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YOUTH, AGE, AND TRANSPORTATION ACCESSIBILITY: AN INTERMETROPOLITAN COMPARISON

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16. Abstract

This study applies measure of transportation accessibility—as distinct from traditional mobility metrics—to six large and one mid-sized metropolitan regions in the United States. By merging accessibility metrics with data from household travel surveys, the study analyzes the distribution of accessibility over the lifespan in the metropolitan regions studied. In general, accessibility is lowest at the younger (i.e., 17-18) and older (65+) ends of the lifespan. At the young end, accessibility variation between regions is quite slight; this variation expands rapidly with large accessibility differences between regions at the middle age ranges.

Transportation engineering and planning frequently center on raising travel speeds by alleviating congestion. Policy towards the mobility of older adults often focuses on access to travel modes, whether a private vehicle, transit, or paratransit. While all these affect the accessibility of the older people, results presented in this study suggest that the relative importance of travel speeds and modal access in providing accessibility decline with age. By contrast, people's proximity to non-work destinations increases in importance (as measured by its contribution to accessibility) at the older end of the lifespan. Results presented here suggest the importance of residential location in accessible zones. Policies to remove obstacles to relocation on the part of the elderly should be central to efforts at ensuring accessibility throughout the lifespan.

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1. Accessibility and Mobility in Transportation Policy

"An experienced Australian traveler once said that on business trips to Australian cities he could reckon to make four meetings in a day," writes Thomson (1977:48). "In Europe he could manage five; in the United States he could manage only three." The reason behind the variations in this traveler's itineraries was not an American propensity for long meetings, or the speed of travel in American cities, which is in any case faster than in Western Europe or Australia (Kenworthy and Laube 1999). Instead, his schedules were determined by the great distances—and hence long travel times—separating his business contacts in metropolitan areas of the United States. What the traveler wanted was interaction in the form of personal contact with the people with whom he did business. The speed with which he was able to travel was relatively unimportant to him; much more central was the amount of interaction he could accomplish in a given time.

This traveler was unwittingly expressing a view of transportation policy based in accessibility, in contrast to the mobility-centered view so dominantly reflected in current policy and in the physical form of the built environment in metropolitan areas in the United States and many countries around the world. This mobility-oriented view extends to the metrics by which transportation systems are assessed. When evaluating the performance of a transportation system, the fundamental criterion for success has long been faster vehicle operating speed (Ewing 1995). Common indicators include delay per capita, dollars wasted while waiting in traffic (Schrank and Lomax 2007) and highway level-of-service (U.S. Department of Transportation 2002; Transportation Research Board 1994; Edwards 1992). This mobility-based perspective of transportation policy dominates the view of the general public as well. The widely publicized congestion measures that routinely appear in newspapers nationwide when the Texas Transportation Institute publishes its annual Urban Mobility Report (Schrank and Lomax 2007) have helped to elevate the alleviation of traffic congestion to a top public policy priority. Under all such mobility-based evaluation measures, planners, engineers, and the general public deem rapid movement as definitive success.

These mobility-based evaluations suffer from a distinct logical flaw. Pursuit of congestion relief through added transportation capacity can induce destinations to move farther and farther apart by making travel to remote destinations faster (Transportation Research Board, 1995). A paradox can thus arise: increased mobility can be associated, over the long run, with more time and money spent in travel, rather than less. Travel to more remote shopping or work locations might be accomplished at a high speed, but the spread of these destinations can demand more travel than in more compact and clustered urban arrangements in which travel is slower.

If travelers do not consume transportation for its own sake but in order to access destinations, then policies that lead to increased costs per destination would be counterproductive because they would leave the travelers with less time and fewer resources to spend at their destinations. This formulation implies a rejection of "mobility" or

congestion relief per se as an independent goal for transportation policy. The goal is more properly specified as accessibility, which has been defined as the "potential of opportunities for interaction" (Hansen 1959, 79) or the "ease of reaching places" (Cervero 1996, 1). Mobility is properly seen as one means to accessibility; other means would include remote connectivity (e.g., via Internet or other electronic means), and spatial proximity (Figure 1).

But mobility and proximity exist in tension with each other: places with many trip origins and destinations near one another tend to be places where surface transportation is slow; conversely, areas of rapid surface travel tend to be areas where origins and destinations are more spread (Kenworthy and Laube 1999). It is thus not immediately apparent which urban forms offer higher accessibility: areas of rapid surface travel and low densities, or areas of high densities but slower travel. Accessibility impacts would be the result of the net effect of speed and distance differences between one urban form and another.

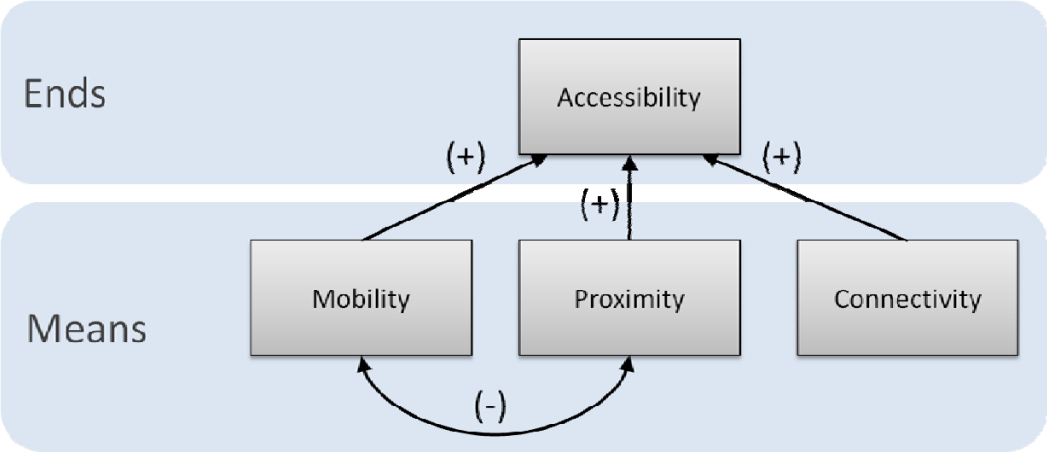

Figure 1: Relationships among mobility, proximity, connectivity, and accessibility

Variations in accessibility are not just a function of different land use or urban development patterns between metropolitan regions. Rather, accessibility varies highly between locations within a region, and between people residing at those locations. Regions may have a higher or lower level of accessibility overall, and they may demonstrate a more or less equitable distribution of accessibility across individuals by income, location, access to private transportation, or age. Across all these dimensions, accessibility is the proper framework within which to gauge transportation outcomes, as long as one accepts the notion that the fundamental purpose of transportation is not movement but access.

Age is a particularly important dimension of a person's experience of accessibility. At younger ages and older ages, the lack of a private vehicle frequently limits accessibility. Yet this problem is not strictly one of transportation modes. Instead, the residential locations that people of various age groups occupy similarly determine their accessibility and its changes over the lifespan. Residential location influences accessibility through such determinants as proximity to important destinations, the speed with which vehicles can travel, and the quality of public transit. Central to evaluating accessibility outcomes is the

development of metrics that are capable of incorporating these various dimensions and applying them to people living in a range of metropolitan regions.

This study seeks to accomplish this task. Different metropolitan areas offer varying mixes of destination types and locations, modes, and travel speeds that ultimately shape their accessibility profiles. This study analyzes the accessibility characteristics of seven U.S. metropolitan regions: Los Angeles, San Francisco, Washington D.C., Seattle, Detroit, Atlanta, and Tucson. Accessibility is initially gauged by travel analysis zone (TAZ), the common geographic unit of transportation modeling. Accessibility measurements are analyzed jointly with data from household travel surveys from the region by geocoding household locations to their respective TAZ and attaching the accessibility attributes of the TAZ to the survey data on the individuals in the household. This enables analysis of the distribution of accessibility by age and by auto availability, since both of these variables were uniformly available in household travel surveys. This study relied on data from metropolitan planning organizations on travel time between zones via automobile and via public transit. Transit data were based on travel times for fixed route transit; thus this study does not incorporate the various forms of paratransit that exist in U.S. metropolitan areas.

The study demonstrates the feasibility of evaluating transportation-demographic outcomes with accessibility metrics. Findings suggest that at advanced ages, the role of proximity in providing accessibility tends to grow, a finding in contrast to the more common focus on availability of transportation modes, reduction of congestion, or maximization of traffic throughput.

2. Mobility and Demographics

Among young travelers, our study focuses on teens (aged 16-17), young adults (18-24) and older adults (65 and over), groups of travelers with distinctive travel behavior characteristics. The mobility of teens and young adults is poorly understood by transportation scholars and practitioners, as indicated by the scarcity of literature on the topic (McMillan 2005). A great deal of research exists on topics such as children traveling to school (McDonald and Aalborg 2009; Schlossberg, et al. 2005), on teens and their propensity to experience vehicular crashes (Shope 2006), to engage in risky behavior such as alcohol consumption (Doherty, Andrey, and McGregor 1989; Shope and Bingham 2002), to experience varying degrees of parental permissiveness (Hillman, Adams, and Whitelegg 1990; Tranter and Pawson 2001), and to encounter a disproportionate incidence of traffic violations and convictions (Bingham, Shope, and Raghunathan 2006). This study, however, is concerned not with these standard inquiries into youth travel but more specifically in their mobility patterns, for which little research exists to substantiate the degree to which young travelers differ from others.

Teens and young adults tend to travel somewhat less than adults in the middle years. In 2001 in the United States, people age 16-24 took an average of 4.0 trips per day and traveled 28.3 miles per day compared to 4.4 trips per day and 32.9 miles per day for people age 25 to 39 (Pucher and Renne 2003). In a study of teenagers and their travel to after-school

activities, Clifton (2003) found that teenagers gain increasing independence to make their own travel choices – in choosing destinations, mode, and the ability to travel without supervision – with increasing age, suggesting that mobility differs in young people between the ages of 16 and 18. Trowbridge and McDonald (2008) confirmed in a study of urban form and youth driving that teenagers who lived in counties characterized by low-density decentralization drove substantially more miles each day than similar teens in more-compact counties.

In contrast to the modest research on the mobility of young travelers, a deep record of scholarship exists on older travelers. Mobility rates are lower for older people than for other adults, both in terms of trips per day and distance traveled per day. For example, in 2001, people age 65 and older traveled 18.7 miles per day compared to 32.9 miles per day for people age 25 to 39 (Pucher and Renne 2003). That older people travel fewer total miles each day than younger adults is not surprising because the lengthy work trip is typically not part of the travel patterns of people over 65. Within the older population, however, are substantial variations in mobility rates. People age 85 and older covered only about a third as many miles per day as people age 65 to 69 in 2001 (Pucher and Renne 2003).

For people over 65, trip purposes other than the journey to work make up a larger share of travel patterns, including, shopping, social activities, and personal business trips. For example, a survey of metropolitan Detroit households in 1993 found that shopping made up about 20 percent of all trips made by older adults, compared to just 12 percent of trips made by people under age 65 (Evans 1999).

Yet it would be a mistake to assume that a large share of older people are "transit dependent," that they are forced to rely on public transit after giving up driving completely. Although public transit serves an important role in meeting the travel needs of many over 65, for the most part older people are not less reliant on automobiles than are younger people (Wachs 1988). Over 90 percent of people over aged 65-69 in the United States are licensed drivers. Nearly 85 percent of men and nearly 80 percent of women 70 years and older are licensed drives (Eby, Molnar, and Kartje 2008). And the reliance on the automobile for trip-making among seniors is intensifying over time, partly because people are now driving in later years of life. People over age 85 still make 80 percent of their trips by car, half as drivers and half as passengers (Rosenbloom 2003). According to 2001 data, those over 65 made about 90 percent of all trips by car, and they made a greater share of total trips by car than did younger people (Pucher and Renne 2003). Older adults are less likely to use public transit than the population as a whole, with just 1.3 percent of this group having traveled by transit compared to 1.7 percent of the population as a whole (Pucher and Renne 2003). The common misconception that older people are mostly carless and do not drive obscures the fact that older adulsts are a diverse group with a wide range of lifestyles and travel needs (Wachs 1979).

Although a substantial share of the older people continue to drive, they exhibit driving behaviors different from other adults. These behaviors include avoiding driving at night, in bad weather, and at periods of peak traffic, in unfamiliar territory, and through unsignalized left turns (Eby and Molnar 2010). Not surprisingly, older people who continue

to drive experience substantially greater mobility than do their counterparts who no longer drive. Straight (1997) studied people 75 and older, finding that those who drove reported making three times as many trips as those who did not drive. Using data from the 1996 National Personal Transportation Survey, Evans (1999) found that 84 percent of people age 65 to 74 who drove left their home for at least one trip on a typical day, compared to just 55 percent of their counterparts who did not drive. For the 75 and older group, 75 percent of drivers compared to just 44 percent of non-drivers made at least one trip from home on a typical day.

Many older people who do not drive rely on family or friends for transportation. Straight (1997) found that two out of three individuals age 75 and older who do not drive reported getting rides from family or friends when they make a trip, compared to just 14 percent who reported using public transportation.

The evidence is clear that older people experience reduced mobility compared to other adults. Throughout the life cycle, travel patterns are largely determined by a few key variables. Travel is influenced substantially by the number of automobiles available to a household. And the number of automobiles is, in turn, influenced by household size and income. So the reduction in mobility experienced by older people compared to younger can largely be explained by the fact that older people tend to live in smaller households, with fewer workers, with fewer automobiles, and lower incomes than middle-aged households (Wachs 1988). Reduced mobility, however, is not necessarily an indication of a reduced *ability* to travel: "It is hard to prove that aging directly affects one's propensity to travel but easier to identify with elderly households certain economic and demographic characteristics that are associated with reduced travel" (Wachs 1988: 171).

