Job Accessibility and Journey to Work: The Case of Boston Metropolitan Area

by

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ABSTRACT

In this study, variations in levels of transit usage to work from block groups in the Boston metropolitan area were explored. The examination of the 2000 Census data showed that there were significant differences in the transit share of the work trip at the block group level. In order to understand this variation, which is required to plan and implement transportation policy in the region, the study area was categorized into three groups based on the level of relative job accessibility. Commuting patterns in these areas were examined and compared to each other. First, the conceptual and measurement issues surrounding accessibility are reviewed. Next, travel time impedance functions were developed using the journey to work data from Census Transportation Planning Package (CTPP) 2000, considering both transit and auto travel time between all origin-destination pairs in the Boston Metropolitan area thanks to the Central Transportation Planning Staff (CTPS), the transportation network data from Massachusetts Geographic Information Systems (MassGIS), and the job location data from Initiatives for a Competitive Inner City (ICIC). Then, job accessibility by auto and transit were calculated based on a hypothesis that job accessibility is an important factor in determining transit mode share from both residential and workplace perspectives. Finally, the spatial robustness of the general trip distribution was examined using GIS to compare mode choice behavior in block groups with different land use characteristics: block groups in the high relative job accessibility areas, block groups in the low relative job accessibility areas, and block groups in the entire study area. The comparison led to the conclusion that it is unrealistic to think that simple models such as those developed earlier in this research could be generally applied to all block groups in the metropolitan area. The geographical analyses suggested that a disaggregate approach should be applied not only to data collection (e.g., collecting individual survey data) but also to developing mode split models in order to improve their explanatory power.

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TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Title</td>
<td>1</td>
</tr>
<tr>
<td>Abstract</td>
<td>2</td>
</tr>
<tr>
<td>Acknowledgement</td>
<td>3</td>
</tr>
<tr>
<td>Table of Contents</td>
<td>4</td>
</tr>
<tr>
<td>List of Figures</td>
<td>6</td>
</tr>
<tr>
<td>List of Tables</td>
<td>8</td>
</tr>
</tbody>
</table>

CHAPTER 1. INTRODUCTION ................................................................. 9

  1.1 Problem Statement ........................................................................ 9
  1.2 Objectives and Research Questions ........................................ 10
  1.3 Thesis Outline ........................................................................... 11

CHAPTER 2. LITERATURE REVIEW AND APPROACHES .................................... 12

  2.1 Factors Affecting Transit Mode Choice ...................................... 12
  2.2 Accessibility Measure .............................................................. 13
    2.2.1 Topological Accessibility .................................................. 14
    2.2.2 Cumulative Opportunity Measure ........................................ 15
    2.2.3 Gravity-Based Accessibility .............................................. 15
    2.2.4 Space-Time Based Accessibility ......................................... 17
    2.2.5 Utility-Based Accessibility .............................................. 18
  2.3 Accessibility Model Applied to this Research ............................ 19
    2.3.1 Definition of Job Accessibility ................................ .......... 21
    2.3.2 Measuring Job Accessibility – Residential Perspective ........... 22
    2.3.3 Measuring Job Accessibility – Employer Perspective ................ 29

CHAPTER 3. DATA AND STUDY AREA ......................................................... 34

  3.1 Data .............................................................................................. 34
3.2 Description of the Study Area ......................................................... 35

CHAPTER 4. MEASURING JOB ACCESSIBILITY ........................................... 44
4.1 Measuring Job Accessibility – Residential Perspective ......................... 44
4.2 Job Accessibility – Residential Perspective ........................................ 47
4.3 Measuring Job Accessibility – Employer Perspective ............................ 52
4.4 Job Accessibility – Employer Perspective ........................................... 56

CHAPTER 5. COMMUTING PATTERN ANALYSES ......................................... 61
5.1 Categorizing block groups .................................................................. 61
5.2 Mode Share versus Travel Time ......................................................... 64
  5.2.1 Drive Alone Trip Distribution ....................................................... 66
  5.2.2 Transit Trip Distribution ............................................................... 68
  5.2.3 Non-motorized Trip Distribution ................................................... 71
5.3 Time Leaving for Work ....................................................................... 73
5.4 Mode Share versus Income ................................................................ 75
  5.4.1 Study Area .................................................................................. 75
  5.4.2 High Relative Job Accessibility Area .......................................... 77
  5.4.3 Low Relative Job Accessibility Area .......................................... 80
5.5 Job Distribution, Income, and Transit Mode share ............................... 82

CHAPTER 6. SUMMARY AND CONCLUSION .............................................. 87
6.1 Summary of Findings ........................................................................ 87
6.2 Contributions of the Research Study ................................................ 102
6.3 Future Research .............................................................................. 103
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-1</td>
<td>Space-Time Prism</td>
</tr>
<tr>
<td>2-2</td>
<td>A Typology of Accessibility Models</td>
</tr>
<tr>
<td>2-3</td>
<td>Accessibility Calculation Process</td>
</tr>
<tr>
<td>2-4</td>
<td>0.25 mile network buffer from transit stops and job locations</td>
</tr>
<tr>
<td>2-5</td>
<td>Average Number of Trips – Auto</td>
</tr>
<tr>
<td>2-6</td>
<td>Average Number of Jobs Accessible by Auto</td>
</tr>
<tr>
<td>2-7</td>
<td>Percentage of Residential Areas within 0.25 mile Transit Catchment Area</td>
</tr>
<tr>
<td>3-1</td>
<td>Study area and its relationship to the Boston Metropolitan Area</td>
</tr>
<tr>
<td>3-2</td>
<td>Mode Share for Working Trips in the Study Area</td>
</tr>
<tr>
<td>3-3</td>
<td>Income Distribution in the Study Area</td>
</tr>
<tr>
<td>3-4</td>
<td>Transportation Network in the Study Area</td>
</tr>
<tr>
<td>3-5</td>
<td>Population and Employment Density in the Study Area</td>
</tr>
<tr>
<td>3-6</td>
<td>Ratio of the Number of Jobs to the Number of Workers in an Area</td>
</tr>
<tr>
<td>4-1</td>
<td>Auto travel impedance function – Residential model</td>
</tr>
<tr>
<td>4-2</td>
<td>Transit travel impedance function – Residential model</td>
</tr>
<tr>
<td>4-3</td>
<td>Average Number of Trips – Transit &amp; Non-motorized modes</td>
</tr>
<tr>
<td>4-4</td>
<td>Job Accessibility (Different Scale) – Residential Perspective</td>
</tr>
<tr>
<td>4-5</td>
<td>Job Accessibility (Same Scale) – Residential Perspective</td>
</tr>
<tr>
<td>4-6</td>
<td>Relative Job Accessibility – Residential Perspective</td>
</tr>
<tr>
<td>4-7</td>
<td>Average Auto Trips per Opportunity – Employer model</td>
</tr>
<tr>
<td>4-8</td>
<td>Areas that need longer than 75 minutes driving to get to downtown Boston</td>
</tr>
<tr>
<td>4-9</td>
<td>Auto travel impedance function – Employer model</td>
</tr>
<tr>
<td>4-10</td>
<td>Transit travel impedance function – Employer model</td>
</tr>
<tr>
<td>4-11</td>
<td>Job Accessibility (Different Scale) – Employer Perspective</td>
</tr>
<tr>
<td>4-12</td>
<td>Job Accessibility (Same Scale) – Employer Perspective</td>
</tr>
<tr>
<td>4-13</td>
<td>Relative Job Accessibility – Employer Perspective</td>
</tr>
<tr>
<td>5-1</td>
<td>Study Area and Selected Block Groups for Comparison</td>
</tr>
<tr>
<td>5-2</td>
<td>Trip Distribution – Drive Alone (normalized)</td>
</tr>
</tbody>
</table>
Figure 5-3 Trip Distribution – Drive Alone (absolute) ............................................. 68
Figure 5-4 Trip Distribution – Transit (normalized) .................................................. 69
Figure 5-5 Trip Distribution – Transit (absolute) ....................................................... 70
Figure 5-6 Trip Distribution – Non-motorized mode (normalized) ......................... 72
Figure 5-7 Trip Distribution – Non-motorized mode (absolute) .............................. 72
Figure 5-8 Leaving Time to Work - Drive Alone ...................................................... 74
Figure 5-9 Leaving Time to Work – Transit ............................................................ 74
Figure 5-10 Leaving Time to Work - Non-motorized mode .................................... 75
Figure 5-11 Mode Share by Income – Study Area (absolute) .................................. 76
Figure 5-12. Mode Share by Income – Study Area (normalized) ........................... 78
Figure 5-13 Mode Share by Income - High Job Accessibility Area (absolute) ........... 79
Figure 5-14 Mode Share by Income - High Job Accessibility Area (normalized) ....... 79
Figure 5-15 Mode Share by Income – Low Job Accessibility Area (absolute) .......... 81
Figure 5-16 Mode Share by Income – Low Job Accessibility Area (normalized) ...... 81
Figure 5-17 Job Distribution by Distance from Downtown Boston ......................... 83
Figure 5-18 Income Distribution by Distance from Downtown Boston .................... 83
Figure 5-19 Edge City & Occupational Distribution .............................................. 84
Figure 5-20 Per Capita Income and Occupational Distribution ............................. 85
Figure 5-21 Per Capita Income and Transit Mode Share ...................................... 86
Figure 6-1 Job Accessibility (Same Scale) – Residential Perspective ...................... 89
Figure 6-2 Job Accessibility (Same Scale) – Workplace model ............................... 90
Figure 6-3 Relative Job Accessibility ................................................................. 91
Figure 6-4 Study Area and Selected Block Groups for Comparison ......................... 93
Figure 6-5 Mode Share by Income - High Job Accessibility Area (normalized) ......... 94
Figure 6-6 Mode Share by Income – Low Job Accessibility Area (normalized) ........ 94
Figure 6-7 Trip Distribution – Transit (absolute) .................................................... 96
Figure 6-8 Trip Distribution – Transit (normalized) ................................................ 96
Figure 6-9 Trip Distribution – Non-motorized mode (normalized) ......................... 97
Figure 6-10 Trip Distribution – Non-motorized mode (absolute) ............................. 97
Figure 6-11 Population and Employment Density in the Study Area ........................................ 99
Figure 6-12 Ratio of the Number of Jobs to the Number of Workers in an Area .................. 100
Figure 6-13 Income Distribution in the Study Area .................................................................. 101

LIST OF TABLES

Table 3-1 US Journey to Work by State & Mode: 2000 .......................................................... 37
Table 5-1 Study Area, High Accessibility Area, and Low Accessibility Area ..................... 62
Table 5-2 Mode Share Comparison ....................................................................................... 64
Table 5-3 Mean Travel Time to Work (minutes) ................................................................. 66
CHAPTER 1
INTRODUCTION

1. Problem Statement

The measure of accessibility to opportunities has been widely used in public transportation planning, highway routing, and siting of public facilities. The basic assumption underlying the use of this measure in transportation planning is that individuals with different levels of accessibility will have different travel patterns, especially different travel frequency (Cervero, 1994). Theoretical formulation of travel demand models reflect this assumption; they have either assumed or deduced a close relationship between travel demand and accessibility to opportunities. However, less attention has been given to the relationship between accessibility to opportunities and travel mode choice.

Even the four-step travel demand model, the most commonly used comprehensive approach to regional transportation analysis, incorporates accessibility to opportunities into its' modeling process in the second step, trip distribution, not in the third step, modal split. Although the impacts of accessibility to opportunities on mode choice is eventually accounted for in the four-step model through the iteration and feedback process, it is not easy to estimate the short-term impact of accessibility to opportunities on mode choice behavior, since the modal split step itself only considers travel cost (or travel utility) in determining mode choice. In addition, the four-step model cannot be used easily and frequently, due to its high cost and technical complexity. As a result, little empirical evidence exists on the possible impacts of accessibility to opportunities on travel mode choice.

In this research, we first review the approaches to measuring accessibility to opportunities, and then develop measures for accessibility to job opportunities (called job accessibility hereafter) for the study area. Then we perform Geographic Information Systems (GIS)
analyses to examine whether job accessibility has an impact on modal share. The geographical analyses reveal how for areas characterized by high or low levels of job accessibility, not only are modal shares different but mobility patterns differ in a rather substantially manner. These insights do not comprise a cause-and-effect relationship vis-à-vis transit accessibility but they do point to the complexity of the land use-transportation interaction.

