs show that under realistic scenario (10% increase in walk accessibility) the reduction is auto mode share is not that significant and we should not overestimate the rule of this variable in increasing non-auto mode share.

Chapter 7: Conclusion

This study incorporated a set of statistical models to estimate the effect of transit-oriented development on mode choice. A mode-share model was developed to estimate the effect of different built environment variables on mode share at household and TAZ levels. This model is sensitive to walking and biking accessibility and can be used to estimate non-motorized travel demand.

Propensity score matching was used in this study to address self-selection in evaluating the impact of TOD. In this method, TOD is considered as a treatment and the outcome variable of interest is non-auto mode share. This method tries to simulate perfect experimental conditions for evaluating the effect of TOD by matching residents of TOD and non-TOD based on their characteristics. Propensity score is a method very popular in sociology for evaluating different social policies and this study used it in the transportation field to capture the complicated relationship between built environment and travel behavior.

The results demonstrated that the success of TOD is dependent on accessibility and land use variables at both TAZ and metropolitan levels. TODs in Washington DC have greater impact on reducing auto-mode share and after controlling for socioeconomic variables. Further investigation is needed to see which variables at metropolitan level are important is TOD success.

The findings indicated that both in Washington DC and Baltimore (two metropolitan areas with different urban forms and transit networks) self-selection accounts for about 40% of the effect of the TOD in reducing auto-mode share. Although the effect of self-selection is significant, it is safe to say that TOD could play an important role in changing the travel behavior of its residents.

In general, this study provides some insights for decision-makers and planners to better evaluate the effectiveness of TODs and the extent they can affect mode choice. The results indicated that TOD could be a successful policy to boost transit ridership and encourage active mode of travel, but its effects are limited and should be estimated properly. Moreover, self-selection is a significant factor in association between TOD and low auto-mode share and should be considered in any prediction.

The main limitation of this study is the lack of attitudinal data for addressing self-selection. Longitudinal and attitudinal data could help us better understand the relationship between the TOD and travel behavior and evaluate the effectiveness of land use plans.

Bibliography

1- Center of Transit Oriented Development Website, http://www.ctod.org/

2- California Department of Transportation. (2002a). *Statewide Transit-Oriented Development Study: Factors for Success in California*, Sacramento: Business, Transportation, and Housing Agency

3- FastTracks. (2008). *Strategic Plan for Transit Oriented Development*. Regional Transportation District.
http://www.drcog.org/documents/TODStrategicPlan_FINAL.pdf

4- Calthorpe, P. (1993). *The Next American Metropolis: Ecology, Community, and the American Dream*, Princeton: Princeton Architectural Press

5- Parker, T. et al. (2002). *Statewide Transit-Oriented Development Study: Factors for Success in California* (Sacramento: California, Department of Transportation, 2002).

6- Cervero, R., Ferrell, C., and Murphy, S. (2002). TCRP Research Results Digest 52: *Transit-Oriented Development and Joint Development in the United States; A Literature Review*. Transportation Research Board. Washington DC

7- Bernick, M. and Cervero, R. (1997). *Transit Villages in the 21st Century*. New York: McGraw-Hill.

8- Lund, H., Cervero, R. and Willson, R. (2004). *Travel Characteristics of Transit-Oriented Development in California*. Oakland, California: CalTrans Transport Grant

9- Cervero, R. (1993). *Ridership Impacts of Transit-Focused Development in California*. Monograph 45, Institute of Urban and Regional Development, University of California: Berkeley, CA.

10- Cervero, R. (2008), *Effects of TOD on housing, parking, and travel*, TransitCooperative Research Program (TCRP) report 128

11- Renne, J. (2005). *Transit Oriented Development: Measuring Benefits, Analyzing Trends, and Evaluating Policy*. Dissertation Submitted to Graduate Program in Urban Planning and Policy Development, Rutgers University

12- Cervero, R. (1993). *Ridership Impacts of Transit-Focused Development in California*. Monograph 45, Institute of Urban and Regional Development, University of California: Berkeley, CA.

13- Tumlin, J. and Millard-Ball, A. (2003). *How to Make Transit-Oriented Development Work*. Planning, (May 2003): 14-19.

14- Lund, H., Cervero, R. and Willson, R. (2004). *Travel Characteristics of Transit-Oriented Development in California*. Oakland, California: CalTrans Transport Grant.