Even though older people travel less than younger people, recent trends suggest that the mobility of older people has been increasing for decades. During the period 1983 to 1995, for example, older people made 77 percent more trips and traveled twice as many miles in 1995 than they had in 1983 (Rosenbloom 2004). The increasing mobility of older people in recent years may be an indication that older people are becoming more active in their travel. However, changes in the built environment that make longer trips necessary may also be part of the explanation for the growing mobility of older adults. A 2004 literature review on the topic of land use and travel behavior revealed that virtually no empirical research currently exists on the role of the built environment on travel among the elderly (Giuliano 2004). Some current research suggests that walkable communities and "smart growth" generally may have an important role to play in safeguarding the accessibility of older adults, other studies argue that these approaches carry problems of their own (Rosenbloom and Herbel 2009).

Moreover, as Wachs (1988: 169) points out, mobility is not ultimately what travelers want out of a transportation system: "Few people drive on freeways or ride buses because they value these experiences; we value instead excellent health care, housing, and recreational activities. Mobility is valued … as a link to other elements of the built and social environments." This study seeks to assess transportation outcomes—and their variation over the lifespan—with the fundamental purpose of accessibility in mind.

3. Measuring Accessibility

This study bases its accessibility metrics in the gravity model (Appendix 1; Isard 1960; Wilson 1971), a powerful conceptual tool because it simultaneously accounts for both the transportation network and its surrounding land-use conditions (Handy and Niemeier 1997). Measures of accessibility derived from a gravity model are commonly used by urban planning scholars to evaluate the relative ease of reaching jobs in a metropolitan region (Cervero, Rood, and Appleyard 1999). We use a common form of the gravity model, proposed by Hansen (1959), and modified to account for two types of trip purposes (work and nonwork destinations) and for two travel modes (auto and transit):

$$(A_i) = \sum_j O_j F(c_{ij}) \qquad (1)$$

where:

(A_i) is the accessibility index for people living in zone i.

O_j is the number of opportunities in destination zone j; for work travel the value is the sum of jobs in a zone, for nonwork travel the value is the sum of nonwork attractiveness (which is explained in Section 3.1 below) in a zone.

$F(c_{ij})$ p is a composite impedance function capturing travel conditions across multiple metropolitan areas, associated with the cost of travel c for travel between zones i and j.

The $F(c_{ij})$ bears some explanation. The term is equal to $\exp(-\beta T_{ij})$, where exp is the base of the natural logarithm, β is a parameter empirically derived to maximize the fit between predictions of the gravity model and observed distributions of travel times. The β term ordinarily varies between metropolitan regions and has an important interpretation. People's willingness to travel a given time differs from region to region: in some, a 20 minute trip would be considered long and would be avoided if possible; in others, it would be considered to be a short trip. The value of β would be lower in the latter region than in the former, indicating a higher impedance of travel.

Variations in willingness to travel are a function both of opportunities nearby and those farther away. Regions in which many destinations were close by and few far away would presumably demonstrate greater reticence to travel (and thus a higher value for β) than those with few nearby destinations and many farther away. In order to compare accessibility between regions, we considered two possibilities: a β term that varies between regions; and a single β term across all comparison regions. The former would have accounted for interregional variations in propensity to travel; the latter would aid consistent comparison of accessibility between regions.

We chose the unitary β option. Variations in β are largely endogenous to land use patterns, as described above. For this reason, using region-specific parameters would have the effect of giving accessibility "credit" to a region in which people readily take long trips. But if their propensity to take long trips is a function in part of lack of nearby destinations, then the region-specific parameter would tend to overestimate the accessibility of these places compared to others where long-distance trips were less necessary.

To develop a shared β parameter, we first estimated individual β values for 16[1] metropolitan regions for which we had complete data. Values of the parameter were negatively correlated with metropolitan population, and we estimated a regression with individual values β dependent and metropolitan population independent.

The search for a single aggregate β was necessary in order to reach meaningful comparisons of accessibility between regions. We note that even a single regional β term is in effect a composite of numerous and varying β terms for individuals within the region. Thus the process of aggregation here is not new; where most travel modeling suffices with a β aggregated to the regional level, this project required a higher level of aggregation.

As generally applied, the gravity model produces an accessibility indicator for a spatial area rather than for individuals. As a place-based measure, it attributes the same level of accessibility to every person in a zone, regardless of their personal preferences for travel. It is a measure of the potential for people living in a spatial zone to reach destinations, but it does not address whether people actually choose to seize the potential. In the current study, these place-based measures are attached to individuals so that their auto-access characteristics can be analyzed jointly with the characteristics of the zone in which they reside. Thus an individual with access to an automobile (defined as possession of a driver's license and at least one car in the household) would enjoy the auto accessibility of the zone; accessibility for those without auto access is determined by the transit accessibility of the zone.

These measures' goal is not to explain travel behavior but rather to assess the capacity of a transportation and land-use system to offer, with an eye toward shaping policy in this realm. The reason for preferring potential opportunities over actual travel behavior is that the former offers a more meaningful indicator of the benefits people receive from destinations available to them. For example, while a person can only eat at one restaurant in a given evening, someone who chose one from 50 accessible possibilities is better off than another with only one restaurant from which to choose.

Our gravity model results in four accessibility indices at each zone in a metropolitan region: travel to work by auto; travel to work by transit; travel to nonwork destinations by auto; and travel to nonwork destinations by transit. Three parameters are required to calculate the indices. The first two parameters (travel time T_{ij}^{m} and friction factor β^{p} in the equations found in the endnotes) are used in the impedance function, which is explained above. The last parameter is the attractiveness factor (O_j^{p} in the equations found in the endnotes). It is a measure of the number of opportunities at destination zones, reflecting the geographic distribution of land-use development, and is not dependent on travel mode. For work accessibility, we use the number of jobs in each zone; for nonwork accessibility, we calculate a "nonwork attractiveness index" explained below.

[1] These 16 regions are: Los Angeles, Chicago, San Francisco, Philadelphia, Washington, D.C., Dallas, Detroit, Seattle, Phoenix, Minneapolis-St. Paul, San Diego, Portland, Cincinnati, Indiannapolis, Hartford, and Bridgeport-Stamford. We used this set of metropolitan regions—larger than the ones that formed the focus of the study—to estimate a broadly based U.S. metropolitan beta. This was part of a study comparing 38 of the largest 50 metropolitan regions in the United States.

3.1. Nonwork Attractiveness Index

Work and work-related trips account for only 17.7 percent of all trips nationwide (National Household Travel Survey 2001), so a definition of nonwork destinations is at least as important as work travel for the study of accessibility. For travel to work, the attractiveness of a zone is straightforward: we use the number of jobs as a measure of the number of opportunities at each destination zone. For travel involving nonwork purposes, the attractiveness of a zone is more complicated because of the wide range of destinations available. Common nonwork trip purposes include shopping, errands, and purchasing goods (28.8% of nonwork trips); meals and other social events (12.9%); visiting friends and relatives (11.3%); exercise or sports (7.1%); and purchasing services (6.9%) (National Household Travel Survey 2001).

The problem of defining nonwork destinations has been approached in a number of ways in previous studies. Ettema and Timmermans (2005) used people's duration of nonwork activities as an indicator of the attractiveness of nonwork destination: the longer a person spent time at a destination, the more valuable it was considered to be. Apparicio and Seguin (2005) defined six types of destinations (cultural services, educational services, health services and facilities, sport and recreational facilities, bank branches and other types of services and facilities) and used cluster and factor analyses to combine these into an accessibility metric. Martin and Reggiani (2007) estimated intercity accessibility via high-speed rail, and used the gross domestic product of each urban agglomeration as their indicator of destination attractiveness. Kwan and Weber (2008) implemented Hägerstrand's (1970) time-space accessibility using locations of actual activity participation from a household travel survey.

The definition of nonwork destinations was key for this study because study focuses largely on the nonwork travel of people 16-24 and particularly people over 65. The measurements needed to meet three principal criteria. They should be capable of being implemented consistently on multiple metropolitan areas with available data. They should incorporate various facets of nonwork travel without preferring a destination type over any other. And they should weight destinations differently according to their attractiveness, and it should be designed for comparability with work accessibility.

The approach was to start with the trip purposes in the National Household Travel Survey (NHTS). The NHTS classifies trip purposes into 35 categories and reports the proportion of trips nationwide that are made for each of these purposes. The measure used here is designed to implement a nonwork attractiveness index for each metropolitan region weighted according to the trip frequency of NHTS trip purposes; thus if retail accounts for X percent of nonwork trips, it should similarly account for X percent of the nonwork attractiveness index. We assumed that the distribution of nonwork trips in a given metropolitan area matches the nationwide distribution of trips in the NHTS. This assumption is a limitation of the method, but the alternative of relying on household travel surveys from multiple Metropolitan Planning Organizations (MPOs) proved impractical.

We classified subsets of jobs as relevant to nonwork travel. For example, while jobs in industrial plants would not serve as nonwork destinations, jobs in facilities including grocery stores, restaurants, or churches would. We needed to develop a correspondence between NHTS destinations and North American Industry Classification System (NAICS) codes, the system used to characterize jobs by industrial sector. Certain modifications needed to be made to develop this correspondence. For example, some classifications in NHTS such as "transport someone," "pick up someone," "take and wait," or "drop someone off" are reasonably clear as trip purposes but cannot readily be linked to specific destinations and were hence dropped from the analysis. Other trip-purpose classifications, such as "buy goods: groceries/clothing/hardware store," "medical/dental services," or "get/eat meal" were easily assigned relevant NAICS codes. Some trip purposes (e.g., "go to religious activity" and "attend funeral/wedding") were merged because while the trip purposes were distinct, there was significant overlap in the destinations. Finally one trip purpose, "visit friends/relatives" had no potential indicator among the employment-based NAICS codes; we used population instead of jobs as the indicator for this trip purpose.

In some cases, business types were excluded from the analysis for lack of relevance to accessibility from one's home zone. For example, hotels and other tourist destinations were excluded since these are usually most relevant when not making trips from home. Car dealerships, which account for a significant number of jobs, were excluded since the low frequency with which people visit these establishments renders them only marginally relevant to home-based accessibility. By contrast, hospitals were included despite their low frequency of visits since these were assumed to have a significant option value: their presence provides an assurance that augments one's accessibility even when they are infrequently used. After dropping and merging categories, we ended up with a set of 24 nonwork trip categories to be linked to NAICS codes.

A problem with using employment as the indicator for attractiveness is that jobs have different capacity to attract trips: for example, a job in a grocery store through which hundreds of people pass daily would effectively attract more trips than a job in an accountant's office. With a set of destinations defined, and the number of jobs or population at those destinations identified, we determined how much a job or person in each category would count as an indicator of nonwork attractiveness based on the "trip draws" of each category (a detailed explanation and formulas can be found in the endnotes). Finally, using the "nonwork attraction index," we calculated nonwork accessibility indicators following the standard gravity model formulation.

3.2. Computation and Verification of Transit Travel Times

Travel times by automobile are reasonably comparable across metropolitan regions as provided by MPOs. Travel times by public transit, however, are more complicated and are not necessarily comparable across metropolitan regions without verification. To verify that transit travel times were comparable across the metropolitan cases required several steps. The first step was to ensure a common set of components in the transit travel times. Transit travel times consist of several components, including access time, egress time, waiting time,

transfer time, and in-vehicle time. The transfer time and in-vehicle time are components that are reasonably consistent among metropolitan regions and we used these data as provided by the MPOs. The components of access time and egress time, by contrast, are not consistent among regions so we calculated these using a common walking speed. Waiting time is the most complicated component of total transit travel time. The common approach among MPOs to calculating waiting times in travel demand models is to use a function that converts the various headways – the amount of time between buses or trains on the same line – into an average waiting time. We obtained these functions from MPOs to verify that the conversion from headways to waiting times was reasonably consistent across regions.

A second step was to ensure consistency in the way that multiple transit modes were handled. In the cases where an MPO provided transit travel times by multiple modes (e.g., bus, express bus, rail, subway), we used the shortest total travel time among the various modes, on the assumption that a traveler typically would select the fastest option available.

A third step was to consistently assign travel times among zones that are not served by public transit. By assuming that a person without a private vehicle has no alternative but to walk, we assigned transit travel time based on a constant walking speed of 3 miles per hour.

Finally, we tested the consistency of total transit travel times across metropolitan regions by comparing a sample of zone-to-zone times from each metropolitan region against a different data source. We compared a random sample of 30 zonal pairs in each region against the predicted travel time by transit produced in Google maps. The transit travel times obtained from MPOs differed from those in Google maps by no more than 10 percent on average for most regions (Atlanta, San Francisco, Seattle and Washington D.C.). Regions with sparser transit availability deviated somewhat more from the Google maps estimate, in part because Google maps offered data from relatively fewer zonal pairs for these regions. Average deviations were between 26% for Los Angeles and 35% for Detroit.

3.3 Composite Accessibility Calculations

In this study, the accessibility of individuals is a function of the accessibility of the zones in which they live and the transportation modes which are available to them. Specifically, people who possess a driver's license and have at least one car in their household are assigned the auto accessibility for the zone in which they reside. People who do not meet both conditions are assigned the transit accessibility for their zone. This is accomplished in three steps:

1. Four types of accessibility scores for a region are calculated for each TAZ in a region, including work accessibility by auto, work accessibility by transit, nonwork accessibility by auto, and nonwork accessibility by transit.
2. The accessibility scores of each TAZ are assigned to the persons in the household travel survey sample who live in that TAZ. Only employed people are assigned a job accessibility score; all people are assigned a non-work accessibility score. Individuals with car access are assigned auto-based accessibility; others are

assigned an accessibility score based on transit travel times. In this project, auto access is defined by having a valid driver's license and having at least one vehicle in the household.

3. The composite nonwork accessibility of each age cohort is calculated as the weighted average of the nonwork accessibilities of all the persons in that age cohort, while the composite work accessibility is calculated as the weighted average of the work accessibilities of only the working persons in that age cohort.