1.2 Objectives, Research Questions and Approach

In order to understand the relationship between transit mode share and job accessibility, this study is aimed at achieving the following objectives:

- To propose a method for measuring accessibility which better represents the accessibility to job opportunities by transit, and which can lead to more accurate transit ridership forecasting and better service design.
- To improve our understanding of the relationship between urban spatial structure, transit mode share, and employment opportunities in the study area.

To achieve these objectives, the following specific questions are addressed:

1) What is job accessibility and how can it be estimated? What are the shortfalls of conventional transit job accessibility analysis? How can the job accessibility calculation be improved so that the job accessibility indices better reflect the real world situation?

In order to answer these questions, Geographic Information Systems (GIS) are used to calculate better measures of job accessibility. Unlike conventional job accessibility measures, which use only zonal data such as number of jobs and workers in an area, job accessibility calculated in this study uses not only aggregate level data but also disaggregate level data, such as the entire street network in an area, zoning data, and actual address of each employer in order to calculate job accessibility by transit. By
combining the aggregate and disaggregate approaches we hope that the job accessibility indices represent the real world more realistically.

2) What are the variations in commuting patterns for workers in high and low job accessibility areas? Could these variations be captured by a single model developed to replicate the area as a whole?

The job accessibility indices developed in this study are used to categorize areas into one of three levels: high accessibility, low accessibility, and the entire study area. Since job accessibility represents the spatial variation of areas by combining job density, population density, and the transportation network, it is used to categorize areas with different land use characteristics. Then the commuting patterns in two extreme areas, the high and low accessibility areas, are examined and compared to understand commuting pattern differences in these areas. The analysis results are also used to test the applicability of general trip distribution functions estimated on the entire study area into areas with different land use characteristics.

1.3 Thesis Outline

To reflect the research questions listed above, this thesis is organized as follows. Chapter 2 provides a brief review of the literature relevant to the study. First, commonly used factors in mode choice modeling are introduced. Then the concept of accessibility is introduced. Five common approaches of measuring accessibility are then explained. After that, job accessibility terms used in this study are defined and the methodology used in this study to calculate job accessibility is introduced. The research data and the study area are described in Chapter 3. In Chapter 4, job accessibility indices for the study area are calculated for automobile and transit. Chapter 5 presents in-depth analyses of commuting patterns in the study area and its relevance to modeling. Lastly, Chapter 6 summarizes findings from the study and discusses future research implications.
CHAPTER 2
LITERATURE REVIEW AND APPROACHES

In this chapter, prior research on travel mode choice and accessibility measures is introduced. First, commonly identified factors that affect mode choice are introduced, then methodologies for measuring accessibility are explained. Finally, the specific methodology for measuring job accessibility used in this study is introduced. It should be noted that the discussion here merely outlines some of the issues and models that comprise a vast literature.

2.1 Factors Affecting Transit Mode Choice

Numerous factors used to model mode choice were found in the literature. A study by the National Center for Transit Research at the University of South Florida entitled “FSUTMS: Mode Choice Modeling: Factors Affecting Transit Use and Access” (2002) listed many of the factors that have been used in modeling modal split. Factors were classified into four categories: 1) travel level of service, 2) accessibility to alternative modes, 3) land use, and 4) passengers’ socio-demographic characteristics. Several regression models were developed to test the relationship between mode choice and each variable, and the result suggested that transit supply variables, such as regional accessibility and service frequency, dominate other factors in contributing to transit use.

Research by Racca and Ratledge (2004) reviewed mode choice-related literature and summarized the ten most popular factors affecting mode choice: travel time, travel cost, income, automobile availability, parking availability and cost, availability of alternative modes, time of day, population density, land use patterns, and transit service factors. A linear regression model was built to examine which variables mattered most when people were deciding on the mode of transportation to work; the results showed that car-ownership is the dominant factor, followed by trip destination. Transit level of service proved not to be
a strong factor when the trip destination variable was included. The results demonstrated that, for the work trip, accessibility was a much more important factor in choosing transit than service quality, although these two variables are closely related.

Taylor and Fink (2003) conducted a similar review of a large amount of transit ridership-related literature in order to identify factors affecting transit ridership. According to the results, automobile access-related variables, such as car-ownership and parking availability, were found in many studies to be the most important factors explaining transit ridership, followed by economic variables including income level and employment level in the central business district. In addition, spatial variables, such as population and employment density, were identified as influential factors. However, the study pointed out the colinearity between spatial variables and economic variables, which raised questions on the relative impacts of those factors on mode choice behavior.

Pedestrian accessibility to transit is also recognized by many studies as an important factor in determining transit use. According to Levinson (1984), transit use decreases as the walking distance to a transit stop increases. Loutzenheiser (1997) examined the relationship between accessibility to Bay Area Rapid Transit (BART) stations and transit ridership and concluded that the availability of transit had a positive impact on transit use. Hsiao et al. (1997) used a GIS-based accessibility calculation method to examine the linkage between transit use and pedestrian accessibility, land use, and demographic characteristics. The results indicated that better transit accessibility increased the likelihood of transit use regardless of workers’ income level.

2.2 Accessibility Measures

Within the transportation planning field, accessibility is generally defined as the ease with which desired destinations can be reached (Koenig, 1980; Niemeier, 1997) and many studies have claimed the accessibility measures to be one of the important factors in
determining transit mode choice. Despite the wide use of the term “accessibility” in transportation planning, accessibility has been a hard term for planners and policy makers to both define and measure (Handy, 2004). As a result, a significant amount of research has introduced various definitions and developed many accessibility measures. In most cases, the measures of accessibility consist of two elements, an impedance factor that reflects the transportation network and an attractiveness factor that reflect land use patterns (e.g., job density, population density). In other words, accessibility measures combine land use patterns and the transportation network, which makes it useful in transportation modeling and transportation policy implementation (Primerano and Taylor, 2004). There are five different ways of defining accessibility in the literature: topological accessibility, cumulative opportunity measure, gravity-based accessibility, space-time framework, and utility-based accessibility.

2.2.1 Topological Accessibility

Topological accessibility is measured in a transportation network as nodes and paths, based on an assumption that “accessibility is a measurable attribute significant only to specific elements of a transportation system, such as terminals (Rodriguez, 2002).” In this measure, better accessibility means fewer links with shorter distances between locations.

\[ A_i = \sum_{j}^{n} C_{ij} \]

Where,

- \( A_i \) = Accessibility at location i.
- \( C_{ij} \) = Travel cost between node i and node j
- \( n \) = Number of Nodes

In topological accessibility models, travel costs are the only component that is taken into account. Travel cost takes the form of travel time, speed, or generalized travel costs from one place/zone to all other places/zones. The advantage of this method is that accessibility values are measured in absolute terms (e.g., minutes) and therefore different regions or
urban areas can be easily compared and evaluated by quantified accessibility level. For example, Allen et al. (1992) calculated topological accessibility measures in 60 US metropolitan areas and compared them. The limitation is that the lack of an opportunity element in the topological model significantly reduces its usefulness in transportation modeling.

2.2.2 Cumulative Opportunity Measure

One of the simplest methods to calculate accessibility is the cumulative-opportunity measure, which counts the number of opportunities (the number of destinations of interests) within a certain time, or distance, of the origin. The opportunities within a band are weighted equally, and the measure is not affected by differences of travel cost within the band (Busby, 2004). This kind of measure provides an idea of the range of choices available to residents within an area. The mathematical equation to obtain the cumulative-opportunity measure is as follows:

\[ A_i = \sum_j O_j W_j \]

Where, 
- \( A_i \) = Accessibility at location i
- \( W_j \) = 1 if \( C_{ij} < C_{ij}^* \), 0 otherwise
- \( O_j \) = Opportunities at destination j
- \( C_{ij}^* \) = Travel cost from origin i to destination j
- \( C_{ij} \) = The defined band within which the activity opportunities are counted

A key factor in calculating the cumulative-opportunity measure is the cut-off travel distance or time, to which accessibility levels can be very sensitive but the literature does not contain a clear method of making this decision. Cumulative measures are easy to calculate but they are based on a somewhat arbitrary threshold.
2.2.3 Gravity-Based Accessibility

Gravity-based accessibility is the most popular method to calculate accessibility. First introduced by Hansen (1959), gravity-based accessibility counts the number of opportunities in the destination zone weighted by travel cost to reach them. The gravity model is analogous to Newton’s law on gravity where in terms of transport, the number of trips made between two locations is proportional to their sizes and inversely proportional to their distance (Primerano et al., 2004). The most basic form of the gravity-based accessibility function is:

\[ A_{ij} = O_j f(C_{ij}) \]

Where, \( A_{ij} \) = Accessibility from origin zone \( i \) to destination zone \( j \)
\( O_j \) = Opportunities in destination zone \( j \)
\( f(C_{ij}) \) = Impedance function
\( C_{ij} \) = Generalized travel cost from origin zone \( i \) to destination zone \( j \)

Kawabata (2002) examined the potential-based accessibility measures in depth in her job matching study and grouped the methods of measuring accessibility into four groups: (1) the number of opportunities in an area of residence—the opportunities-per-area measurement; (2) the ratio of opportunities to opportunity seekers in an area of residence—the opportunities-to-opportunity seekers-per area ratio; (3) the travel time; and (4) the gravity-based measure of accessibility. She then claimed that the gravity-based measure of accessibility was the most desirable since it accounts for both the supply and demand sides of the labor market as well as differences in travel modes.

Busby (2004) also examined potential-based accessibility (Isochronic and Gravity-based model) and preference-based accessibility (Expected Maximum Utility) models and determined that the gravity-based model is the most commonly used method to calculate accessibility due to its relatively low data requirement and ease of use. He then developed gravity-based job accessibility metrics using GIS technology and Census data to aid transit.
planners who need preliminary project design and evaluation tools. Despite its popularity, however, gravity-based accessibility has been criticized in many studies, along with other zonal accessibility measures because it ignores differences among individuals within a zone and neglects the distribution of activity sites.

2.2.4 Space-Time Based Accessibility

The space-time framework was first developed by Hagerstrand (1970) who combined constraints of time with space to determine the behavioral options for an individual. Space-time accessibility measures evaluate individual accessibility by delimiting the space-time prism, which is determined by the locations of activities, their separation, and the amount of time available for travel and activity participation, as well as travel speeds (Kwan, 1999).

![Space-Time Prism](image)

Figure 2-1 Space-Time Prism (Kwan, 1999)

The space-time based accessibility estimates individual accessibility rather than place accessibility by considering space-time constraints that may render many opportunities in the urban environment unreachable by an individual (Burnett, 1980). The major problems with space-time measures are that they depend on large amounts of information about complete activities and trips (Kwan, 1998), which makes it difficult to apply in large-scale
projects. Lack of feasible operational algorithms for handling the complexity of real-world transportation networks is another obstacle in using space-time based accessibility.

2.2.5 Utility-Based Accessibility

Accessibility measured by the logsum term from the logit discrete choice model is, probably, the most sophisticated and complex approach. Based on microeconomic theory, logsum models are defined as the expected maximum utility associated with all travel alternatives available to individuals. Ben-Akiva and Lerman (1977) developed an accessibility model by summing up the destination utility and travel (dis)utility gained from the potential trips made by an individual (or a group of individuals). In this context, accessibility refers to the set of activities to which a person has the potential to travel, even if such a trip is not made.

\[
A_n = \frac{1}{\mu} \ln \sum_d e^{\mu U_n(d)}
\]

Where, \( A_n \) = Accessibility of individual \( n \)
\( U_n(d) \) = Individual \( n \)'s utility associated with destination \( d \)
\( \mu \) = Scale parameter of the error associated with each destination \( d \)

One comprehensive study of accessibility models was conducted by Zhang (2002) who categorized accessibility models into three groups: performance-based models, potential-based models, and preference-based models (See Figure 2-2). Performance-based models measure the ability to move from one place to another based solely on travel cost, while potential-based models evaluate the spatial interactions of opportunities based on travel cost and opportunities. Preference-based models evaluate travel utility based on microeconomic theories. Of these three models, Zhang asserted that the preference-based model is the most suitable accessibility model of all because, unlike the other models, the
preference-based model uses a disaggregate approach to calculate accessibility, which is believed to reflect people’s travel behavior more accurately. Despite its theoretical and empirical advantages over other accessibility measures, however, the high burden of data requirement and technical difficulties have so far prevented wide use of utility-based models (Busby, 2004).