15- Cervero, R. (2008), *Effects of TOD on housing, parking, and travel*, Transit Cooperative Research Program (TCRP) report 128.

16- Cervero, R. (1994). *Transit-Based Housing in California: Evidence on Ridership Impacts*. Transport Policy. Vol.3, pp. 174-183.

17- Cervero, R. (2008), *Effects of TOD on housing, parking, and travel*, Transit Cooperative Research Program (TCRP) report 128.

18- Ewing, Reid, and Robert Cervero. "Travel and the built environment: a synthesis." *Transportation Research Record: Journal of the Transportation Research Board* 1780.1 (2001): 87-114.

19- Cao, Xinyu, Patricia L. Mokhtarian, and Susan L. Handy. "Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings." *Transport Reviews* 29.3 (2009): 359-395.

20- Handy, Susan L., and Kelly J. Clifton. "Evaluating neighborhood accessibility: Possibilities and practicalities." *Journal of Transportation and Statistics* 4.2/3 (2001): 67-78.

21- Hammond, D. (2005) Residential location and commute mode choice. Doctoral dissertation, University of Wales, Cardiff.

22- Handy, Susan, Xinyu Cao, and Patricia L. Mokhtarian. "Self-selection in the relationship between the built environment and walking: Empirical evidence from Northern California." *Journal of the American Planning Association* 72.1 (2006): 55-74.

23- Cao, Xinyu, Susan L. Handy, and Patricia L. Mokhtarian. "The influences of the built environment and residential self-selection on pedestrian behavior: evidence from Austin, TX." Transportation 33.1 (2006): 1-20.

24- Handy, Susan, Xinyu Cao, and Patricia Mokhtarian. "Correlation or causality between the built environment and travel behavior? Evidence from Northern California." Transportation Research Part D: Transport and Environment 10.6 (2005): 427-444.

25- Chatman, Daniel Gregory. *How the built environment influences non-work travel: theoretical and empirical essays*. Diss. UNIVERSITY OF CALIFORNIA Los Angeles, 2005

26- Bagley, Michael N., and Patricia L. Mokhtarian. "The impact of residential neighborhood type on travel behavior: A structural equations modeling approach." The Annals of Regional Science 36.2 (2002): 279-297.

27- Bhat, Chandra R., and Jessica Y. Guo. "A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels." Transportation Research Part B: Methodological 41.5 (2007): 506-526.

28- Scheiner, Joachim, and Christian Holz-Rau. "Travel mode choice: affected by objective or subjective determinants?." *Transportation* 34.4 (2007): 487-511.

29- Boarnet, Marlon G., et al. "Evaluation of the California Safe Routes to School legislation: urban form changes and children's active transportation to school."American journal of preventive medicine 28.2 (2005): 134-140.

30- Meurs, Henk, and Rinus Haaijer. "Spatial structure and mobility."*Transportation Research Part D: Transport and Environment* 6.6 (2001): 429-446.

31- Handy, Susan, Xinyu Cao, and Patricia L. Mokhtarian. "Self-selection in the relationship between the built environment and walking: Empirical evidence from Northern California." *Journal of the American Planning Association* 72.1 (2006): 55-74.

32- Boer, Rob, et al. "Neighborhood design and walking trips in ten US metropolitan areas." American journal of preventive medicine 32.4 (2007): 298-304.

33- Cao, Xinyu. "Exploring causal effects of neighborhood type on walking behavior using stratification on the propensity score." Environment and Planning A 42.2 (2010): 487-504.

34- Cao, Xinyu Jason, Zhiyi Xu, and Yingling Fan. "Exploring the connections among residential location, self-selection, and driving: Propensity score matching with multiple treatments." Transportation research part A: policy and practice 44.10 (2010): 797-805.

35- Nasri, Arefeh, and Lei Zhang. "The analysis of transit-oriented development (TOD) in Washington, DC and Baltimore metropolitan areas." Transport Policy32 (2014): 172-179.

36- Rosenbaum, Paul R., and Donald B. Rubin "The central role of the propensity score in observational studies for causal effects." *Biometrika* 70.1 (1983): 41-55

37- Peikes, Deborah N., Lorenzo Moreno, and Sean Michael Orzol. "Propensity score matching." *The American Statistician* 62.3 (2008)

38- Kuzmyak, J. Richard, et al. *Estimating Bicycling and Walking for Planning and Project Development: A Guidebook*. No. Project 08-78. 2014.