The rationale of calculating a weighted average rather than a simple average is to adjust the over-sampling or under-sampling in the household travel survey. The weights are computed based on the sampling method documented by the agencies who conducted the survey. According to the specific research focus of this project, eight age cohorts were chosen: 16-17 years old; 18-24 years old; 25-34 years old; 35-44 years old; 45-54 years old; 55-64 years old; 65-74 years old; and 75-98 years old. Persons aged younger than 16 or older than 98 are not included in the analysis. The middle age ranges (25-64) are included as needed to establish a basis for comparing with younger and older people.

3.4 Data and Sources

This study compares seven metropolitan regions, as defined by their respective metropolitan planning organizations (MPOs) (Table 2). For all regions, the geographic unit of analysis is the Travel Analysis Zone (TAZ), a spatial division designed for tabulating transportation-related data. These areas general consist of one or more census blocks, block groups, or tracts, and range in number from 859 to 4,109 for the metropolitan regions studied (Table 2).

Metropolitan Region	Abbreviation	Size Rank	Population	Population Density for Urbanized Area (persons/km^2)	Number of TAZs
Los Angeles-Long Beach-Santa Ana, CA	LAX	2	16,406,000	1,970	4109
San Francisco-Oakland-San Jose, CA	SFR	4	6,782,000	1,851	1454
Washington D.C.	WAS	5	5,740,000	1,056	1972
Detroit, MI	DET	10	4,810,000	1,040	1442
Atlanta, GA	ATL	13	4,226,000	652	2027
Seattle, WA	SEA	14	3,258,000	973	938
Tucson, AZ	TUC	42	830,000	896	859

Table 1: Metropolitan Regions Included in the Study

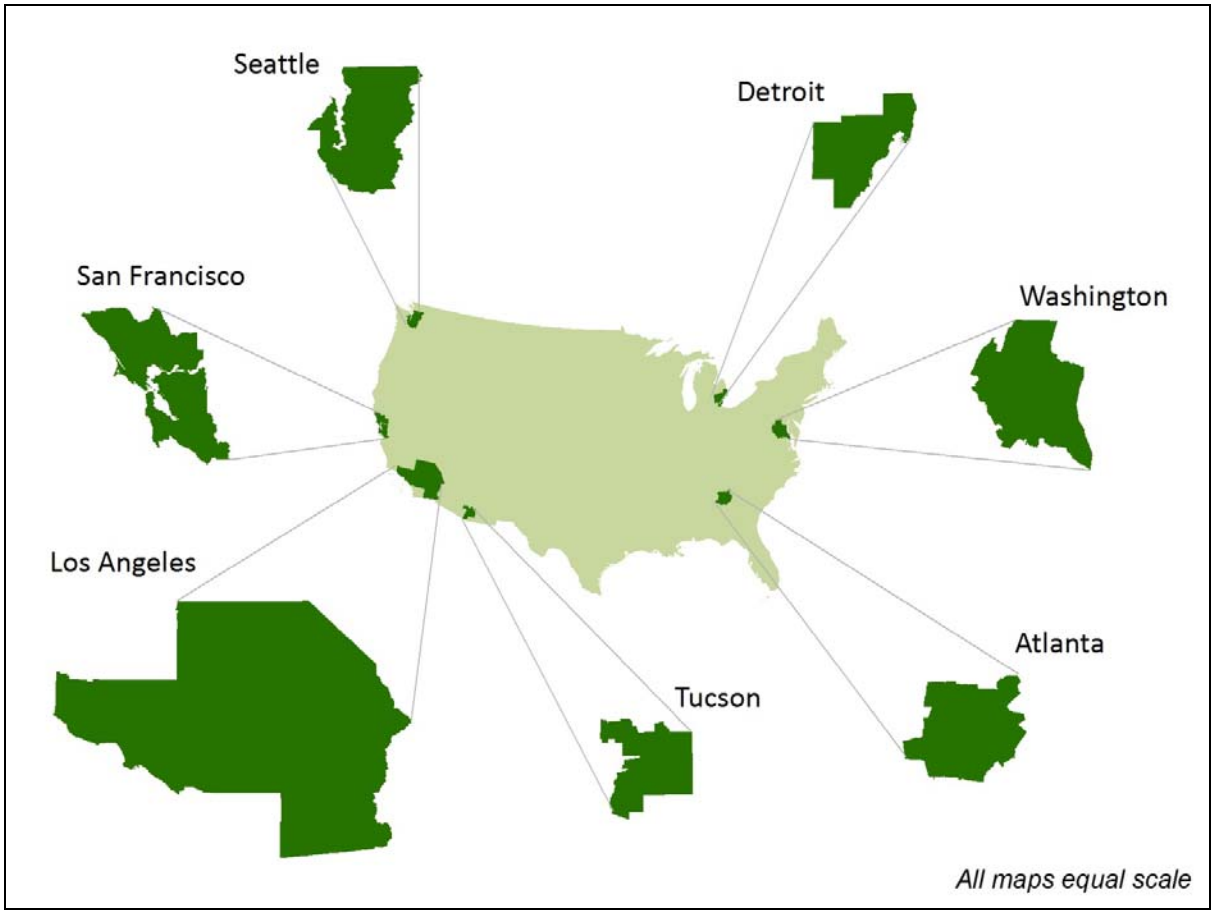

Figure 2: Metropolitan Regions in the Study

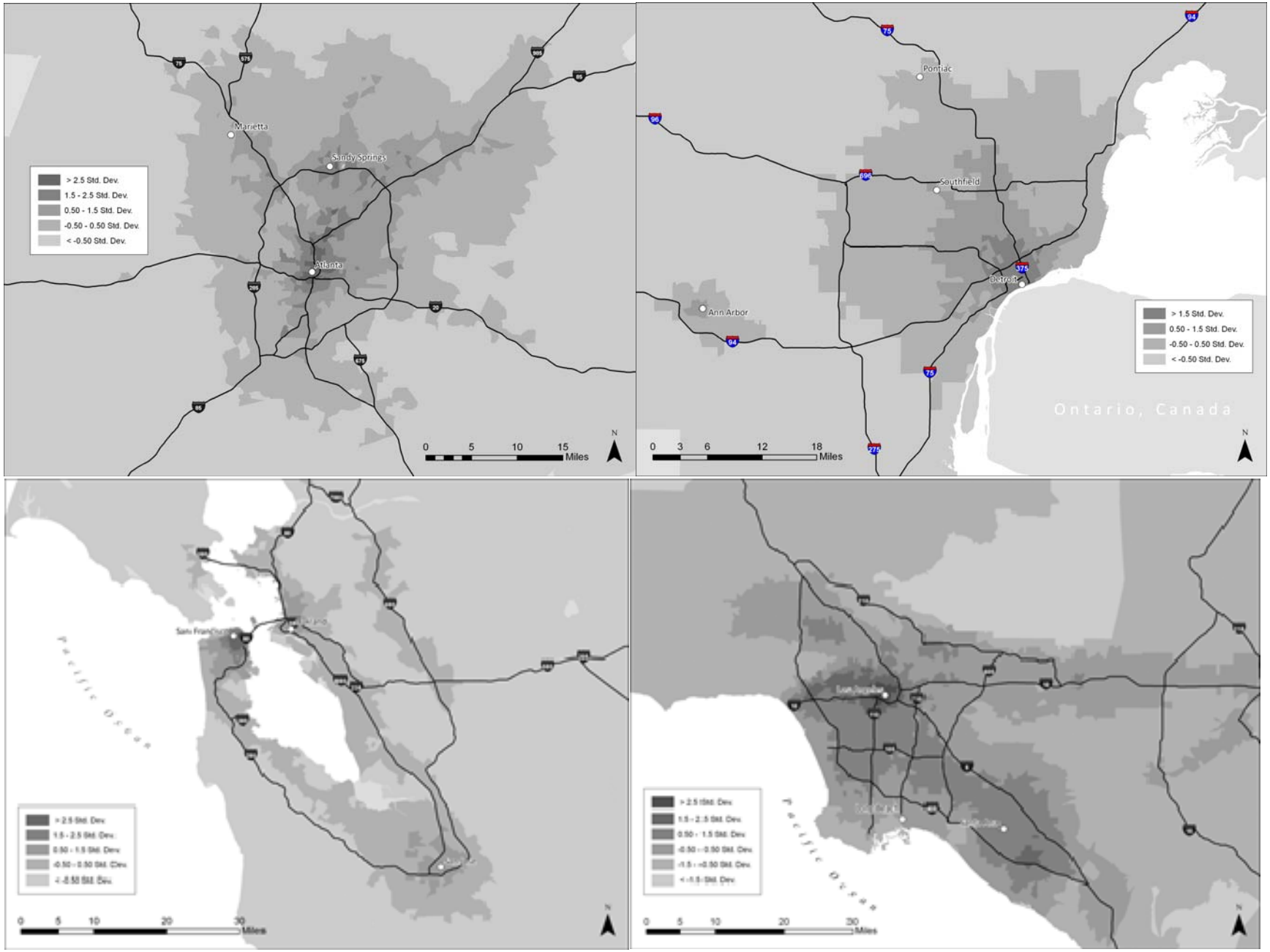

Figure 3: Study Regions with Nonwork Accessibility (Clockwise from upper left: Atlanta, Detroit, Los Angeles, San Francisco.

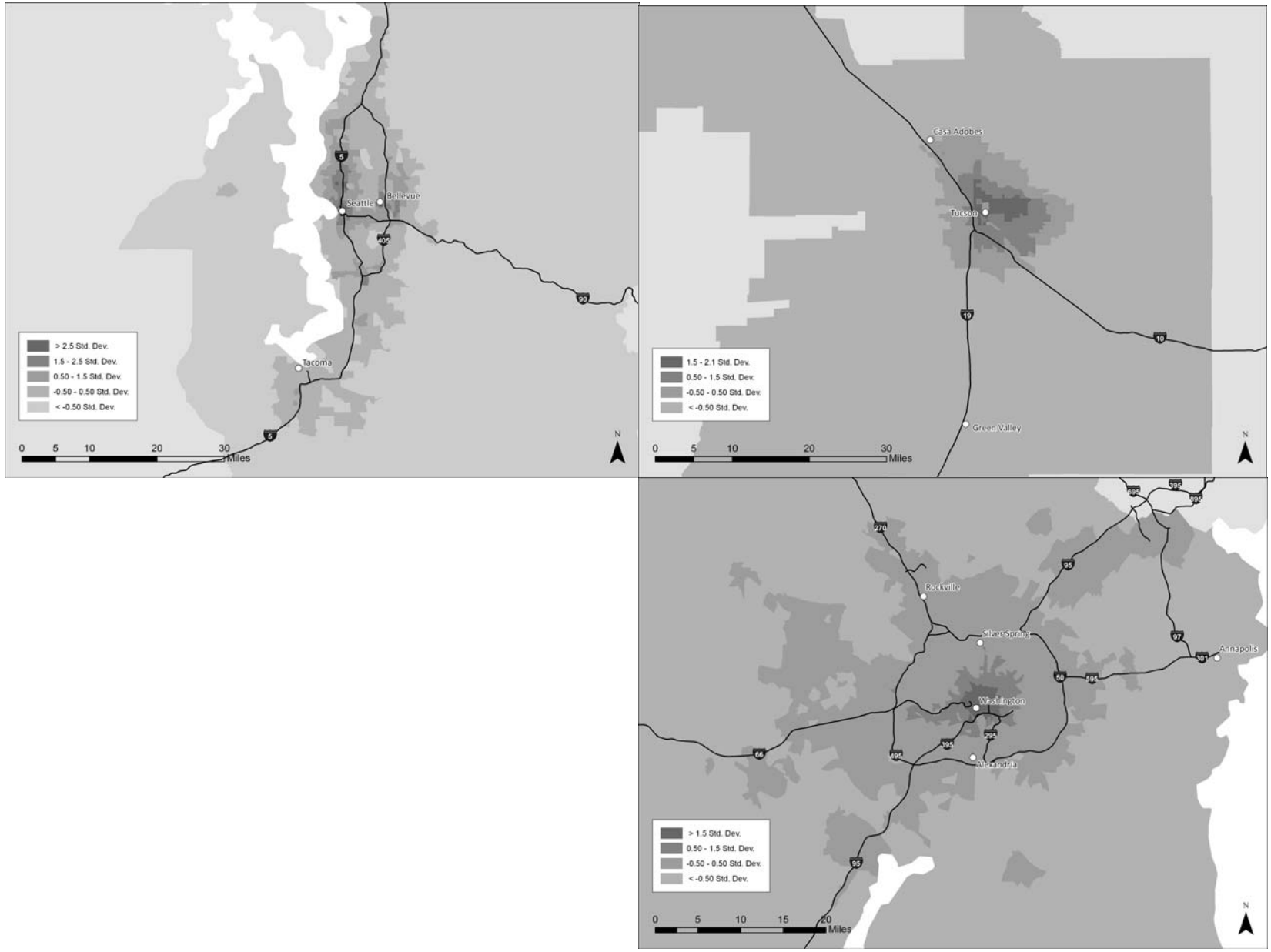

Figure 4: Study Regions with Nonwork Accessibility (Clockwise from upper left: Seattle, Tucson, Washington, D.C.)

We collected data from five main sources. First, the most important data item is travel demand modeling data, collected from the MPO. These data contain matrices of interactions between all zones in the region, including travel times and the number of trips between zones. The zonal interactions are provided in several levels of detail, by travel mode (auto and transit), by time period (during congested peak period conditions and less congested off-peak conditions), and by trip purpose (home-based work and home-based nonwork trips).

Second, we purchased data on business establishments from the private vendor Claritas, Inc. (Claritas 2002). These data are collected from a variety of sources, including the U.S. Department of Labor, telephone books, county agencies, the U.S. Postal Service, and private utility companies. Business establishments include the number of jobs at a location in 2008, and classification codes from the North American Industry Classification System (NAICS) allowing us to identify businesses by industry type. We geocoded establishments to the street-address level, then aggregated the number of jobs to the TAZ. We compared 2008 Claritas data on a county-by-county basis with 2005 employment data from the U.S. Bureau of Economic Analysis (BEA). Of the 28 counties and county equivalents in the two regions, Claritas and BEA data were no greater that 3.2 percent apart on a regionwide basis, and no county deviated by more than 11 percent on the two datasets.