2.3 The Accessibility Model Applied to this Research

In this paper, the gravity-based model has been selected for measuring job accessibility considering computational complexity and available data. Since we are using aggregate data, disaggregate level accessibility models, such as time-space and utility-based approaches are not feasible for this research. Topological accessibility model and cumulative opportunity measure are excluded because these measures are too coarse to be used in mode choice analyses.

The gravity-based model calculates accessibility based on two elements: the total number of opportunities that could be reached within a threshold travel time or distance and the effect of distance or travel time on trip likelihood, expressed through an impedance function. This model considers the effect of opportunities and travel costs uniformly within the threshold and is suitable for an aggregate level study. This type of aggregate method is used by many practitioners who are looking for quick estimates of travel demand with limited technical and financial resources and readily available data, such as Census data.

The usefulness of this model can be criticized due to its’ aggregate nature, however, compiling individual survey data requires significant resources in terms of money and time. In the case of Boston, the most recent individual survey data were obtained more than ten years ago. Therefore, in this research the aggregate approach is used toward modeling job accessibility in the Boston metropolitan area. Unlike conventional gravity-based models that ignore differences between travel modes (Shen, 1998, 2001), however, the approach
taken in this study takes into account travel mode differences to improve the accuracy of job accessibility measure. In doing that, several disaggregate level data, including zip code based job location data and the Topologically Integrated Geographic Encoding and Referencing system (TIGER) street network data, are used to count the number of job opportunities accessible by transit and automobile in order to alleviate the limitations of aggregate level gravity models.

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<thead>
<tr>
<th>ACCESSIBILITY MODELS</th>
<th>Performance-Based Models [measuring travel cost or mobility]</th>
<th>Travel Time (e.g. Allen, et al. 1992)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>• $A_t = \sum_j C_{ij}$; or</td>
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<td></td>
<td>• $A_t = \frac{1}{n(n-1)} \sum \sum C_{ij}$</td>
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<tr>
<td></td>
<td></td>
<td>Space-Time Prism (Burns 1979)</td>
</tr>
<tr>
<td></td>
<td>Potential-Based Models [measuring spatial interaction]</td>
<td>Isochronic Cumulation (Wachs &amp; Kumagai 1973)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Supply-Side Measure</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• $A_t = \sum_j O_j f(C_{ij})$</td>
</tr>
<tr>
<td></td>
<td>Preference-Based Models [measuring utility]</td>
<td>Supply-Demand Measure</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• $A_t = \sum_j O_j f(C_{ij}) / D_j$</td>
</tr>
</tbody>
</table>

Alternative models of $f(C_{ij})$:

- $f(C_{ij}) = C_{ij}^\alpha, \alpha > 0$ (Hansen, 1959);
- $f(C_{ij}) = \exp(-\beta \cdot C_{ij})$ (Wilson, 1971);
- $f(C_{ij}) = \exp(-C_{ij}^\gamma / \gamma)$ (Ingram 1971)

$D_j = \sum_i P_{ij} f(C_{ij})$ (Weibull 1976; Shen 1996);

$U(d), U(t)$: individual utilities associated with destination $d$, travel $t$ respectively;

$A_i$: the accessibility evaluated for zone $i$;  
$n, g$: individual $n$ or group $g$;

$C_{ij}$: distance or time from zone $i$ to zone $j$;  
$P_{ij}^m$: population or workers taking mode $m$;

$O_j$: activities or attraction in zone $j$;  
$\alpha, \beta, \gamma$: parameters reflecting distance deterrence.

Figure 2-2 A Typology of Accessibility Models (Zhang, 2002)
2.3.1 Definition of Job Accessibility

While in general, accessibility can be defined as the ease with which desired destinations can be reached (Koenig, 1980; Niemeier, 1997), in this research, accessibility is used to refer to accessibility to job opportunities. Job accessibility measures how easy it is for people to reach job opportunities and three job accessibility indices, transit job accessibility (job accessibility by transit), auto job accessibility (job accessibility by auto), and relative transit job accessibility (the ratio of transit job accessibility to auto job accessibility) are calculated. Furthermore, job accessibility can be defined from two perspectives:

(a) accessibility from the employee point of view, where the opportunities are expressed in terms of jobs

(b) accessibility from the employer point of view, where the opportunities are expressed in terms of the available pool of potential employees.

Since we are mainly using aggregate data (Census 2000, CTPP 2000, and CTPS data), a gravity-based accessibility model was chosen to calculate job accessibility. As discussed in
the previous section, gravity-based accessibility is the most commonly used method for measuring accessibility due to its’ relatively low data requirements and technical demands. The most basic form of the gravity-based accessibility function consists of an opportunity term and an impedance function:

\[ A_{ij} = O_j f(C_{ij}) \] ..........................................................(1)

Where,
- \( A_{ij} \) = Accessibility from origin zone i to destination zone j
- \( O_j \) = Opportunities in destination zone j
- \( f(C_{ij}) \) = Impedance function
- \( C_{ij} \) = Generalized travel cost from origin zone i to destination zone j

### 2.3.2 Measuring Job Accessibility – Residential Perspective

As described in the previous section, the gravity model requires two elements--opportunities and impedance-- to calculate job accessibility. Since this research focuses only on the journey to work and the number of jobs in a destination zone is counted as the level of opportunity, a travel time based impedance function is used as the impedance. Briefly, job accessibility is defined as follows:

\[ A_{im} = \sum_{j=1}^{n} O_{jm} f(T_{ijm}) \] ..........................................................(2)

Where,
- \( A_{im} \) = Job Accessibility from origin zone i to all destinations j by mode m
- \( O_{jm} \) = Number of jobs in destination zone j that can be reached by mode m
- \( f(T_{ijm}) \) = Impedance function by travel time
- \( T_{ijm} \) = Travel time from origin zone i to destination zone j by mode m

Using the gravity model above, job accessibility is measured for two transportation modes, auto, and transit. In this research, the auto mode includes drive alone and carpool, and the transit-mode includes bus, subway, and commuter rail. Other motorized modes, such as vanpool, and taxi are excluded from the study along with any non-motorized modes, such as walking and bicycling due to the lack of zone to zone travel time information, which is required to estimate job accessibility. Figure 2-3 summarizes the methodology used to calculated job accessibility.
Zonal Data

Observed No of Trips from zone i (CTPP)

Observed No of workers in zone i (CTPP)

Residence i

Workplace j

Network Data

Estimated Travel Time From i to j (EMME2, CTPS)

No of Trips
CTPP Travel Time
No of Jobs
CTPS Travel Time
Average Trips per Job
Travel Time

Trip Distribution
Opportunity Distribution

Impedance Function

Job Accessibility

Figure 2-3 Accessibility Calculation Process
Number of Opportunities

Since the purpose of this study is to understand journey to work travel patterns, the number of jobs was used as the number of opportunities as in many other studies (Cervero, 1995; Kawabata, 2002; Levinson, 1998; Shen, 1998; Zhang, 2004). The different approach here was to count the number of jobs accessible by transit and auto separately. More specifically, in many accessibility studies, the number of jobs available in a destination zone is the same for all modes if the modes provide connection to the destination zone. As a result, transit accessibility is over-estimated which can lead to over-estimation of ridership. In this study, however, the number of jobs counted as accessible by transit was considered only the jobs that are located within the transit catchment area, not in the whole zone, in order to estimate more realistic accessibility indices.

In order to determine the number of job opportunities for transit, GIS software (ArcGIS 9.0) is used to create a walk distance (0.25 mile network distance) buffer around each transit stop so as to count the number of employment opportunities within the buffer of each zone. For auto, all jobs in a zone are counted as reachable. Figure 2-4 visualizes the relationship between job locations and a 0.25 mile transit station buffer area. As we can see from the figure, especially in the suburban areas, the number of jobs accessible by transit will be over-counted if all jobs in a block group are counted as accessible by transit.
Figure 2-4 0.25 mile network buffer from transit stops and job locations
Estimating Impedance Function

The dependant variable in estimating impedance functions is the number of trips made by each mode divided by the number of job opportunities that can be reached, to which a natural log transformation was applied. Since the Census and the CTPP provide travel time to work information by categorized data (5 minute cohorts up to 60 minutes then 15 minutes cohorts above 60 minutes), the number of trips in each time segment was counted. In order to count the number of opportunities, the research identified destination zones that can be reached in each travel time based on CTPS travel time data and then summed up the number of jobs in all destinations zones. As mentioned in the previous section, GIS software was used to identify job locations within a transit service area in each zone in order to count the number of job opportunities available to transit users. This method used two different sources of travel time data: reported travel time from CTPP 2000, and estimated travel time using EMME2 from CTPS. So it is assumed that these two travel time sources are comparable.

Figures 2.5 and 2.6 show trip distribution and opportunity distribution, which help us to understand general trip tendency in the study area. Also these figures reveal one of limitations of method we used in this study to calculate the average trips per opportunity. As explained in the previous paragraph, it is assumed that CTPP reported travel times and CTPS estimated travel times are comparable. However, as can be seen from Figure 2-5, people tend to choose familiar numbers when they report travel time: travel time cohorts that have 30, 45, and 60 minutes have very high values compared to the values before and after that time range. On the other hand, the opportunity distribution (Figure 2-6) based on CTPS estimated travel time does not have fluctuations that the trip distribution has. Therefore, the average trips per opportunity calculated based on the trip distribution by reported time and opportunity distribution by estimated time may not perfectly be comparable to each other. Also it should be noted that the average trips per opportunity could not be obtained by simply dividing average trips by average opportunities. A more
detailed description about how to calculate the average trips per opportunity is given in the following section.

Figure 2-5 Average Number of Trips - Auto

Figure 2-6 Average Number of Jobs Accessible by Auto
Since the impedance function is a critical element in measuring job accessibility, a more detailed description of the method used in this study to obtain the dependent variable (average trips per opportunity) is presented below as a series of steps:

1) Identify block groups that can be reached by each travel time cohort (15 cohorts) from each origin defined by CTPP. As a result, block groups were categorized into 15 areas for each origin, based on travel time. In this step, EMME2 estimated travel time was used.

2) Count the total number of jobs available in each of the 15 areas for each origin using GIS. Then the results were imported to a database.

3) Extract the number of trips made from each block group for each time cohort.
   In this step, observed number of trips, reported by CTPP part 1, was used.
4) Obtain the number of trips per opportunity for each time cohort and for each origin by dividing the number of trips from an origin by the total number of job opportunities that can be reached within each travel time cohort.

<table>
<thead>
<tr>
<th>STFID</th>
<th>ATR4</th>
<th>ATR9</th>
<th>ATR14</th>
<th>ATR19</th>
<th>ATR24</th>
<th>ATR2</th>
</tr>
</thead>
<tbody>
<tr>
<td>250250203002</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>250250302001</td>
<td>0</td>
<td>4.974648E-05</td>
<td>0.0003101737</td>
<td>0.0001789811</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>250250305002</td>
<td>0</td>
<td>2.671083E-05</td>
<td>0.0002166827</td>
<td>0.0002474650</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>250250303004</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001244773</td>
<td>0</td>
<td>3.37271e52</td>
</tr>
</tbody>
</table>

5) As a result of steps 1) through 4), trips per opportunity values for all origin block groups (2060 block groups) were obtained.

6) Calculate the average number of trips per opportunity for each time cohort by summing all trips per opportunity values and divide them by 2060, the total number of block groups.

2.3.3 Measuring Job Accessibility - Employer Perspective

Job accessibility by transit and auto was calculated using the same method as used for the residential model. The difference is that for the residential model accessibility implies how easy it is for workers who live in a zone to get to job opportunities, while the employer model quantifies how easily job opportunities in a zone can be reached by workers throughout the region. Accessibility for employer model is estimated as follows:

\[ A_{im} = \frac{\sum_{j=1}^{n} W_{jm} f(T_{jim})}{2060} \]  

Where, 
\[ A_{im} = \text{Job Accessibility to destination zone } i \text{ from all origin zones } j \text{ by mode } m \]
\[ W_{jm} = \text{Number of workers in origin zone } j \text{ who are accessible by mode } m \]
\[ f(T_{jim}) = \text{Impedance function by travel time} \]
\[ T_{jim} = \text{Travel time to destination zone } i \text{ from origin zone } j \text{ by mode } m \]
Number of Employed Workers

A problem when calculating the job accessibility by transit from the employer perspective is how to estimate the number of workers who live in a transit catchment area. In this study, a rough estimation was made as follows: the number of residents are calculated by multiplying total workers in a block group by the proportion of residential areas within the transit catchment area under the assumption that the population is evenly distributed over the residential area. This assumption may underestimate the job accessibility by transit, considering that residential areas near transit stations are usually more densely populated.

In order to calculate the proportion of residential areas within a transit catchment area, GIS software was used to overlay the zoning data and the quarter mile transit service area. Then the proportion of residential areas within the transit service area was multiplied by the number of employed residents in each zone to estimate the number of transit accessible workers. Figure 2-7 visualizes the percentage of residential areas within the quarter mile transit catchment area.
Figure 2-7 Percentage of Residential Areas within 0.25 mile Transit Catchment Area
Estimating Impedance Function

For the workplace model, the dependent variable for estimating the impedance function is the number of trips made to a census block group by each mode (auto and transit) divided by the total number of workers who live in block groups within each travel time zone (5-minute time cohorts up to 60 minutes’ travel time and 15 minute cohorts after that). In order to calculate the average number of trips per opportunity the following steps are required:

1) Identify origin zones that could be reached in each travel time and then sum up the number of commuters in all origin zones. As in the residential model, EMME2 estimated travel time was used.

2) Count the total number of workers available for each destination for each time cohort using GIS.

3) Extract the number of trips made to a destination for each time cohort. In this step, observed number of trips reported by CTPP part 2 was used.
4) Obtain the number of trips per opportunity for each time cohort and for each
destination by dividing the number of trips to a destination by the total number of
potential workers that can be reached for each travel time cohort.

5) As a result of steps 1) through 4), trips per opportunity values for all destination block
groups (2060 block groups) were obtained.

6) Calculate the average number of trips per opportunity by summing up all 2060 trips per
opportunity values and divide them by 2060, the total number of block groups.

One of the problems of using this method to obtain the dependent variable is that it is
assumed that the reported travel times by CTPP and the estimated times by CTPS are
perfectly comparable, which may not be true. Also, in this method, all block groups were
treated same; no weight was applied. This may cause problems since a block group with
small number of workers were treated same as a block group with large number of workers.
For example, a block group in the city of Waltham, one of the Edge Cities along route 128,
has 2,885 commuters, the largest in the study area while a block group in the
Allston/Brighton area in Boston has only 4 commuters, the smallest. The differences are
greater in the workplace case: a block group in the financial district in downtown Boston
has 72,600 employees while some block groups have none. Despite these variations,
however, all block group were treated same when calculating the average trips per
opportunity.
CHAPTER 3
DATA AND STUDY AREA

Having outlined the research questions and the theoretical background for this study, this chapter describes the research data, and the study area used to explore the research questions raised in Chapter 1.

3.1. Data

Journey to work data from the Census Transportation Planning Package (CTPP) for the 2000 Census is used for the analysis. CTPP 2000 is a special tabulation of responses from households completing the Census long form designed to address various transportation planning related issues. The CTPP 2000 consists of three parts, At Residence, At Workplace, and Worker Flows. Parts 1 and 2 contain the number of persons, number of households, number of workers, and number of housing units, while Part 3 counts the number of workers traveling from the residence to the other end of the commuting trip, workplace or school.

Central Transportation Planning Staff (CTPS) in Boston provided transportation network data that includes travel time for each origin-destination (O-D) pair by auto and transit, locations of transit stops (bus, subway, and commuter rail), and the average headway and the number of transfers for each O-D pair. All these data points are estimated values compiled by EMME2 software on Traffic Analysis Zone (TAZ). TAZ based travel time was then converted to block group based travel time using GIS. In this study, transit refers to bus, subway, and commuter rail.

Job locations and employment information are critical for calculating job accessibility. These data are obtained from Initiatives for a Competitive Inner City (ICIC), a non-profit organization in Boston and geo-coded using GIS software. The employment data are ZIP
code based location data with Standard Industrial Classification (SIC), number of jobs, and gross profit information. Once the locations are geo-coded, the number of job locations and the number of jobs in each zone (Census block group or TAZ) are counted by spatially joining the location data with the Census block group and the TAZ boundary data. In order to perform spatial analyses and visualization, several GIS data layers were downloaded from the Massachusetts Geographic Information System (www.mass.gov/mgis/), including TIGER street network, TAZ boundaries, Census block group boundaries, Town boundaries, and Zoning data. TIGER street network data are used as a base map for geo-coding job locations, and boundary layers are used to extract and visualize zonal values; zoning layer is used to calculate transit stop proximity index.

In addition to the above data, Census 2000 data are used to extract income data, such as median household income, and per capita income at the Census block group level. Census block group level is chosen rather than census tract or census block, because census block group is the smallest geographic unit in the CTPP data and can be easily summed up (or divided) into TAZs, a geographic unit on which CTPS data items are prepared.

3.2 Description of the Study Area

The area selected for this study is shown in Figure 3-1. This area covers the central part of the Boston Metropolitan Area, which has 164 cities and towns with a total population of approximately 4.1 million. This study area includes 74 cities and towns, including the city of Boston, 616 TAZs, 534 Census tracts, and 2061 Census block groups in Essex, Middlesex, Norfolk, and Suffolk counties. These areas are chosen based on the location of public transit stops in order to examine travel mode choice behavior where transit is an option for commuting. The “data acquiring area” is the area from which CTPP data were obtained. The data acquiring area covers a larger area than the study area in order to minimize boundary effects, especially on the block groups located on the periphery of the study area.
New Hampshire

Study Area (2000)
Population: 2.5 Millions
Land Area: 706.464 sq Miles
# of Cities/Towns: 74

Rhode Island Data Acquiring Area
# of Cities/Towns: 114
It covers all cities and towns in the study area and additional 40 cities and towns surrounding it

Figure 3-1 Study area and its relationship to the Boston Metropolitan Area
Massachusetts is one of the most transit friendly states in the US with the oldest subway systems and extensive bus and commuter rail network. According to the 2000 Census, auto mode share in Massachusetts is the fourth lowest in the US following Washington D.C. (45%), New York (64%), and New Jersey (82%). However, automobile is still the dominant transportation mode for commuting serving about 83% of all work trips. The transit share is the fourth highest among US states with 9.8% of work trips using transit (Table 3.1). The study area includes the most densely populated areas in Massachusetts, and as a result, automobile share is much lower and transit share is much higher than for the complete state as shown in the Figure 3-2.

Table 3.1 Journey to Work by State & Mode: 2000  
- Ranked by Transit Mode Share (Top 10 & bottom 10)

<table>
<thead>
<tr>
<th>Rank</th>
<th>State</th>
<th>Automobile</th>
<th>Drive Alone</th>
<th>Carpoools</th>
<th>Transit</th>
<th>Non-Motor</th>
<th>Work at Home</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Washington D.C.</td>
<td>48.62%</td>
<td>39.99%</td>
<td>8.51%</td>
<td>34.68%</td>
<td>12.67%</td>
<td>4.04%</td>
</tr>
<tr>
<td>2</td>
<td>New York</td>
<td>63.97%</td>
<td>55.74%</td>
<td>8.19%</td>
<td>26.82%</td>
<td>6.45%</td>
<td>2.76%</td>
</tr>
<tr>
<td>3</td>
<td>New Jersey</td>
<td>82.00%</td>
<td>72.34%</td>
<td>9.61%</td>
<td>11.25%</td>
<td>4.04%</td>
<td>2.71%</td>
</tr>
<tr>
<td>4</td>
<td>Massachusetts</td>
<td>82.24%</td>
<td>73.47%</td>
<td>8.73%</td>
<td>9.88%</td>
<td>4.96%</td>
<td>2.92%</td>
</tr>
<tr>
<td>5</td>
<td>Illinois</td>
<td>83.89%</td>
<td>73.21%</td>
<td>10.58%</td>
<td>9.34%</td>
<td>4.00%</td>
<td>2.77%</td>
</tr>
<tr>
<td>6</td>
<td>Maryland</td>
<td>85.38%</td>
<td>73.29%</td>
<td>12.04%</td>
<td>8.29%</td>
<td>3.02%</td>
<td>3.31%</td>
</tr>
<tr>
<td>7</td>
<td>Hawaii</td>
<td>85.44%</td>
<td>66.78%</td>
<td>17.72%</td>
<td>6.47%</td>
<td>4.47%</td>
<td>3.63%</td>
</tr>
<tr>
<td>8</td>
<td>Pennsylvania</td>
<td>86.51%</td>
<td>76.78%</td>
<td>9.62%</td>
<td>5.72%</td>
<td>5.03%</td>
<td>2.74%</td>
</tr>
<tr>
<td>9</td>
<td>California</td>
<td>86.61%</td>
<td>72.40%</td>
<td>13.94%</td>
<td>5.38%</td>
<td>4.34%</td>
<td>3.67%</td>
</tr>
<tr>
<td>10</td>
<td>Washington</td>
<td>85.84%</td>
<td>74.10%</td>
<td>11.53%</td>
<td>4.89%</td>
<td>4.59%</td>
<td>4.68%</td>
</tr>
<tr>
<td>42</td>
<td>North Carolina</td>
<td>93.61%</td>
<td>80.84%</td>
<td>12.69%</td>
<td>0.74%</td>
<td>2.70%</td>
<td>2.95%</td>
</tr>
<tr>
<td>43</td>
<td>Mississippi</td>
<td>94.63%</td>
<td>82.95%</td>
<td>11.61%</td>
<td>0.59%</td>
<td>3.04%</td>
<td>1.74%</td>
</tr>
<tr>
<td>44</td>
<td>New Hampshire</td>
<td>92.77%</td>
<td>83.24%</td>
<td>9.36%</td>
<td>0.55%</td>
<td>2.87%</td>
<td>3.81%</td>
</tr>
<tr>
<td>45</td>
<td>Oklahoma</td>
<td>92.92%</td>
<td>81.87%</td>
<td>11.00%</td>
<td>0.51%</td>
<td>3.72%</td>
<td>2.85%</td>
</tr>
<tr>
<td>46</td>
<td>North Dakota</td>
<td>87.88%</td>
<td>77.74%</td>
<td>10.12%</td>
<td>0.47%</td>
<td>6.47%</td>
<td>5.18%</td>
</tr>
<tr>
<td>47</td>
<td>South Dakota</td>
<td>87.24%</td>
<td>76.64%</td>
<td>10.35%</td>
<td>0.44%</td>
<td>5.91%</td>
<td>6.41%</td>
</tr>
<tr>
<td>48</td>
<td>Montana</td>
<td>86.35%</td>
<td>75.12%</td>
<td>11.10%</td>
<td>0.43%</td>
<td>7.37%</td>
<td>5.86%</td>
</tr>
<tr>
<td>49</td>
<td>Alabama</td>
<td>95.71%</td>
<td>84.56%</td>
<td>11.10%</td>
<td>0.40%</td>
<td>1.94%</td>
<td>1.96%</td>
</tr>
<tr>
<td>50</td>
<td>Arkansas</td>
<td>93.88%</td>
<td>82.11%</td>
<td>11.66%</td>
<td>0.40%</td>
<td>2.70%</td>
<td>3.02%</td>
</tr>
<tr>
<td>51</td>
<td>Kansas</td>
<td>91.44%</td>
<td>82.95%</td>
<td>8.42%</td>
<td>0.38%</td>
<td>3.80%</td>
<td>4.38%</td>
</tr>
</tbody>
</table>
The study area includes parts of major highways in the metropolitan area and also the City of Boston, which is a highly populated and densely developed core area. As seen in Figure 3-3, the study area also includes several relatively low-density suburban towns and cities with varying incomes. There are several features of this map that are noteworthy. First, as indicated by darker colors, higher income households are generally further from downtown Boston. Census block groups with light gray are the areas of lowest median household income and are generally found closer to the downtown. If we look at the per capita income distribution in Figure 3-3, there is a clearly identifiable wedge of high-income households that stretch to the East of downtown Boston. It should also be noted that there are a small number of middle and high-income areas in the downtown area. To understand the mode choice behavior of residents in the area, it is necessary to include transit routes and highly congested roadways in the study area (see Figure 3-4).

Figure 3-5 describes the population and employment distribution in the study area. The city of Boston and the adjacent area are the most populated and densely developed part of the study area. The population distribution map in Figure 3-5 clearly illustrates the close relationship between land use and public transportation systems as high-density areas are located along Boston’s subway system. As we can see from the employment density map
in Figure 3-5, there are two concentrations of job locations, near downtown Boston along the subway lines and the suburban area along highway 128, including Braintree, Burlington, Natick, Waltham, and Woburn. Both of these areas support the strong linkage between land use and transportation.