A third source of data is the National Household Travel Survey, providing data on national travel patterns in 2001, which we used in the calculation of the nonwork attractiveness index (U.S. Department of Transportation 2004).

Fourth, we collected data on population at the block group level from the 2000 Census of Population and Housing, Summary Files 1 and 3 (U.S. Bureau of the Census 2002).

Finally, we used the most recent household travel surveys from the seven metropolitan regions studied. Dates for the surveys are shown in Table 2.

Metropolitan Region	Date of Survey	Households Surveyed	Spatial Extent of Household Travel Survey
Los Angeles	2000	16,506	Six counties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, Ventura
San Francisco	2000	18,068	Nine counties: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, Sonoma
Washington DC	1994	4,865	Twelve Counties: Washington (DC); Calvert, Charles, Frederick, Montgomery, Prince George's (MD); Arlington, Fairfax, Fauquier, Loudon, Prince William, Stafford (VA)
Seattle	2006	4,745	MPO boundaries Four Counties: King, Kitsap, Pierce, Snohomish
Detroit[2]	2005	2,249	SEMCOG[3] Seven Counties: Livingston, Macomb, Monroe, Oakland, St. Clair, Washtenaw, Wayne
Atlanta	2001	8,069	Thirteen counties: Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding, Rockdale
Tucson	1999	2,076	MPO boundaries (Eastern Pima County)

Table 2: Metropolitan Household Travel Surveys

[2] In all seven regions but Detroit, weights and expansion factors were applied to take into account the under- and over-sampling in the survey. For the Detroit sample, however, no sufficient information on weights or expansion factors was available. To detect the presence of under- or over-sampling problem in the Detroit sample, we calculated the auto-ownership rate for each age cohort and compared the results with those obtained from Census 2000 data. The disparity between the two was no more than five percent for any age cohort. Therefore, we were confident to use the Detroit survey sample as a reasonable representation of the entire region even without the weights or expansion factors.

[3] The original survey was conducted for the State of Michigan, yet SEMCOG counties were over-sampled to retrieve a sample size large enough for a regional study.

Our data sources range from 2000 to 2008. In this project we always use the most current data available, recognizing that comparative analysis across multiple metropolitan areas with several data sources will inevitably result in mismatches in years. Although it would be ideal if all sources were from the same year, our collection represents the closest temporal aggregation possible.

4. The Study Regions

The study regions—Atlanta, Detroit, Los Angeles, San Francisco, Seattle, Tucson, and Washington, D.C. -- were chosen in large measure on the basis of data availability. These were regions whose MPOs were able to provide data sufficient to calculate auto and transit accessibility to work and nonwork destinations. They also provided data from household travel surveys, to enable a linkage between the accessibility characteristics of a zone and the demographic and mode-access characteristics of individuals. The metropolitan areas are drawn from among the largest fifteen metropolitan regions in the United States, with a much smaller region (Tucson, AZ) added for comparison (Table 1). The regions differ in realms relevant to accessibility calculations, including size and density. The regions also represent a geographic range with three in the West, and one each in the Southwest, South, Northeast, and Midwest (Figure 2). In each case the study area was defined by the boundary of the relevant MPO. This yielded areas of roughly equal size, with the exception of Los Angeles, an enormous MPO that takes up most of southern California.

4.1 Accessibility by Age in the Seven Regions

Accessibility by age cohort is summarized in Figure 5 for nonwork accessibility and Figure 6 for work accessibility. Since the focus of this study is on the younger and older ends of the age spectrum where workforce participation is lower than in the middle ages, subsequent analyses will focus on nonwork accessibility. The figures are designed to demonstrate the feasibility of accessibility metrics to compare transportation outcomes both between metropolitan regions and along the age dimension. Differences in accessibility observed between the regions are a function of travel speeds, auto access, and travel distances in the region. Thus a region that is relatively compact but has very slow travel times would be a low-accessibility region; a region with rapid travel speeds but great distances between origins and destinations might demonstrate a similar result.

Another dimension of accessibility is the equity or inequity of its distribution over the lifespan. In general, nonwork accessibility is low for the youngest age group whose auto access tends to be low; the interregional variation for this cohort is relatively slight. Accessibility tends to peak around the age 25-34 cohort; this is also the age at which accessibility variations between the regions are the greatest. Nonwork accessibility drops off slowly thereafter through to old age. The high accessibility in the younger-middle age range would be both a function of auto ownership (in all metros studied, those with cars available

will have much higher accessibility than those without) and location in accessible parts of the metropolitan region. (The focus in this study is at the younger and particularly the older ends of the age spectrum; data on the middle of the range are presented for comparison.)

Metropolitan San Francisco, the nonwork accessibility leader overall (Figure 5), demonstrates a highly inequitable pattern of accessibility throughout the lifespan, with accessibility of the 25-34 year-old population double that of the oldest cohort. As shown below, this is partly because of locational advantages: in the San Francisco region, areas of concentrations of older residents are largely suburban (with a notable exception in the city of San Francisco itself). By contrast, Atlanta and Seattle, with their lower accessibility overall, demonstrate much more constancy in accessibility across the lifespan.

The accessibility scores shown are indicators whose units are not directly interpretable; they are best understood as an index for comparison. No standard exists for what counts as "high" or "low" accessibility, though it may be inferred from the comparisons below that scores around 40,000 or 50,000 are relatively low, and scores above 100,000 are relatively high.

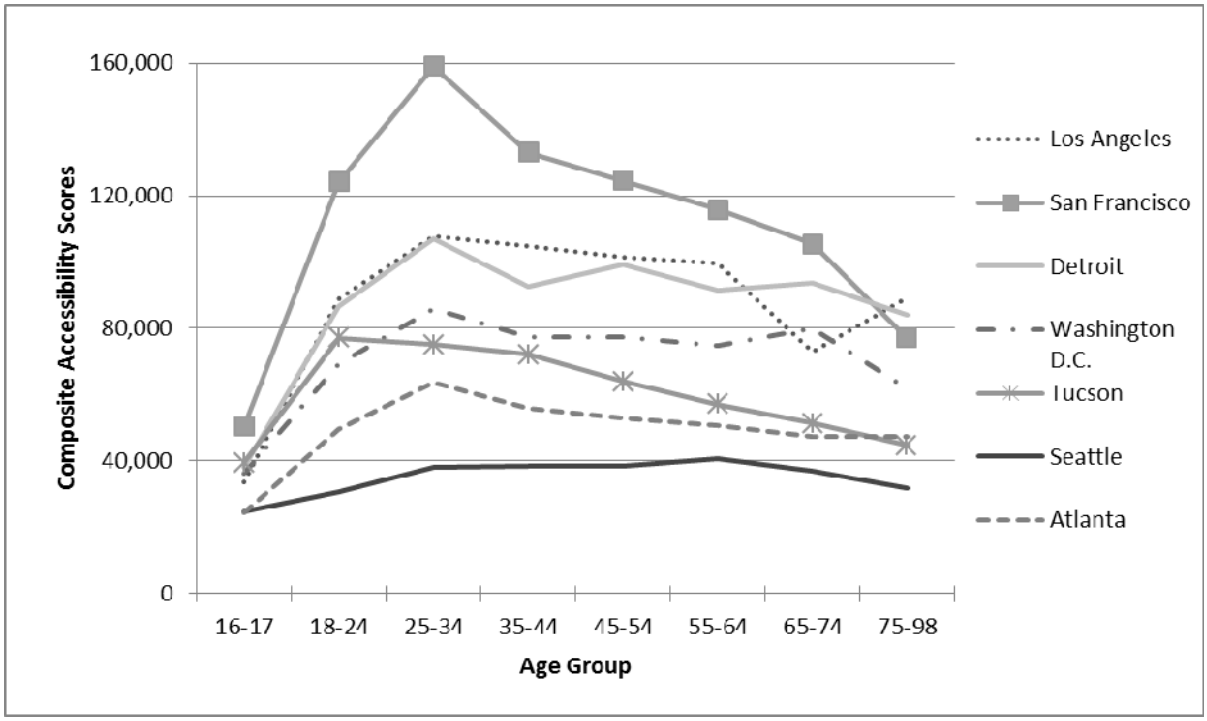

Figure 5: Composite Nonwork Accessibility By Region and Age Cohort

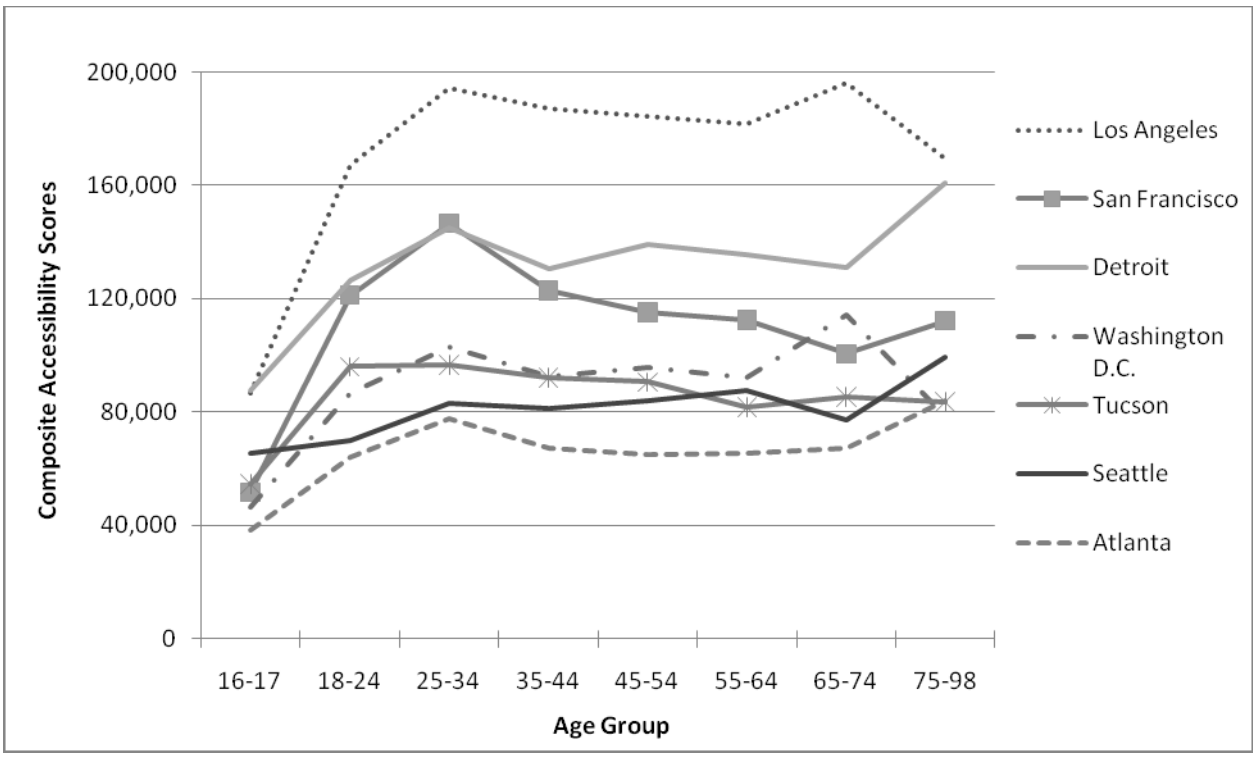

Figure 6: Composite Work Accessibility by Region and Age Cohort

5.1 Paired Comparisons: Decomposing Accessibility Distributions

Observed differences in accessibility between regions are determined by three factors: the mode effect (i.e., the level of auto access by each age cohort); the speed effect (i.e., the impact of roadway travel speeds), and the proximity effect. In order to make comparisons across multiple study areas with regard to the accessibility levels of different age cohorts, we analyzed each region in comparison with a baseline region – Atlanta in this case. Atlanta is the lowest accessibility region for work travel and the second lowest for nonwork, and thus is a useful starting point for comparison.

The mode effect captures the difference in accessibility between the two MPOs that is caused by the share and the spatial distribution of people who have access to driving. The speed effect is the difference in accessibility between the two MPOs that is due to the discrepancy in traveling speeds in the two regions (including both by automobile and public transit). The proximity effect captures the remaining difference that could not be explained by either mode availability or traveling speeds. It reflects the impacts of proximity, or how closely home locations and travel destinations are connected, on the accessibility of residents. Such decomposition allows us to 1) identify the major factors that lead to the accessibility difference between the two regions, and 2) detect the variation in the relative significance of each factor as it relates to accessibility across the life span. The method for accomplishing this comparison is presented in Appendix 2; it involves sequentially substituting in the attributes of one region to another in order to isolate the components of accessibility differences. For example, substituting in travel speeds from region A into the accessibility

calculations of region B would yield the accessibility distribution of region B if it had the speed characteristics of region A. The difference between that and the actual accessibility distribution of region B would be the "speed effect" differential between the regions.

The following figures decompose differences between each metropolitan area in our study and Atlanta, established as the base case. For example, in comparing metropolitan Los Angeles and San Francisco with metropolitan Atlanta (Figure 7 and Figure 8), it is evident that Atlanta has a slight advantage in travel speeds and auto ownership over both California regions (green and blue bars below the horizontal axis). These advantages to Atlanta are more than outweighed by a proximity advantage to Los Angeles and San Francisco—that is, the tendency for the Californians to live closer to nonwork travel opportunities.