The location of job centers can be easily identified from Figure 3-6 which visualizes the ratio of the number of workers working in the block group to the number of commuters in the same block group. The black block groups are employment centers that have more jobs than workers. As can be seen from the map, the locations of job centers are closely related to the highways. However, it should be noted that the ratio of jobs to workers, as a relative indicator, sometimes generates misleading results in absolute terms: an area with a small number of jobs but with a much smaller number of workers has a high jobs to workers ratio and can be falsely identified as a job center. Block groups in the city of Billerica would be a good example of this.
Figure 3-3 Income Distribution in the Study Area
Figure 3-4 Transportation Network in the Study Area
Figure 3-5 Population and Employment Density in the Study Area
The Ratio of Jobs to Workers

I M
Jobs to I Major Highway Workers Ratio = 1 (Min = 0) 
< <= 3
3 < <= 6
6 < <= 9
> 9 (Max = 614.5)
Study Area

Figure 3-6 Ratio of the Number of Jobs to the Number of Workers in an Area
CHAPTER 4
JOB ACCESSIBILITY

One of the essential components to address the questions in this research is to construct an improved measure of job accessibility that represents the level of accessible job opportunities from a residential area and the level of accessible workers with respect to workplace. This chapter presents the computation of job accessibility by automobile and transit from two perspectives, residential and workplace, in the Boston metropolitan area. Then computed measures are visually presented using GIS.

4.1 Measuring Job Accessibility – Residential Perspective

As described in Chapter 2, job accessibility from residential point of view by two different modes, auto and transit was calculated using following formula.

\[ A_{im} = \sum_{j=1}^{n} Q_{jm} f(T_{ijm}) \]  \hspace{1cm} (4)

Where,

\[ A_{im} = \text{Job Accessibility from origin zone } i \text{ to all destinations } j \text{ by mode } m \]
\[ Q_{jm} = \text{Number of jobs in destination zone } j \text{ that can be reached by mode } m \]
\[ f(T_{ijm}) = \text{Impedance function by travel time} \]
\[ T_{ijm} = \text{Travel time from origin zone } i \text{ to destination zone } j \text{ by mode } m \]

The regression equations for auto and transit mode follow (t-score shown in brackets under the corresponding variable and * means \( p < .05 \), using the two tailed t-test). For auto, the adjusted R square value is 0.629 with a standard error of estimate of 0.802 and an equation F ratio of 24.695 (\( p < .001 \)).

\[ f(T_{ija}) = \exp \left( -5.556 - 0.421 T_{ija}^{0.5} \right) \]  \hspace{1cm} (5)

Where, \( T_{ija} = \text{Travel time between zone } i \text{ to zone } j \text{ by auto} \)

Figure 4-1 displays the estimated impedance function, and observed values.
For transit, the adjusted R square value is 0.489 with a standard error of estimate of 2.143 and an equation F ratio of 14.390 ($p < .005$).

$$f(T_{ij}) = \exp (-3.281 - 0.859 T_{ij}^{0.5})$$ ............................................................. (6)

Where, $T_{ij}$ = Travel time between zone i to zone j by transit

Figure 4-2 displays the estimated impedance function, along with the observed values. Since the gravity model requires a continuously declining impedance function, the estimated functions did not capture the increase in trip frequency as travel time increased to a certain point (up to 20 minutes in transit travel time), and this may bias the modeling result. One of the reasons for having very low numbers of trips at less than 15 minutes travel time may be that people use non-motorized modes to get to work if transit travel time is less than 20 minutes. As we can see from Figure 4-3, which shows total transit trips and non-motorized trips by travel time in a single graph, the non-motorized mode is dominant at less than 20 minutes travel time. Therefore, if we could combine transit and non-motorized mode in that range, a better impedance function could be obtained. However,
the non-motorized mode could not be incorporated into estimating the transit impedance function due to lack of information about non-motorized travel time between origin-destination (O-D) pair. Without O-D travel time data, number of opportunities in each travel time cohort cannot be calculated and as a result, the average trips per opportunity, the dependent variable for estimating impedance function cannot be obtained.

Figure 4-2 Transit travel impedance function – Residential model

Figure 4-3 Average Number of Trips – Transit & Non-motorized modes
4.2 Job Accessibility – Residential Perspective

Figure 4-4 and Figure 4-5 show the calculated job accessibility indices by auto and transit for the Census block groups in the study area. Figure 4-4 shows the spatial relationship between the transportation network (major highways and subway stops) and job accessibility for each mode. Figure 4-5 compares the degree of job accessibility for each mode by visualizing the job accessibility index with the same scale. Several spatial patterns are evident from these outputs.

First, job accessibility shows a radial pattern emanating from downtown Boston along with major highways and public transit lines. As a result, block groups with the highest job accessibility, ignoring occupational match, are in downtown Boston downtown; and the most job inaccessible areas are at the periphery of the region, especially to the Northeast and Southwest. Second, as Figure 4-4 shows, job accessibility by transit is much better in block groups around downtown Boston. On the other hand, auto commuters’ high job accessibility areas extend well into the suburban areas. These results are consistent with the findings of other job accessibility studies on Boston metropolitan area (Kawabata, 2002; Shen, 1998, 2001).

This spatial pattern partly reflects the land use patterns of these areas as predominantly residential communities. Relative job accessibility (ratio of job accessibility by transit to job accessibility by auto) in Figure 4-6 shows which block groups have balanced transportation options in the study area. According to this result, block groups along the coast from Salem to Braintree, including the City of Boston have higher relative job accessibility than other regions in the Northwest and the East part of the study area that have similar transit job accessibility. This result reveals that some block groups that have high transit accessibility also have much higher job accessibility by auto, a finding that may lead to less transit usage. These results seem reasonable, given that Boston is the largest job center in the entire Commonwealth of Massachusetts with a highly transit friendly
environment. Job accessibility patterns mimic the transit service lines and highway systems.

The biggest limitation of our approach is that job accessibility as defined here does not include a match between job types and the skills of the potential employees. If we had access to this information, we could have obtained a clearer match between observed reality and local knowledge. Since the employment data only gave us the location and total number of jobs, occupational matching was infeasible in this research. Occupational matching is an important factor in considering job accessibility because proximity to opportunities means nothing if workers are not qualified for the jobs that are available. As a result, the job accessibility patterns drawn from this research may not reflect the true degree of job accessibility throughout the region.
Job Accessibility Index - Auto

- <= 500 (Min = 249)
- 500 < <= 700
- 700 < <= 900
- 900 < <= 1100
- > 1100 (Max = 1558)

Job accessibility represents the number of jobs that can be reached from each block group weighted by travel time impedance.

Job Accessibility by Auto - Residential

Job Accessibility Index - Transit

- <= 100 (Min = 0)
- 100 < <= 200
- 200 < <= 300
- 300 < <= 400
- > 400 (Max = 831)

Job accessibility represents the number of jobs that can be reached from each block group weighted by travel time impedance.

Job Accessibility by Transit - Residential

Figure 4-4 Job Accessibility (Different Scale) – Residential Perspective
Job Accessibility Index - Auto

- <= 100
- 100 < <= 300
- 300 < <= 500
- 500 < <= 700
- > 700 (Max = 1558)

Job accessibility represents the number of jobs that can be reached from each block group weighted by travel time impedance.

Job Accessibility by Auto - Residential

Job Accessibility Index - Transit

- <= 100 (Min = 0)
- 100 < <= 300
- 300 < <= 500
- 500 < <= 700
- > 700 (Max = 831)

Job accessibility represents the number of jobs that can be reached from each block group weighted by travel time impedance.

Job Accessibility by Transit - Residential

Figure 4-5 Job Accessibility (Same Scale) – Residential Perspective
Relative Job Accessibility - Residential

Figure 4-6 Relative Job Accessibility – Residential Perspective
4.3 Measuring Job Accessibility - Employer Perspective

As presented in Chapter 2, job accessibility from the employer perspective by auto and transit was calculated using the following equation:

\[ A_{im} = \sum_{j=1}^{n} W_{jm} f(T_{jm}) \]  

Where,

- \( A_{im} \) = Job Accessibility to destination zone \( i \) from all origin zones \( j \) by mode \( m \)
- \( W_{jm} \) = Number of workers in origin zone \( j \) who are accessible by mode \( m \)
- \( f(T_{jm}) \) = Impedance function by travel time
- \( T_{jm} \) = Travel time to destination zone \( i \) from origin zone \( j \) by mode \( m \)

In order to estimate the impedance function, several exponential functions were tested, but none were chosen due to very low R square values. Low R square value stemmed from the number of trips per opportunity longer than 60 minutes, which increases with travel time as shown in Figure 4-7.

![Figure 4-7 Average Auto Trips per Opportunity – Employer model](image)

A most plausible explanation for having a sharply increasing tail above 75 minutes is that many who work in the study area and drive more than 75 minutes actually live outside the
study area. According to the travel time data from CTPS, none of the block groups in the study area requires more than 75 minutes driving to reach downtown Boston area. However, figure 4-8 displays the outside the study area that require more than 75 minutes by auto to get to downtown Boston.

As a result, the number of potential workers who can be reached from downtown (i.e., the number of opportunities) was determined using data from the study area (CTPS) while the number of trips made to downtown as per the CTPP data includes trips made from outside the study area. This inconsistency was have caused unexpected high values of average trips to opportunities for a small number of block groups (less than 2%). These block groups resulted in the increase above 75 minutes travel time, which is obviously realistic. Therefore, the impedance function was estimated based only on trips of less than 75 minutes' travel time and then applied to the entire travel time zone. Figure 4-9 shows the actual data and the estimated function. This may be problematic since the impedance function did not reflect true travel behavior after 60 minutes of travel time. At this point, however, the single impedance function shown below was be used for the job accessibility analysis.
Figure 4-8 Areas with greater than 75 minutes driving to downtown Boston
The regression equation for auto follows (the t-score appears in brackets under the corresponding variable and * means \( p < .05 \), using the two tailed t-test). The adjusted R square value is 0.789 with a standard error of estimate of 0.558 and an equation F ratio of 42 (\( p < .001 \)).

\[
f(T_{ija}) = \exp (-3.516 - 0.625 T_{ija}^{0.5}) \tag{8} \]

Where, \( T_{ija} \) = Travel time between zone i to zone j by auto

![Figure 4-9 Auto travel impedance function – Employer model](image)

For the transit case, the problematic time range is from 10 to 25 minute where the number of trips increases as travel time increases. This trend is also acceptable, as similar trends have been observed in many urban areas (Ortuzar et al, 2001). However, in order to generate a continuously decreasing impedance function, as the gravity model theory requires, the impedance function was estimated by excluding three observations made in that time range (0 to 5 minutes, 5 to 10 minutes and 10 to 15 minutes). Figure 4-10 shows the observed values, and the chosen (estimated) line. As mentioned in the residential model (Figure 4-3), combining trip frequency of transit and non-motorized may be a better alternative to eliminating observations but due to lack of O-D pair non-motorized travel time, this method could not be used. Below is the estimated impedance function for the
transit case with the adjusted R square value of 0.341, standard error of estimate of 1.301, and an equation F ratio of 6.686 (p < .05).

\[ f(T_{ij}) = \exp(-5.173 - 0.574 T_{ij}^{0.5}) \text{ (9)} \]

Where, \( T_{ij} = \) Travel time between zone i to zone j by transit mode

4.4 Job Accessibility – Employer Perspective

Job accessibility of workplaces by auto and transit is shown in Figure 4-11. Downtown Boston is the most accessible place both by auto and transit with job accessibility indices declining with distance from the City of Boston. Workplaces in the East and the North of Boston have higher auto accessibility than do the South, while the East and the South of Boston have higher transit accessibility than does the North. This result is a reflection of the transportation network around the City of Boston; there is a denser highway network in the North and the West part of Boston and a denser Subway network in the East and the South of Boston.
Figure 4-12 compares the degree of job accessibility by the two modes. In order to compare the two accessibility indices, the scale of the map was kept the same, and the map shows that auto job accessibility is much higher than is transit job accessibility, even in the downtown area. This result reveals that except for downtown Boston, workplaces are much more accessible by auto than by transit. The result may be biased toward the auto due to the lack of travel cost information, such as parking fees. Since parking fees is one of the most influential factors discouraging auto usage, inclusion of parking fees may drop auto accessibility of some workplaces significantly, especially areas near downtown Boston.

Relative job accessibility (transit job accessibility over auto job accessibility) is shown in Figure 4-13. This map indicates that the workplaces in the South of the study area provide more balanced transportation options to workers compared to the Western and Northern parts of the study area. Downtown Boston has, of course, the highest relative job accessibility. One thing should be mentioned again here is that job matching was not considered in the job accessibility estimation. As mentioned in the previous section, job matching is one of the important factors determining job accessibility since physical proximity to opportunities means nothing if workers nearby are not qualified for the available job opportunities.
Major Highway
Town Boundary
Auto Job Accessibility - Workplace
\( \leq 10000 \) (Min = 2958)
\( 10000 < \leq 15000 \)
\( 15000 < \leq 20000 \)
\( 20000 < \leq 25000 \)
\( > 25000 \) (Max = 29708)
- Job accessibility represents the number of workers who can come to each block group to work weighted by travel time impedance

Job Accessibility by Auto - Employer Perspective

Subway Stops
Town Boundary
Transit Job Accessibility - Workplace
\( \leq 700 \) (Min=0)
\( 700 < \leq 1200 \)
\( 1200 < \leq 1700 \)
\( 1700 < \leq 2200 \)
\( > 2200 \) (Max =3240)
- Job accessibility represents the number of workers who can come to each block group to work weighted by travel time impedance

Job Accessibility by Transit - Employer Perspective

Figure 4-11 Job Accessibility (Different Scale) – Employer Perspective
Job accessibility represents the number of workers who can come to each block group to work, weighted by travel time impedance.

Figure 4-12 Job Accessibility (Same Scale) – Employer Perspective
Figure 4-13 Relative Job Accessibility – Employer Perspective
CHAPTER 5
COMMUTING PATTERN ANALYSES

This chapter examines commuting patterns from the residential perspective in a more
disaggregate way, using GIS techniques to understand the differences between travel
behavior of the entire study area and that of selected block groups with distinct job
accessibility characteristics.

5.1 Categorizing block groups

A small number of block groups were selected from the study area based on the degree of
relative job accessibility and the data were categorized into two groups; high job
accessibility areas and low job accessibility areas. Although relative job accessibility
indices were used to select block groups, the groups are referenced to as high and low
accessibility area to keep the terminology simple. Commuting patterns for these groups,
such as mode share, commuting time, and leaving time to work, were then compared to
each other and to the entire study area.

Relative job accessibility (ratio of transit job accessibility to auto job accessibility) and not
transit accessibility was used to extract block groups with high and low accessibility
because, relative job accessibility measures the degree of transportation options of an area,
and has more explanatory power for mode share than does transit job accessibility. Block
groups with a relative job accessibility of at least 0.4 are classified as high accessibility, and
those with relative job accessibility of 0.09 or less were classified as low accessibility.
Block groups with 0 relative job accessibility were not included in the low accessibility
group in order to examine the commuting patterns in an area that had both options (transit
and auto) available. The threshold for the high and low accessibility was set so that a
similar number of block groups in each group could be chosen. As a result of this selection
process, 143 low accessibility block groups and 144 high accessibility block groups were
chosen. Due to the smaller block group size of the denser areas', such as downtown Boston, spatial coverage of high accessibility block groups was smaller than spatial coverage in the low accessibility areas. Since the selection process did not consider political boundaries (e.g., town or city boundaries), selected block groups were scattered all over the study area. Figure 5-1 shows the selected high and low accessibility block groups.

As we can see from Figure 5-1, the low accessibility areas are located on the periphery of the study area. Most of the block groups in the low accessibility areas are residential communities with relatively high incomes. Block groups in downtown Boston and two of the surrounding towns, Brookline and Cambridge, were selected as high accessibility areas as well as block groups in the city of Quincy. Downtown Boston is the biggest employment center and also has a densely populated residential area with a highly developed transit network. Major highways, subway, bus, and commuter rail systems provide high accessibility to workers and residents. The city of Quincy is one of the satellite cities around Boston and is well connected to other employment centers by highway, subway, and commuter rail. The average Median household income in the high accessibility area is lower than that of the low accessibility area as well as the study area as a whole.

<table>
<thead>
<tr>
<th></th>
<th>TOT_POP</th>
<th>MEDINC</th>
<th>POPDEN</th>
<th>AT_ACC</th>
<th>TR_ACC</th>
<th>RT_ACC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study Area</td>
<td>2,482,554</td>
<td>$58,262</td>
<td>5.492</td>
<td>738.074</td>
<td>135.668</td>
<td>0.164</td>
</tr>
<tr>
<td>LOW ACC</td>
<td>205,549</td>
<td>$76,255</td>
<td>2.104</td>
<td>500.994</td>
<td>16.442</td>
<td>0.033</td>
</tr>
<tr>
<td>HIGH ACC</td>
<td>155,375</td>
<td>$43,971</td>
<td>25.310</td>
<td>1,368.569</td>
<td>480.009</td>
<td>0.351</td>
</tr>
</tbody>
</table>

* According to the Bureau of Census, each Census block group is designed to contain 400 housing units. They generally vary in size between 250 and 550 housing units. As a result, the size of the block groups in denser areas is smaller than the size of the block groups in less dense areas.

** TOT_POP: Total population, MEDINC: Average median household income, POPDEN: Average population density per dry acre, AT_ACC: Average auto job accessibility, TR_ACC: Average transit job accessibility, RT_ACC: Average relative job accessibility, Income, Population data from Census 2000
Selected Block Groups

Figure 5-1 Study Area and Selected Block Groups for Comparison
CTPP 2000 journey-to-work data for 2060 block groups in Middlesex, Essex, Norfolk, and Suffolk counties in Massachusetts are examined. Table 5-2 summarizes the mode share for work trips in the study area, as well as for high accessibility, and low accessibility areas. As we can see from the table, transit commuting varies substantially across these areas.

Table 5-2. Mode Share Comparison

<table>
<thead>
<tr>
<th></th>
<th>Drive Alone</th>
<th>Carpool</th>
<th>Transit</th>
<th>Non-motor</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study Area</td>
<td>66.02%</td>
<td>8.37%</td>
<td>17.52%</td>
<td>7.34%</td>
<td>0.75%</td>
</tr>
<tr>
<td>High Accessibility Area</td>
<td>26.50%</td>
<td>4.88%</td>
<td>29.52%</td>
<td>37.20%</td>
<td>1.90%</td>
</tr>
<tr>
<td>Low Accessibility Area</td>
<td>84.57%</td>
<td>6.90%</td>
<td>6.52%</td>
<td>1.48%</td>
<td>0.53%</td>
</tr>
</tbody>
</table>

In the following pages we present variations of some key parameters, such as travel time, time leaving for work, and average income for the study area as a whole and for the two extreme categories we have just presented, in terms of high and low relative job accessibility.

5.2 Mode Share versus Travel Time

In this section, mode share of different parts of the study area are compared based on travel time. Travel time is considered to be one of the decisive factors determining people’s mode choice. Therefore, much research has used travel time to estimate the trip distribution function or utility function for modeling travel behavior. As indicated in Chapter 4, job accessibility indices were calculated based on a travel time based trip distribution function. Travel time is one of the most important components of this study.

This section attempted to answer whether the correlation between travel time and mode choice in the overall study area also applies to areas with very different land use characteristics, namely high and low accessibility areas. In order to examine the differences in travel time and mode choice relationship in different circumstances, trip
frequency as a function of travel time for each mode (drive alone, transit, and non-
motorized mode) for different areas (entire study area, high accessibility area, and low
accessibility area) were estimated and then compared.

Table 5-3 compares the mean commuting time by different modes, drive alone, transit,
bicycle, and walking for the Boston metropolitan area, the study area, and the high and low
accessibility areas. From Table 5-3, the average travel time for motorized modes-- drive
alone, and transit -- ranges between 24 minutes to 30 minutes, less than a 5-minute
difference. For non-motorized modes, mean bicycle travel time ranges from 2 to 8 minutes
and mean walking time ranges from 8 to 15 minutes.

The mean auto travel time to work is virtually the same among the four areas, less than a
minute difference between the shortest and the longest mean travel times. The transit travel
time is also quite similar, with less than a four-minute difference between the shortest and
the longest. However, non-motorized modes tell a different story; more than five minutes
difference in bicycle mode and more than six minutes difference in walking mode.
Considering the relatively short travel time of non-motorized modes, five- to six-minute
difference is a huge one. One thing should be clearly understood: short bicycle and walk
travel time in the low accessibility area does not mean that the low accessibility areas
provide better walking and bicycling environment. On the contrary, the urban landscape of
low transit accessibility areas serves to suggest an unattractive environment for pedestrian
not only to fewer walk trips, but also to shorter ones. The non-motorized mode share in the
low accessibility area is less than 2% and those numbers were calculated based on only a
very few workers who live near their workplaces.
Table 5-3 Mean Travel Time to Work (minutes)

<table>
<thead>
<tr>
<th></th>
<th>Drive Alone</th>
<th>Transit</th>
<th>Bicycle</th>
<th>Walk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston Metropolitan Area</td>
<td>26.12</td>
<td>27.97</td>
<td>4.38</td>
<td>10.11</td>
</tr>
<tr>
<td>Study Area</td>
<td>26.00</td>
<td>29.14</td>
<td>5.02</td>
<td>10.85</td>
</tr>
<tr>
<td>High Accessibility Area</td>
<td>26.22</td>
<td>24.50</td>
<td>7.47</td>
<td>14.05</td>
</tr>
<tr>
<td>Low Accessibility Area</td>
<td>25.60</td>
<td>28.44</td>
<td>1.95</td>
<td>7.93</td>
</tr>
</tbody>
</table>

5.2.1. Drive Alone Trip Distribution

First we estimate the drive alone trip distribution as a function of travel time in absolute terms for the study area as a whole and the for the low and high accessibility areas. Figure 5-2 shows the three resulting trip distribution functions in one graph to visually compare the functions. Each trip distribution function was estimated, based on drive alone mode share among the selected block groups. Trip frequency was normalized by using total drive alone trips in each of the three areas for ease of comparison.

As we can see from the graph (Figure 5-2), the general shape of the trip distribution function is similar in that trip frequency sharply increases up to about 20 minutes of driving time then decreases sharply to 55 to 60 minutes of driving time. The 20-minute threshold coincides well with the mean travel time to work by the drive alone mode as shown in Table 5-3. Slight differences among the three estimated distributions can be detected from the graph. Workers in the high accessibility areas seem to be a little more sensitive to auto travel time than workers in the low accessibility areas. This result seems reasonable since workers in the high accessibility areas have much better transit accessibility to get to work, and workers will switch to transit if the drive alone travel time exceeds a certain threshold.

The generalized trip distribution function (the trip distribution function for the entire study area) shows a similar pattern. The phase changed at about 20 minutes of driving time and became steady after 90 minutes. The general function thus remains in between two functions, but a little closer to the low accessibility curve. This observation indicates that
the drive alone mode choice for the study area is more affected by workers in the low accessibility area where there are higher number of auto users. Based on the visual comparison of the three trip distribution functions, we could conclude that the general trip distribution function would work well to represent the drive alone mode choice behavior in all accessibility areas.

Figure 5-2 Trip Distribution – Drive Alone (normalized)

Figure 5-3 displays the trip distribution functions for drive alone based on absolute mode share to compare the magnitude of drive alone trips in each of three areas. As clearly shown in the graph, drive alone mode share in the low accessibility area is much higher than in the high accessibility area even though the general shape of the trip distribution functions is similar. The trip distribution function in the entire study area is in the middle, little biased toward the low accessibility area. Therefore, if the general trip distribution curve based on absolute mode share is used to estimate drive alone trip frequency, it may cause unrealistic results for the high and low accessibility areas.
5.2.2 Transit Trip Distribution

Unlike the drive alone and carpool cases, which showed a similar pattern in terms of shape and travel time threshold, the transit trip distribution functions for each of the selected block groups showed very different patterns. The first thing we noticed is the longer transit travel time in the low accessibility areas, a statistic that coincides with the fact that the location of the low accessibility areas is on the periphery of the study area and farther away from downtown Boston. As we can see from Figures 5-4 and 5-5, the travel time peak for workers in the high accessibility areas was 20 to 25 minutes, compared with about 35 minutes in the low accessibility area, a 10- to 15-minute difference. This 15-minute difference is huge, considering that the average transit travel time to work in the Boston Metropolitan is less than 30 minutes as demonstrated in Table 5-3.

The increasing tail of the trip distribution function of the low accessibility area is mainly due to longer travel time of commuter rail users who live in suburban areas. According to the CTPP data, about 53% of transit users in the low accessibility area use commuter rail,
and 44% of those rail users travel longer than 60 minutes to reach their workplace*. On the other hand, only 2.4% of transit users in the high accessibility area use commuter rail and about 21% of them travel longer than 60 minutes.