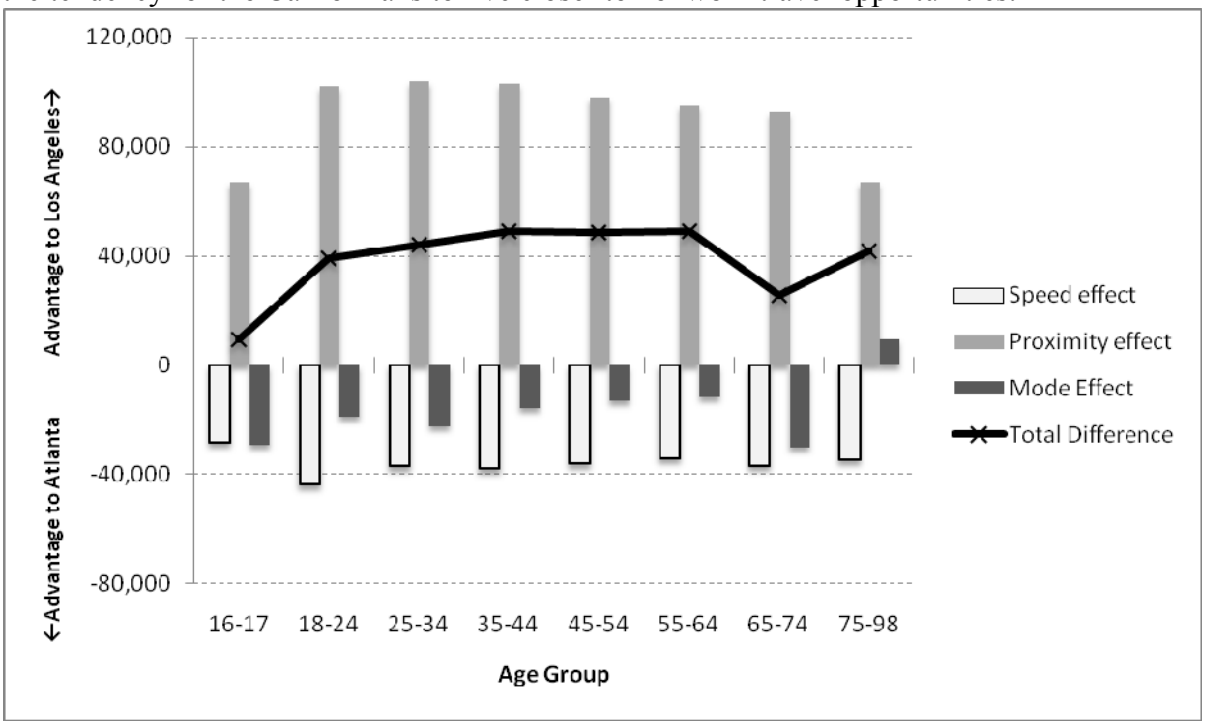

Figure 7: Decomposition of Nonwork Accessibility Differences between Los Angeles and Atlanta

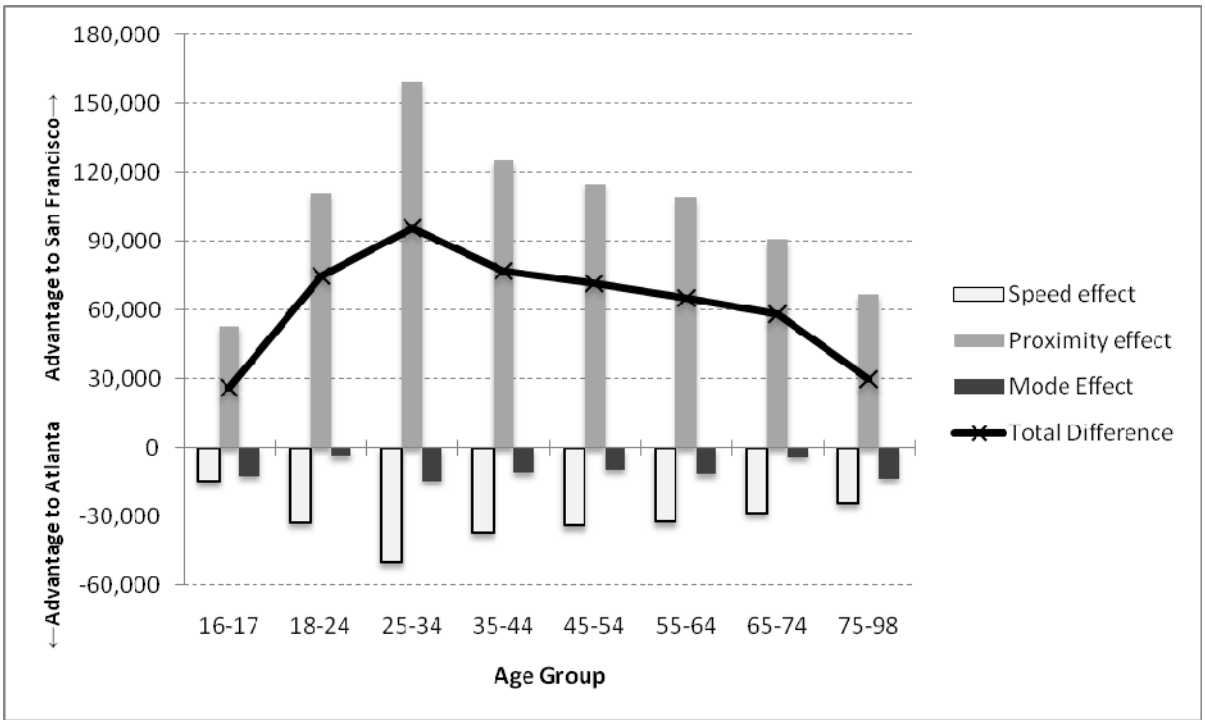

Figure 8: Decomposition of Nonwork Accessibility Difference between San Francisco and Atlanta

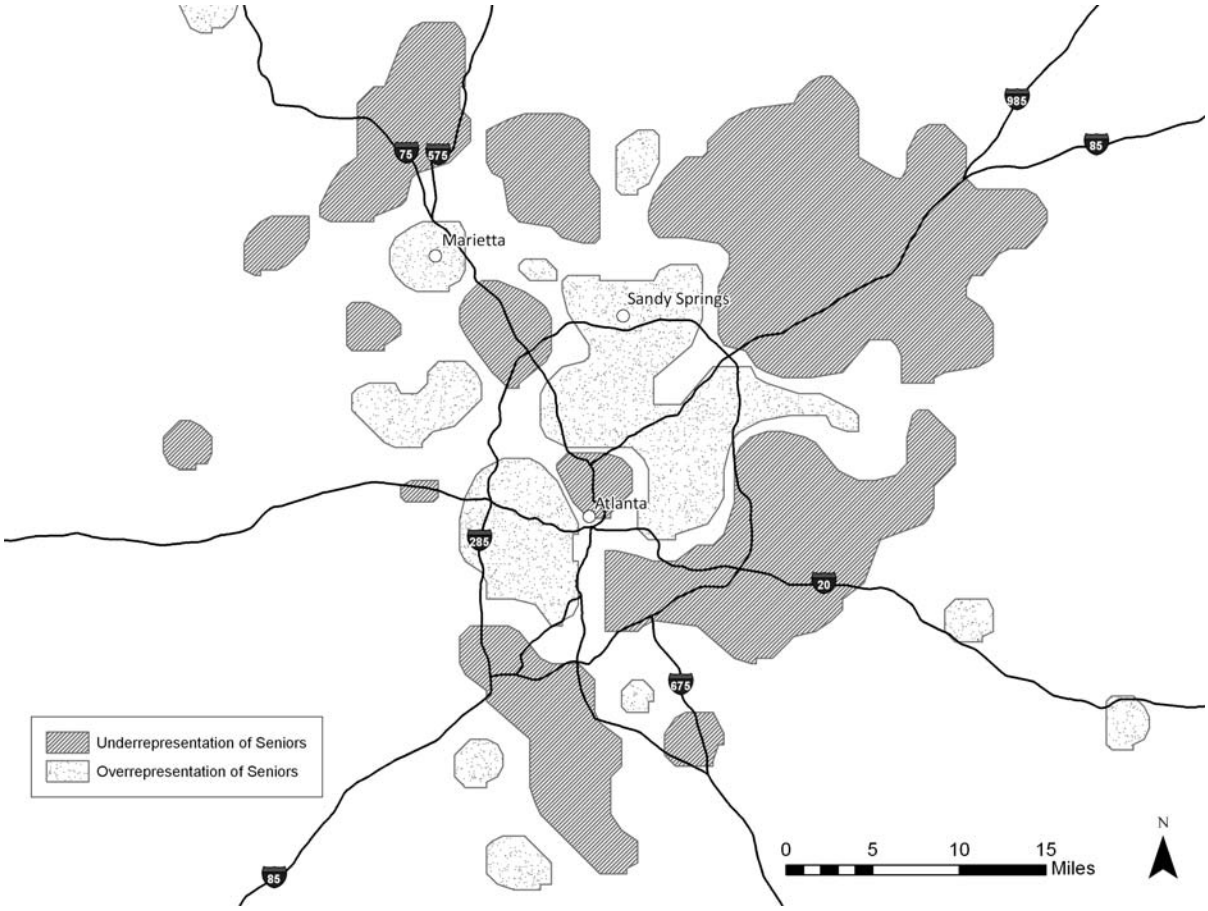

Figure 9: Under- and Overrepresentation of Seniors in the Atlanta Area (see Appendix 3 for definitions and methods)

In order to aid in the interpretation of the decomposition graphs, this section analyses residential locations of people 65 and older in each of the regions studied. The base case, Atlanta, is presented in Figure 9. The inner suburbs—a relatively high accessibility area because of their centrality—contain a concentration ("overrepresentation" compared to the population at large) of seniors. The spatial pattern of settlement by age in Atlanta is relatively clear, with the outer suburbs and exurbs tending to demonstrate an underrepresentation of older people. In the decomposition figures that follow below, the locational advantages of a region are gauged relative to the Atlanta spatial pattern (note the red bars extending upward from the horizontal axis on the figures). For example, neither San Francisco (Figure 10) nor Los Angeles (Figure 11) demonstrate as clear a pattern of central locations by older residents—hence their dwindling locational advantage at older age ranges. As a consequence, the proximity advantage of San Francisco relative to Atlanta dwindles significantly with age. This is largely a function of the relatively central location of older adults in Atlanta (Figure 9) when compared to their diffusion in San Francisco (Figure 10).

Since central locations are generally more accessible (whether by transit or by auto), their residents will tend to enjoy an accessibility advantage.

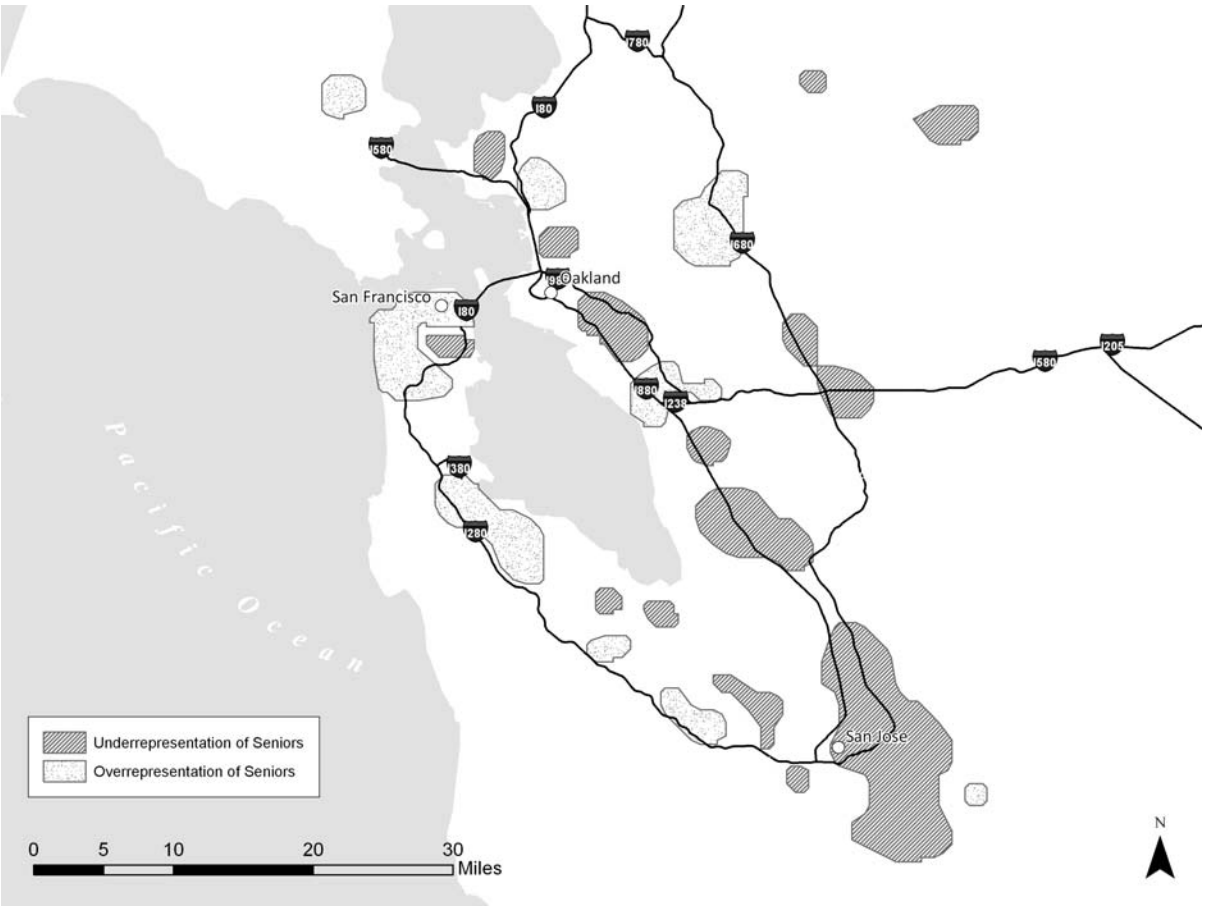

Figure 10: Under- and Overrepresentation of Seniors in the San Francisco Area (see Appendix 2 for definitions and methods)