* One thing should be noted here is that CTPP reports the data as railroad and ferryboat users but it is assumed that all commuters take railroad.
As in the previous case, Figure 5-5 displays trip distribution functions for transit in absolute terms and it shows the differences in transit travel time peaks as well as the huge difference in transit usage. The trip distribution function for the entire study area does not reflect the transit usage behavior of either the high or the low accessibility areas. According to Figure 5-5, the travel time threshold for the generalized function is set at 40 minutes of travel time, about 15 – 20 minutes higher than the threshold for the high accessibility function and about 5 minutes higher than the function for the low accessibility area. The function is also much flatter compared to the functions for the high and low accessibility areas. Therefore, unlike the drive alone case, where the generalized function can be used to explain the mode choice behavior of both high and low accessibility areas, in the transit case, applying the general trip distribution function to characterize high and low accessibility areas may not be acceptable.
5.2.3 Non-motorized Trip Distribution

The trip distribution functions for the non-motorized modes also reveal a commuting pattern difference between the high and low accessibility areas. Since these modes are walking and bicycling, the function is very sensitive to travel time as shown in Figure 5.6. In the low accessibility areas, non-motorized trip frequency drops dramatically after a 5- to 10-minute travel time range, while in the high accessibility area, the travel time threshold increases to 15 minutes. The 10-minute travel time difference in non-motorized mode is large, considering the conventional belief that people in the U.S. often do not walk more than 10 minutes (or more than 0.5 mile). The 10-minute threshold is also supported by the average walking travel time to work 10.85 minutes for the study area as seen in Table 5-3. Simply put, workers in high accessibility areas are willing to walk or bicycle to work much longer distances than are workers in low accessibility areas.

In the latter areas, the urban environment and the lack of activities at the street level, tends to discourage pedestrian trips both in frequency and duration. The general trip distribution function is, in this case, biased toward the function of the high accessibility areas because a much higher number of workers in the high accessibility areas walk or cycle to work. Figure 5-7 shows the huge difference in non-motorized mode use among the three groups and confirms that the high and the low accessibility areas should be treated separately in order to understand non-motorized mode share in these areas. As will be pointed out later while discussing mode share versus income, walk trips coincide with transit usage given the right urban environment.
Figure 5-6 Trip Distribution – Non-motorized mode (normalized)

Figure 5-7 Trip Distribution – Non-motorized mode (absolute)
5.3 Time Leaving for Work

In this section, time leaving from home to work by mode and by area type are compared to see whether there is a noticeable difference among the three groups. In order to focus on the commuting pattern in the morning peak hours, workers leaving home after 10:00 AM were not considered in the comparison. Therefore the universe is all commuters who leave home for work between 5:00 and 10:00 AM. The initial hypothesis was that workers living in the low accessibility block groups leave earlier than those who live in high accessibility areas due to the longer distance to their work places. According to three graphs, Figures 5-8, through 5-10, workers who live in low accessibility areas in general do leave earlier than workers in high accessibility areas. In a sense, time leaving for work could be understood as a proxy for trip duration, given their correlation.

The most noticeable leaving time difference between the high and low accessibility area can be found for transit commuters; more than 45% of transit users in low accessibility areas leave home between 6:30 and 7:30 compared with less than 20% of workers in the high accessibility areas. About 45% of workers in high accessibility areas leave home between 7:30 and 8:30 and about 25% of workers leave home after 8:30. Only 6% of workers in the low accessibility area leave home after 8:30. For the auto case, difference in leaving time is not large, although workers in low accessibility areas seem to leave earlier than those in high accessibility areas.

An interesting finding for the non-motorized case is that despite much shorter average travel time to work (2 minutes for bicycle, and 8 minutes for walk) in the low accessibility area, about 40% of workers in low accessibility areas who walk or bicycle leave home before 7:30 AM. Less than 20% of workers who use non-motorized mode in the high accessibility area leave home before 7:30. The early departures in low accessibility areas could be related to the types of jobs they have but this issue has not been addressed in this study. The time leaving for work is a proxy for travel time to some extent as these figures
show. Again, both transit and non-motorized modes show significant differences between the two extreme accessibility cases.

![Figure 5-8 Leaving Time to Work - Drive Alone](image)

![Figure 5-9 Leaving Time to Work - Transit](image)
5.4 Mode Share versus Income

5.4.1 Study Area

In this section we are looking at the relationship between mode share and income. It is commonly believed that lower income workers use transit more than higher income workers due to the high auto operating cost. Workers were categorized into six groups based on their earnings as reported in the CTPP 2000. The absolute share of each group by mode is shown in Figures 5-11 and 5-12 as is the normalized share by mode for each group for the study area as a whole. From Figure 5-11, workers who earn between $20,000 and $35,000 contribute more than 25 percent of all commuting trips, the highest of all groups, followed by the $5,000 to $20,000 group at 21 percent. Interestingly, as we can see from the bar chart, transit mode share in absolute terms is the highest in the $20,000 – $35,000 income group (5%) and decreases to less than 1% as income decreases to less than $5,000 and to 2% as income increases to more than $75,000.
Figure 5-12 shows that the normalized transit mode share among different income groups remain relatively steady, with a difference of only 6% between the lowest and the highest mode share, compared to a 28% difference in auto share. If we compare transit mode share among income groups with less than $50,000 income, the difference is even smaller; less than 2%. This comparison also showed that, at least in the study area, there is only a weak correlation between transit mode share and workers’ income level. A strange correlation is apparent when transit and non-motorized mode share are combined; combined mode share steadily decreases as the income level rises from about 40% in the lowest income group to about 19% in the highest income group.

![Mode Share by Income – Study Area (absolute)](image-url)
5.4.2 High Relative Job Accessibility Area

As shown in Figure 5-1, residence block groups with high relative job accessibility are located in downtown Boston, and in Cambridge, Brookline, and Quincy where job density and population density are both high and transit friendly. Workers who live in these block groups use transit and non-motorized means more; only about 31 percent of commuters use auto (Table 5-1). The very high percentage of non-motorized mode share (about 37%) also indicates that many workers in these block groups live near their job locations, regardless of income level.

It is unclear whether the high transit and non-motorized mode share in the high accessibility area is a result of land use patterns (e.g., high density, pedestrian, and transit-friendly
environment) or "self selection*. In either case, however, transit job accessibility plays an important role in shaping commuting patterns in this area; the job accessibility index reflects the land use patterns of the area by considering job density and ease of travel between locations. At the same time, job accessibility could be an important factor in choosing a place to live.

It is difficult to see any relationship between mode share and income from the absolute mode shares shown in Figure 5-13. According to Figure 5-14, which shows the normalized mode share, the relationship between income level and transit mode share in the high accessibility area seems to be subtle. Unlike the auto mode share (drive alone and carpool), which steadily increases from 14% to 41% as income increases, the transit mode share peaks at the $20,000 – $35,000 income group and declines as income both increases and decreases from this range. As in the entire study area, transit and non-motorized mode share added together have a higher correlation with income; the combined mode share (transit plus non-motorized share) increase from 56% to 85% as income decreases from the highest to the lowest income group. However, for income above $20,000, the joint share of walk and transit is roughly constant, pointing to the seemingly strong influence of the land use mix environment in these areas.

* A theory disclaims the connection between land use and travel behavior. In the self-selection theory, the connection between travel behavior and land use pattern is more a matter of residential location selection.
Figure 5-13 Mode Share by Income - High Job Accessibility Area (absolute)

Figure 5-14 Mode Share by Income - High Job Accessibility Area (normalized)
5.4.3 Low Relative Job Accessibility Area

The block groups in this category are located on the periphery of the study area principally along the Interstate highways 93 and 95. These areas have more suburban land use patterns along with lower population and employment densities and poor public transit services compared with areas with high relative job accessibility. As a result of poor transit quality in the low accessibility area, most commuting trips were by auto regardless of income level as shown in Figures 5-15 and 5-16. From these figures, the block groups with low relative job accessibility show extremely different commuting patterns from those in the high relative job accessibility areas. Again, the influence of the urban environment seems to dictate the resulting modal share.

In the low accessibility block groups, more than 90% of trips are by auto (drive alone and carpool combined) while only 31% of commuting trips in the high accessibility area are by auto. High auto mode share results in less transit and non-motorized mode share in low accessibility areas: 6.5% and 1.5% respectively. These numbers are far less than the 30% transit and 37% of non-motorized mode shares in the high accessibility areas (Table 5-1). Even, in the low accessibility area, the normalized figure (5-16) shows that transit mode share increases with income level, opposite to the common belief. This trend could be explained by the fact that most of the lower income workers who live in the low accessibility areas may work in suburban areas where transit is not a viable option. Unlike the previous two cases, namely the study area and the high accessibility area, the combined mode share (transit plus non-motorized mode share) does not show a clear relationship with income; the combined mode share is lowest in the $20,000 – $35,000 income group and then slightly increases as income goes either up or down.

As we can see, workers in high accessibility and low accessibility areas show completely different commuting patterns. There is only a similarity in commuting patterns between areas with high and low accessibility where there is a loose correlation between income
level and transit mode share. This result implies the possible shortfalls of applying a generalized modal split model to explain or predict travel behavior in totally different areas.

Figure 5-15 Mode Share by Income – Low Job Accessibility Area (absolute)

Figure 5-16 Mode Share by Income – Low Job Accessibility Area (normalized)
5.5 Job Distribution, Income, and Transit Mode Share

As discussed in Chapter 3, the distribution of jobs has two foci: one in downtown Boston, and the other, the typical suburban sprawl of offices and technology parks around highway 128. Referred to as Edge Cities, the term first used by Joel Garreau (1991), these cities and towns around route 128 contain 20 to 25% of all office space in the Boston metropolitan area. About 35 to 40% of office space is located in downtown Boston with the remainder scattered throughout the metropolitan area (Lang, 2003). Figure 5-17 shows the job distribution by the distance from downtown Boston. Each point represents the number of jobs in each block group and it clearly indicates the high number of jobs located around route 128, about 10 miles from downtown Boston. Income distribution by distance from downtown (Figure 5-18) shows that median household income, in general, increases with distance from downtown Boston. Data points in Figure 5-17 represent median household income in each block group in the study area and the line is a moving average trend line which connects the average value of the closest (based on distance from downtown) five data points.

Job distribution certainly affects residential locations and, as Garreau asserted, high-income white-collar workers reside near Edge Cities along route 128. Figure 5-19 shows the locations of workplaces and the locations of persons in professional or managerial occupations and we can see a strong relationship between the location of Edge Cities and the locations of high-income residents. The locations of high-income residents are reflected in the income distribution of an area as Figure 5-20 clearly demonstrates. As we can see from these figures, block groups where large numbers of professional and managerial workers resides have higher per capita income.

Transit mode share seems also to be affected by the land use patterns of an area. Since high-income residences are located in suburban areas where transit is not a feasible option to get to work, transit mode share of these areas are the lowest in the region. Figure 5-21
describes the relationship between high-income residences near Edge Cities and transit mode share. As we can see, the land use differences among downtown Boston, Edge Cities, and the remainder of metropolitan area have a strong impact on the commuting experiences described in the previous sections.

Figure 5-17 Job Distribution by Distance from Downtown Boston

Figure 5-18 Income Distribution by Distance from Downtown Boston
Major Highway Jobs to Workers Ratio
\[ \leq 1 \text{ (Min = 0)} \]

1 < \leq 3
3 < \leq 6
6 < \leq 9
> 9 \text{ (Max = 614.5)}

Study Area

Locations of Persons in Professional or Managerial Occupations

Figure 5-19 Edge City & Occupational Distribution
Figure 5-20 Per Capita Income and Occupational Distribution
Figure 5-21 Per Capita Income and Transit Mode Share
CHAPTER 6
SUMMARY AND CONCLUSION

In this chapter, we summarize findings, and discuss the planning implications of the relationship between job accessibility and mode choice behavior. Then the contributions of this research are briefly presented leading to ways in which the methodology we have explored could be improved in future research.

6.1 Summary of Findings

In this study, several attempts have been made to understand the mode choice behavior of the population of the Boston metropolitan area. Based on this work, we can advance the following:

- The job accessibility measure, as defined in this study, provides a better way to represent the study area by combining land use patterns and the transportation network.