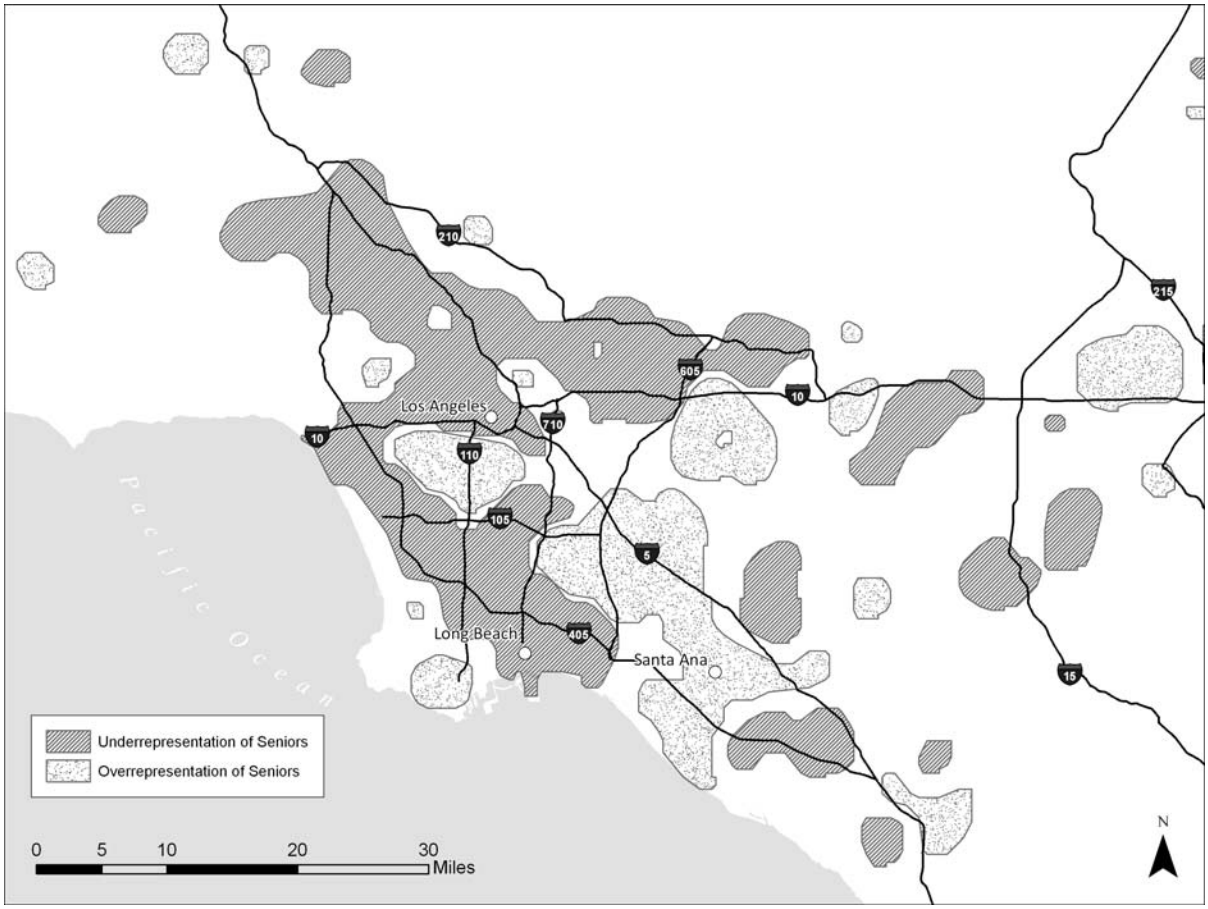

Figure 11: Under- and Over-representation of Seniors in the Los Angeles Area

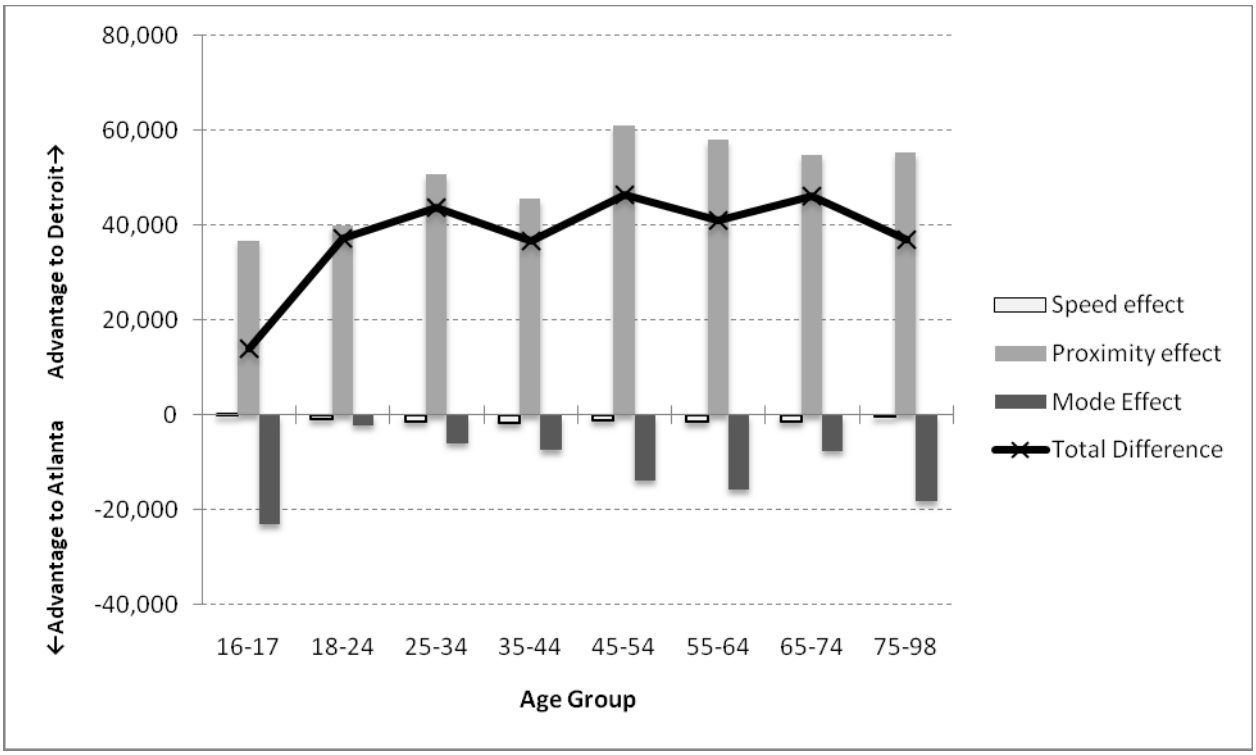

Figure 12: Decomposition of Nonwork Accessibility Differences between Detroit and Atlanta

A comparison between Detroit and Atlanta similarly demonstrates a proximity advantage to Detroit (Figure 12). Atlanta enjoys a notable advantage in the mode effect (that is, greater access to cars at each age slice) and a negligible advantage in travel speeds. But Detroit's significant proximity advantage outweighs these, leading to greater accessibility overall. In contrast to San Francisco, Detroit's proximity advantage does not dwindle over the lifespan, a function of the location choices of different age cohorts of residents. Younger Detroiters are not as concentrated in the high accessibility areas—i.e., central city—of their region as their San Francisco counterparts. The proximity advantage to Detroit (compared to Atlanta) overall may be puzzling; Detroit is after all a sprawling region with a weak central city. Yet it has developed at considerably greater residential densities overall than metropolitan Atlanta: 1,040 persons per square kilometer for the Detroit urbanized area versus 652 for Atlanta.

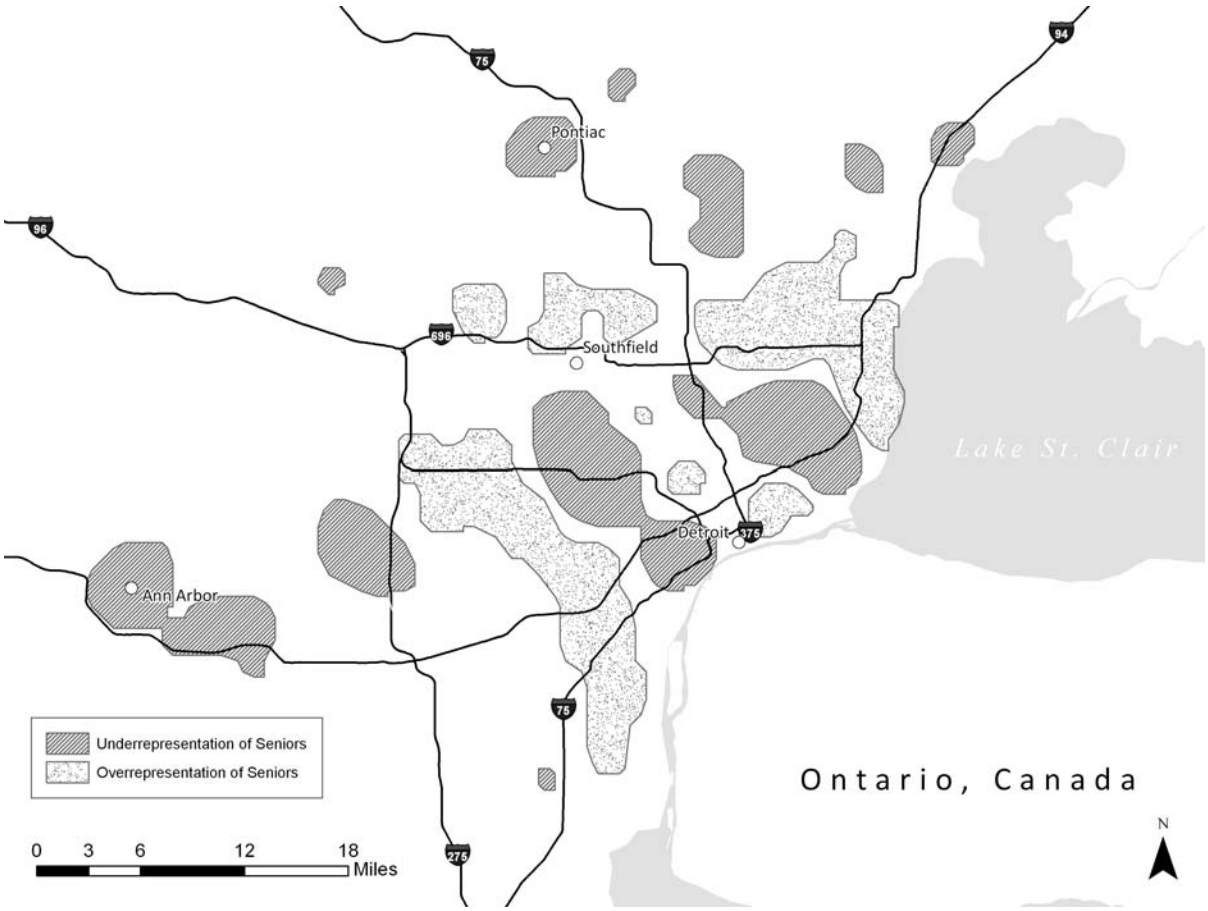

Figure 13: Under- and Over-representation of Seniors in the Detroit Area

Washington D.C. -- like San Francisco, Los Angeles, and Detroit -- presents a significant proximity advantage when compared with Atlanta—and one that is relatively well maintained over the lifespan (Figure 15 and Figure 16). But the travel-speed disadvantage of Washington D.C. is so great that the proximity advantage is nearly overcome by the region's slow travel. By age 75, Washington's poor travel speeds and relative lack of cars erases the small accessibility advantage that it holds for younger age cohorts. The situation is more extreme in Seattle, where a significant proximity advantage (Figure 19) is overwhelmed by slow travel speeds.

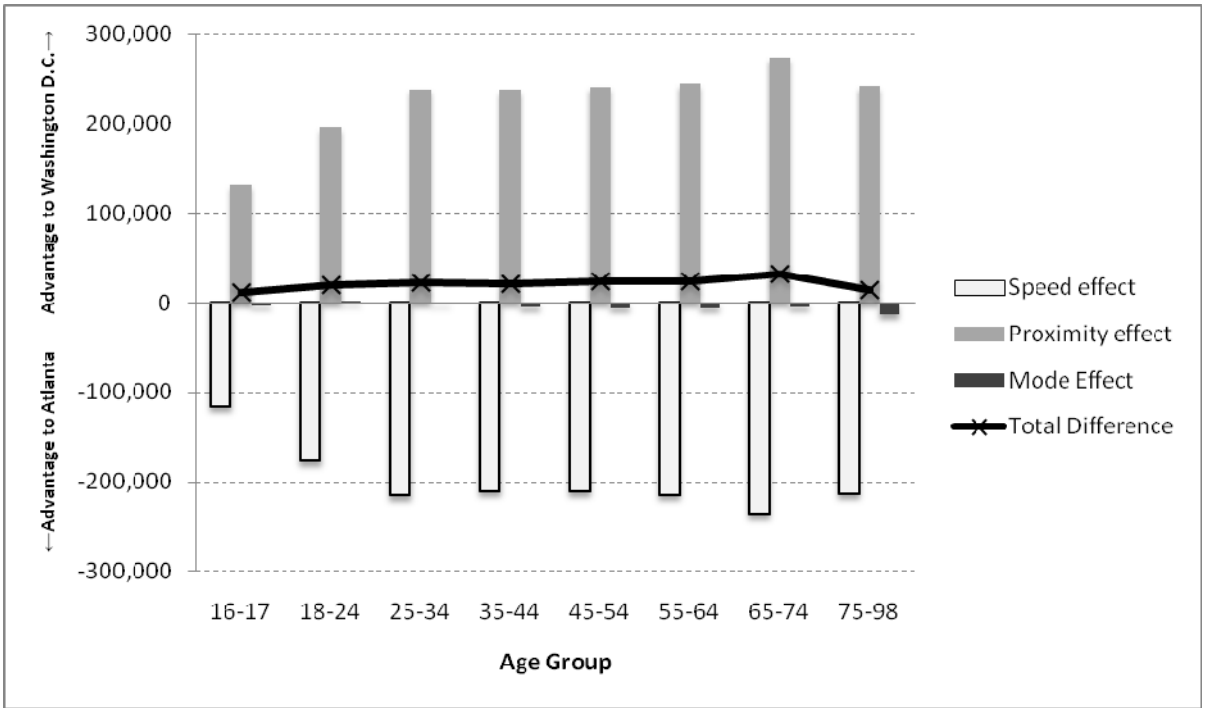

Figure 14: Decomposition of Nonwork Accessibility Differences between Washington, D.C. and Atlanta

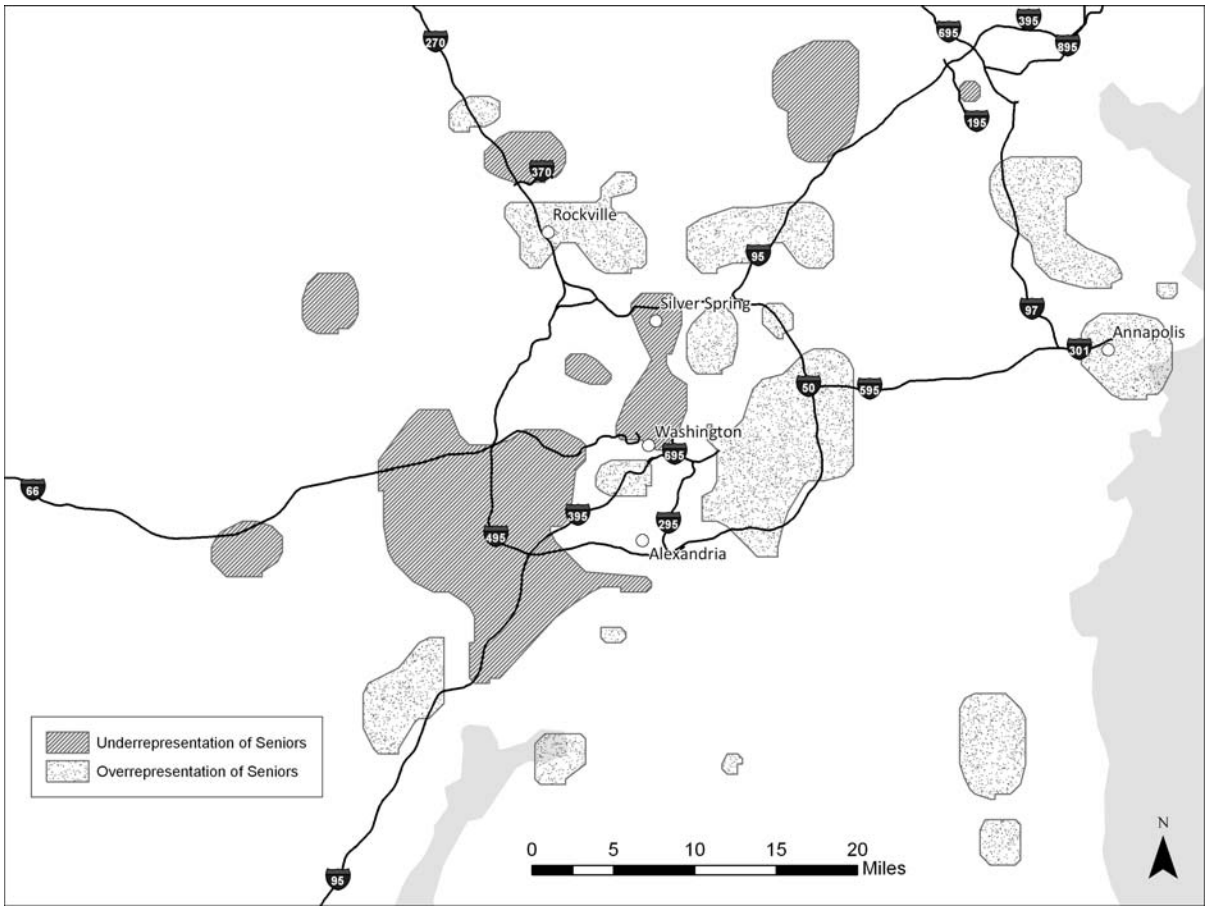

Figure 15: Under- and Overrepresentation of Seniors in the Washington, D.C. Area

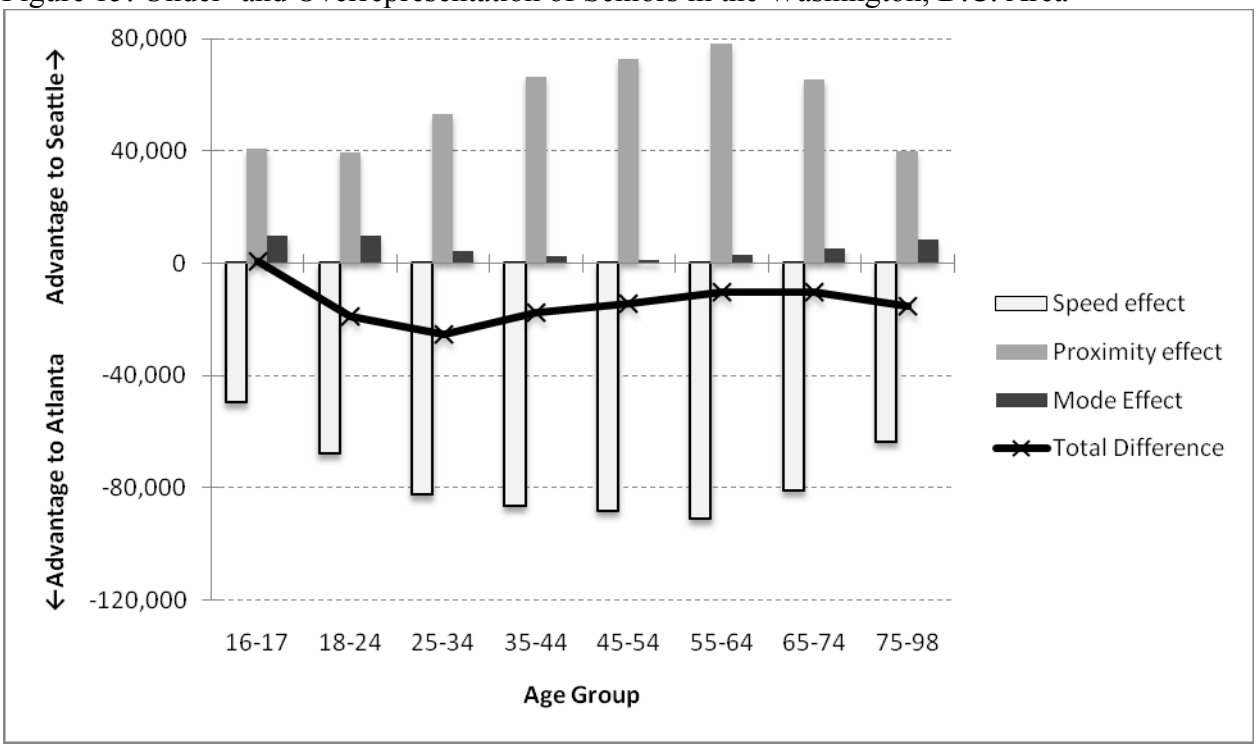

Figure 16: Decomposition of Nonwork Accessibility Differences between Seattle and Atlanta

Figure 17: Under- and Overrepresentation of Seniors in the Seattle Area

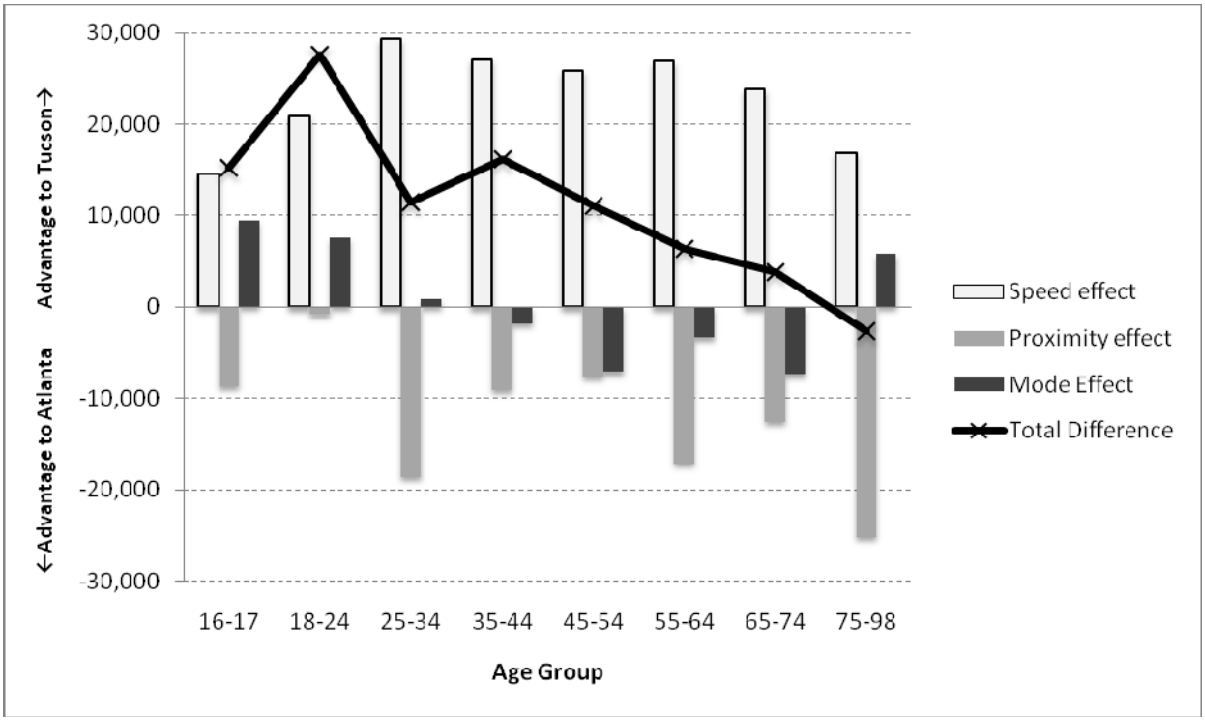

Figure 18: Decomposition of Nonwork Accessibility Differences between Tucson and Atlanta

The Tucson case presents a different picture. Here, Tucson enjoys a speed advantage compared to Atlanta, which is partly (or entirely for the oldest ages) overcome by Atlanta's proximity advantage. While Atlanta's development densities are lower than those of Tucson's, it may be that the much greater size of the Atlanta region puts more destinations closer to Tucson residents than to Atlanta residents. The proximity advantage of Atlanta grows with age, most likely a function of the more central location of Atlanta's older adults compared to those of Tucson.

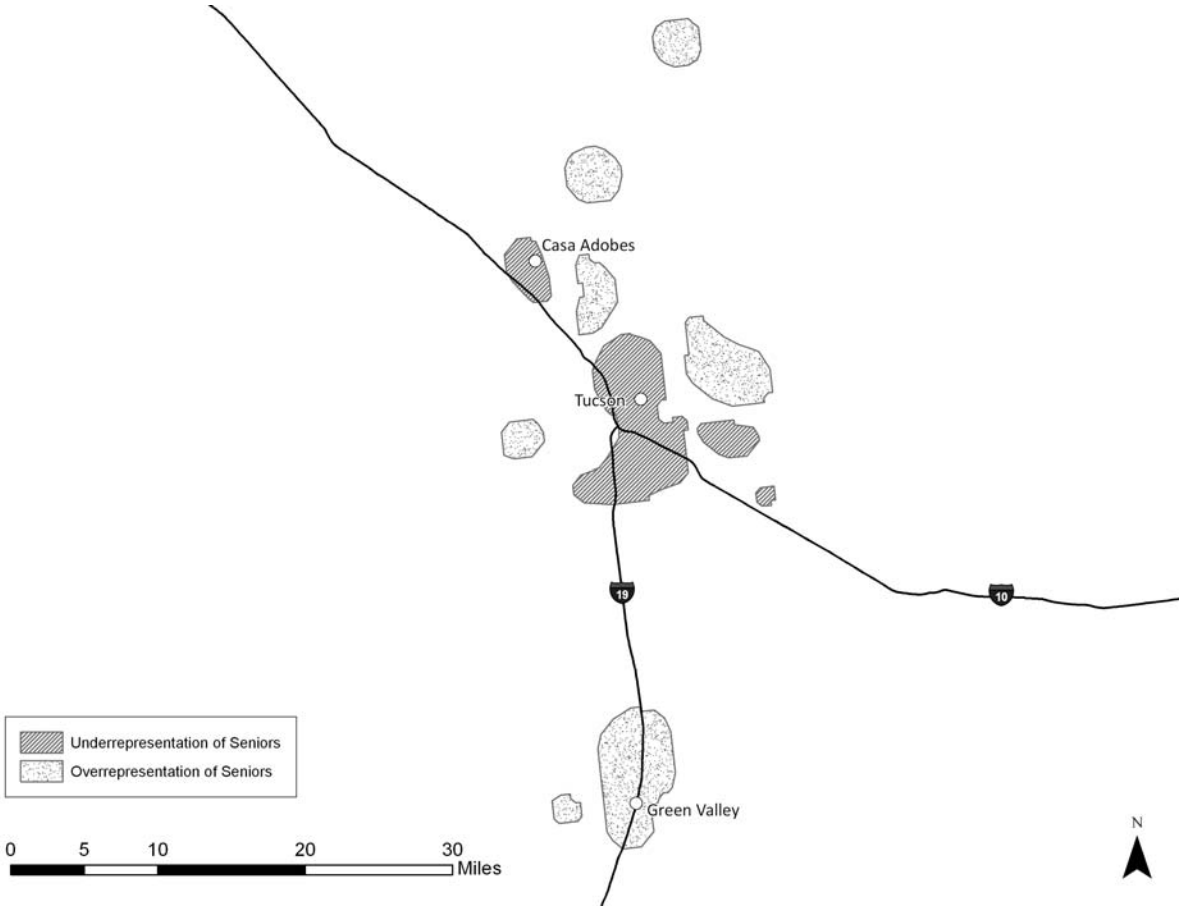

Figure 19: Under- and Overrepresentation of Seniors in the Tucson Area

The relative roles of speed, proximity, and mode in generating accessibility over the lifespan are represented in Figure 20 through Figure 22. For each paired comparison against the Atlanta baseline, these figures represent the ratio of each individual factor to the total accessibility difference observed. While much of transportation policy focuses on travel speeds, results presented in Figure 20 suggest a declining importance for this factor in generating accessibility at older ages. This is observed in the figure with the turn-down at older ages in the comparisons of Atlanta to Seattle, Los Angeles, and Washington, D.C. In addition, speed differences have a somewhat lower influence on accessibility overall at younger ages in several of the cases observed. These findings suggest that the traditional focus of transportation policy on travel speeds is most relevant to the accessibility of people in their middle years, with declining importance for the older population.