Job accessibility by auto and transit were calculated from both the residential and workplace perspectives by combining aggregate zonal attributes such as travel time and trip frequency between zones, disaggregate data such as job locations, and road and transit network parameters. Job accessibility measures are important in deciding on a journey to work mode because accessibility incorporates land use patterns, which are postulated by many studies to be one of the most influential factors in people’s mode choice behavior. However, in conventional methods, job accessibility by transit is determined using the total number of jobs in a zone, assuming that all jobs in a zone can be reached by transit users if the zone can be reached by transit. This assumption leads often to the overestimation of transit job accessibility by over-counting the number of jobs accessible by transit, resulting in the overestimation of transit ridership. In order to alleviate this problem, transit job
Accessibility was calculated based on the number of jobs (or workers) within the transit catchment area.

Determining the travel deterrent function is one of the challenges in calculating job accessibility. Since travel cost information, including parking fees and transit fares, were not available, for this study simple travel time-based deterrent functions were estimated. A total of eight models for each mode (transit and automobile) were tested, and the best fitting functions were chosen. Based on the deterrent functions, gravity-based job accessibility by auto and transit was calculated. Transit travel time data were prepared by Central Transportation Planning Staff (CTPS) in Boston using EMME2 software while the catchment areas were obtained using a network analysis function in ArcView 3.3.

The accessibility models developed in this study improved conventional accessibility models by combining aggregate and disaggregate approaches. The main limitation other than not including parking costs and fares, is that these job accessibility indices developed in this study could not consider occupational matches. Therefore, the utility-based deterrent function could be improved if all utility-related data, including travel cost data, were available. More importantly, job accessibility measures should stratify accessibility indicators along socio-demographic and other qualitative dimensions. While residents of a neighborhood might be closer to many job opportunities, if they do not have the skills or education to qualify for those jobs, then they are hardly candidates for employment opportunities. Therefore, job accessibility indicators need to incorporate occupational matching.

Relative job accessibility was another unique approach used in this study. The relative job accessibility was derived simply by dividing transit job accessibility by automobile job accessibility to reflect the balance of transportation options in an area to get to job opportunities. This simple measure could easily be used as a step toward prioritizing transportation projects by planners and policy-makers to provide balanced transportation
options for a region. Figures 6-1, 6-2, and 6-3 show the wide spatial variations of job accessibility from a residential and a workplace perspectives.

Figure 6-1 Job Accessibility (Same Scale) – Residential Perspective
Job Accessibility by Auto - Employer Perspective

Job Accessibility by Transit - Employer Perspective

Figure 6-2 Job Accessibility (Same Scale) – Workplace model
Figure 6-3 Relative Job Accessibility
A GIS analysis of Greater Boston reveals a non uniform universe

The commuting patterns of block groups with different land use patterns were compared to visualize the differences in the mode choice behavior among workers living in block groups which are either average or belong to two extremes: high and low relative transit accessibility. Relative job accessibility indices developed in Chapter 4 were used to categorize block groups, and the relationship between mode choice and income, travel time, and leaving time were examined. The main purpose of comparing the mode choice of block groups with different land use characteristics was to examine the applicability of general trip distribution functions to explain travel behavior of areas with different circumstances. As shown in Figure 6-4, block groups in downtown area and two surrounding towns, Cambridge, and Brookline as well as the block groups in a satellite city, Quincy, were categorized as high relative job accessibility areas. Block groups on the periphery of the study area along the route 128 are identified as low relative job accessibility areas.

Several findings were made based on the analyses. First while the relationship between income level and auto usage did show statistical significance, the linkage between income level and transit usage was, surprisingly, not statistically significant. These findings reveal a very important flaw of the conventional approach of mode choice models: auto usage versus transit usage may not provide a clear picture of how people choose the transportation mode to work in certain urban environments such as the two “extremes” identified here. For the low accessibility areas (Figure 6-5), workers use more transit as income increases. On the other hand, for the high accessibility areas, a close relationship was detected between a combined mode share of transit and non-motorized mode, and income as figure 6-6 described.
Figure 6-4 Study Area and Selected Block Groups for Comparison
Figure 6-5 Mode Share by Income - High Job Accessibility Area (normalized)

Figure 6-6 Mode Share by Income – Low Job Accessibility Area (normalized)
For low transit accessibility areas, where transit options are minimal, income did not show any statistical significance on mode choice behavior because, in general, there is no attractive alternative to the auto. This finding also showed that applying a general model to explain mode choice behavior for the high and low accessibility areas will not generate sufficiently accurate data. Transit mode share in the low accessibility area (Figure 6-6) shows substantially different commuting patterns compared with the high accessibility area. The main point here is that the built environment, such as densities and proper mixes of land uses in high accessibility areas, provide transit and pedestrian friendly environments to the point at which income does not play a role in mode share in spite of conventional wisdom.

Examining the relationship between transit mode share and travel time also demonstrates huge differences in commuting patterns between the high and low transit accessibility areas. Similarly to the comparison between income versus mode choice, described in previous paragraph, the relationship between automobile usage and travel time showed little difference, regardless of the degree of transit job accessibility. The transit mode, however, tells a different story. The workers in high and low transit accessibility areas exhibit very different reactions towards transit travel time when choosing a mode; workers in the low transit accessibility area, presumably boarding far from the downtown area, are more willing to take longer transit trips than workers in the high transit accessibility area, which indirectly reveals that the low accessibility areas are located in suburban areas which require longer commutes. These differences are clearly visualized in Figures 6-7 and 6-8, which compare the travel time distribution functions for the high accessibility area, the low accessibility area, and the entire study area. In addition, due to large differences in commuting patterns in the high and low accessibility areas, the general trip distribution function which is obtained based on the entire study area does not apply to the commuting patterns of either high or low accessibility areas. Therefore, if a general distribution function is used to explain transit mode share for the high and low transit accessibility areas, the transit mode share will not generate realistic results.
Figures 6-9, 6-10 also display huge differences in the non-motorized mode use among the three groups and confirms that the high and the low accessibility areas should be treated separately in order to understand non-motorized mode share in those areas.
Detailed data analysis using GIS approach should be pre-requisite for model formulation.
An overall analysis of any given study area is part of the orthodox approach to understand overall patterns in terms of densities and land use mix. A simple analysis of the spatial distribution in absolute and relative terms of residential and work centers, as shown in the Figures 6-11, 6-12, and 6-13, reveals patterns with a clear difference in the commuting patterns. For instance, the comparison of residential and employment densities appear as a first starting point (Figure 6-11), which is better understood once we describe visually the ratio of jobs to workers (Figure 6-12). Figure 6-13 depicts a clear background for the tension in job locations (downtown versus edge cities) so well described by Joel Garreau.

However, examining data on a smaller, more disaggregate level provides a different insight into commuting patterns in the Boston metropolitan area for an aggregate perspective. For instance, the negative relationship between the transit mode share and the low-income population may not appear correct, as the detailed data analyses reveal that there is only a loose connection between income level and transit mode share, at least for the study area. This finding leads to the conclusion that analyzing in detail the study area prior to modeling is an important step in building better travel-forecasting models. There are many site-specific characteristics and, if a model is built based only on average values without a detailed examination of the study area, it may not produce realistic results.

GIS analyses can aid data analyses dramatically not only by quantifying but also by visualizing the differences in mode choice behavior of workers under different circumstances. Detailed data analyses using GIS techniques revealed that there are at least two different worlds in the study area; the high and low transit accessibility areas, which cannot be fitted into average values. In the high transit accessibility area, for instance, non-motorized mode and transit mode should be considered together as the combined mode share (transit & non-motorized) in order to explain its modal split vis a vis the automobile.
Figure 6-11 Population and Employment Density in the Study Area
Figure 6-12 Ratio of the Number of Jobs to the Number of Workers in an Area
Figure 6-13 Income Distribution in the Study Area
Again these commuting pattern differences stem from differences in land use patterns in selected areas; workers living in high density, mixed use, high transit accessibility areas and those in low density, single use, low accessibility areas act differently when they choose a transportation mode to work. This study does not aim to prove causality between land use patterns and travel behavior as it is a very complex, multi-dimensional research question that cannot be easily answered. However, it is clear that there are significant differences in commuting patterns between workers in high and low transit accessibility areas that may not be correctly portrayed by a single, generalized model. The results lead to the next level: modeling based on market segmentation. As is evident from the analyses, people who live in neighborhoods with balanced transportation options (high relative job accessibility areas) behave differently from those who do not have alternative options: They live in a different transit market. In other words, transit usage (or other mode) is highly dependent on the urban circumstances of the traveler and the availability of acceptable services; if these factors are incorporated into the model, accuracy is dramatically improved.

6.2 Contributions of the Research Study

It has been important to develop a methodology to calculate job accessibility indices that take into account different travel modes (auto and transit). As Shen (1999) asserted, consideration of travel modes in measuring job accessibility is critical in order to realistically represent the real world. However, in the conventional method, job accessibility is calculated without considering these travel modes, which causes over-estimation of job opportunities by transit and eventually causes over-overestimation of the transit mode share as well. In this study, a disaggregate approach was incorporated into the job accessibility calculation by counting the number of job opportunities within the transit catchment area using GIS. Taking into account the travel mode in calculating job accessibility more accurately reflects the true job accessibility of an area.
Estimating a travel time impedance function is another contribution of this study. Unlike several similar studies which use distance impedance functions (Cevero, 1994) or simple thresholds (Shen, 1998; Kawabata, 2002), this study estimates travel time impedance using the number of trips per job opportunity as the independent variable. CTPP trip data, CTPS network travel time data, ZIP+4 based job location data, and street network data are combined using GIS and database technology to calculate this function. By doing this, impedance functions were developed which represent reality better although the accuracy of the function was still limited by not incorporating job matching.

The examination of commuting patterns of two contrasting areas (a high relative job accessibility area and a low relative job accessibility area) is a unique contribution of this study. The research results reveal profound travel pattern differences among areas with different levels of job accessibility, which indicate that the use of generalized models to estimate transit shares in the low and high accessibility areas may not produce accurate results regardless of the level of goodness of fit of the generalized model. This finding leads us to understand the importance of the disaggregate approach in the study area selection process, while modeling travel behaviors and the job accessibility index would be a good indicator in categorizing study areas because it measures land use patterns (population density and job density) in accordance with the transportation network.

6.3 Future Research

One important extension of this research is to measure job accessibility using a travel cost-based impedance function instead of using the simple travel time-based impedance function. As indicated several times in the previous sections, many important variables in defining travel impedance (such as transit fares, gasoline prices, and parking fees) were not incorporated into the impedance function estimation process because of the lack of proper data. As a result, the impedance function used in the study area does not fully represent the
deterrence of travel to work. In order to incorporate these missing variables, additional information needs to be collected, as incorporating this missing data would make job accessibility better fit the real world.

Another direction to improve the job accessibility measurement is to include the concept of job-matching. Job accessibility indices can be calculated based on industry types as provided in the CTPP data. Because job accessibility as calculated in this study does not consider job matching, job accessibility may be biased toward some areas. For example, low income/high density neighborhoods near the central business district show a much higher job accessibility than actually exists because the current method counts all job opportunities in the CBD as job opportunities for workers living in low-income neighborhoods, which is hardly true.

Modeling transit share also requires further research. In-depth analyses have suggested that to estimate travel behavior more accurately, separate models should be developed and applied to areas with different land use patterns. As the analyzed results show, in the high transit accessibility areas, the combined mode share of transit and non-motorized modes shows a higher correlation with independent variables than transit mode share alone. Therefore, this study can be extended by fitting mode share models on particular sections of the metropolitan area differentiated by job accessibility by travel modes, and then comparing the model results with the generalized models so that the effectiveness of the disaggregate modeling approach in the study area selection process can be tested. Automobile versus combined mode share of transit and non-motorized mode also can be tested mathematically by developing and comparing modeling results in the selected study area.

In-depth analyses about the relationship between land use patterns and travel behavior can also be a good extension of this study. As shown in Chapter 5, this research demonstrates that there are fundamental differences in commuting patterns in areas with different job
accessibility; however, it does not explain any causality between travel behavior and job accessibility. Much research has been done to prove the strong relationship between urban form and travel behavior, but despite ambitious research and modeling efforts, the results of those studies have been mixed. As Hess (2000) claimed, the weak relationship between land use pattern and travel behavior is in large part due to poorly constructed land use variables which do not fully capture actual land use patterns. Therefore, more in-depth analyses on land use and commuting patterns with the aid of geographical information systems will provide a more concrete idea of the relationship between land use pattern and commuting behavior in metropolitan areas.
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