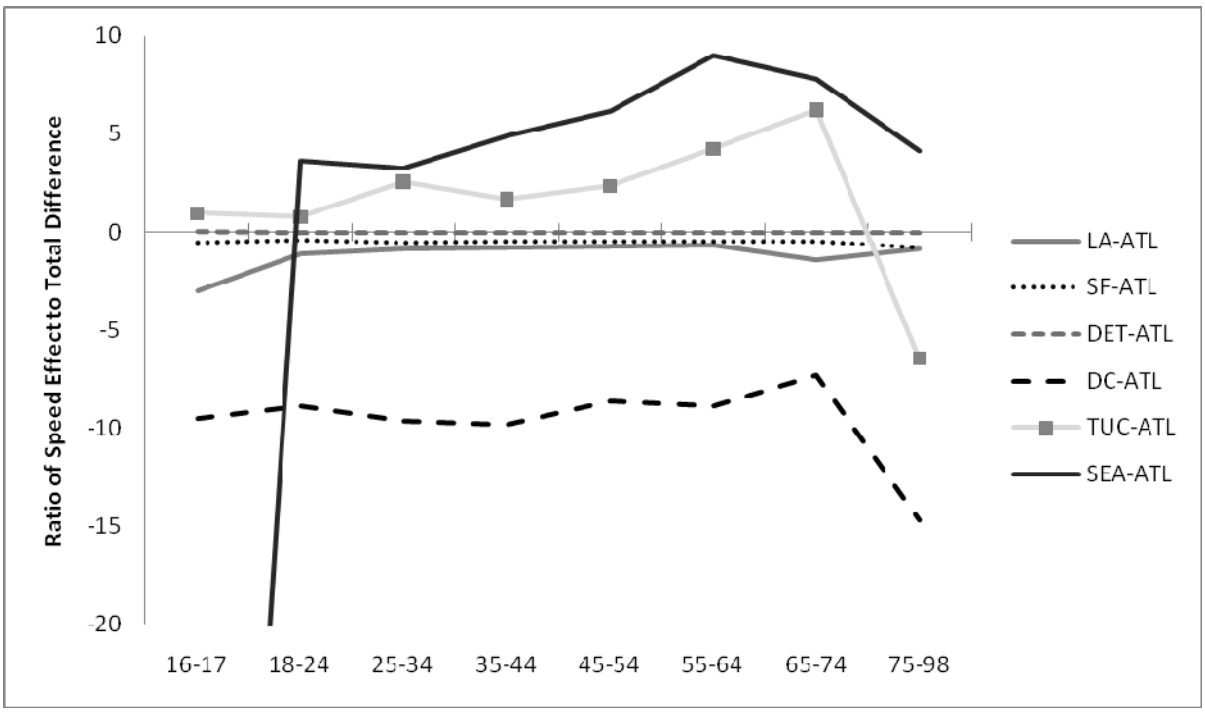

Figure 20: Ratio of Speed Effect to Total Difference in Composite Nonwork Accessibility

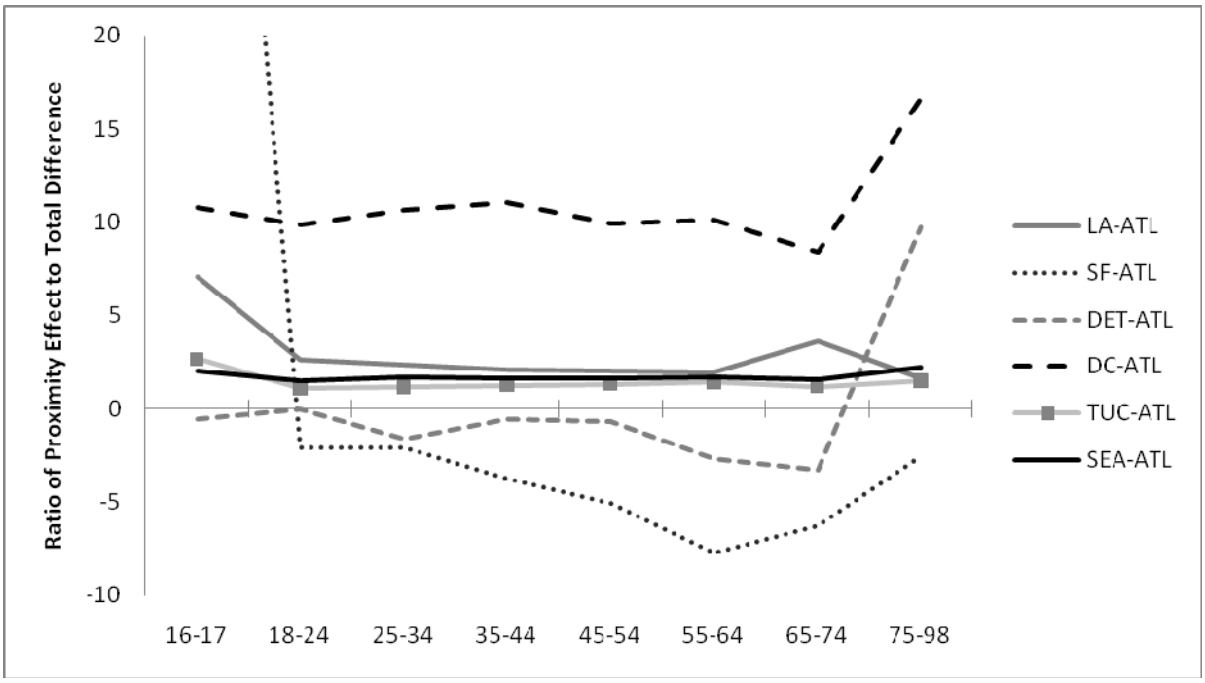

Figure 21: Ratio of Proximity Effect to Total Difference in Composite Nonwork Accessibility

In contrast to the speed effect, the proximity effect shown in Figure 21 appears to increase in importance for a person's accessibility at both ends of the life span: for the youngest (16-17 year olds) and for people 65 and older . This is observed in San Francisco, Detroit, and Washington DC at the older end of the age spectrum, and in several of the cases at younger ages (although to a lesser extent, with the exception of Seattle).

The impact of auto availability overall is similar to that of travel speeds (Figure 22); the importance of this factor to people's accessibility tends to be lower at the younger and older ends of the age spectrum than in the middle. Tucson and Seattle are the exceptions to this rule at the younger ages; Los Angeles seems to buck the trend at older ages.
The lowered importance of auto availability to accessibility at both ends of the age spectrum may be puzzling given the huge impact car availability has on one's accessibility. The reason for this appears to be the very high levels of auto availability throughout the studied populations. The lowest observed level of auto ownership was in the 16-17 age category in the Los Angeles metropolitan area; this was 29.8% (as seen in Table 3 below). Thus most of the accessibility variation in the sample is observed among those with car availability, rather than between those with and without car availability. Thus the findings presented in Figure 20 through Figure 22 are influenced most by people who have access to cars; for this group, the role of proximity increases at the younger and older ends of the age spectrum. This analysis highlights primarily the components of accessibility among those who have access to cars. An analysis of the accessibility of those without cars follows in the next section.

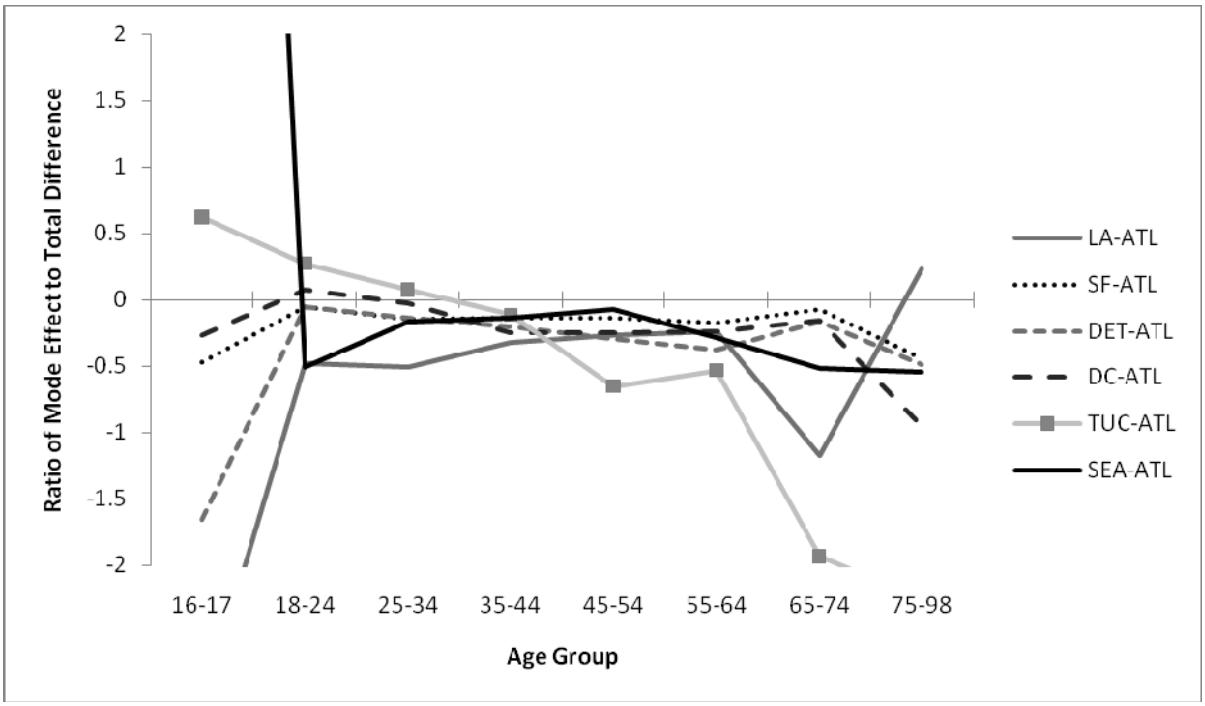

Figure 22: Ratio of Mode Effect to Total Difference in Composite Nonwork Accessibility

Metropolitan Area	Age Group							
	16-17	18-24	25-34	35-44	45-54	55-64	65-74	75-98
Atlanta	47.5%	68.8%	87.6%	92.4%	94.0%	92.7%	86.4%	65.0%
Detroit	47.4%	79.0%	90.0%	92.4%	90.2%	89.4%	86.2%	65.9%
Los Angeles	29.8%	67.4%	81.4%	87.1%	89.5%	89.2%	67.4%	83.5%
San Francisco	46.8%	79.6%	88.6%	92.4%	91.9%	90.5%	86.4%	64.4%
Seattle	54.3%	83.7%	91.0%	93.9%	94.2%	93.4%	89.4%	80.9%
Tucson	64.7%	75.0%	88.9%	91.8%	89.7%	89.7%	77.0%	78.1%
Washington, D.C.	53.2%	80.6%	92.3%	91.3%	92.1%	91.3%	85.4%	59.4%

Table 3: Auto Availability Rates by Age Cohort and Metropolitan Area

5.2 Accessibility for People without Cars

In all regions studied, accessibility via transit fell far short of accessibility via car—even for the most transit-accessible zones. Where the analysis in the above section focused on the population as a whole (which is dominated by people with cars available), this section focuses on those without the ability to drive cars. Two phenomena are observed. First, many of the households without cars reside in the central city (ranging from 16.8 percent in Los Angeles to 28.9 percent in Seattle—and 82.9 percent in Tucson), which tends to be the highest-accessibility zone of the region. Second, this center-city territory tends to be among

the most auto-accessible in the region. In many regions, some of the lowest-accessibility individuals reside on the highest-accessibility territory. Notwithstanding the findings of the section above regarding the importance of proximity for the population as a whole, even the high proximity of the center-city carless population to work- and nonwork destinations often fails to lift them out of the lowest quartile of accessibility region wide.

Figures 23 through 29 depict this phenomenon spatially. The grayscale represents three classes of auto accessibility zones (calculated for nonwork accessibility). Where individuals have access to an automobile, their accessibility equals that of their zone. Where they do not have a car available for their use, their accessibility is the transit accessibility for the zone. One gauge of inequity in accessibility is the presence of lowest-accessibility people in the highest accessibility zone, observed as red dots in the dark grey zone. In all cases, the highest accessibility zones contain carless people, but in some regions (Detroit and Seattle in this study), residence in the highest accessibility zones is sufficient to keep people out of the bottom quartile of regional accessibility, even if they do not own cars. In others (Atlanta in this study) the highest accessibility zone contains numerous lowest-accessibility carless individuals.

These results suggest two strategies to augment transportation equity: high levels of auto mobility, or high levels of transit access for people without cars. Table 4 summarizes these results, with the Gini coefficient being the indicator of distributional equity. The indicator ranges from 0 to 1; lower values indicate a more equitable equitable distribution of the measured resource. Tucson and Los Angeles offer the most equal distribution over all.

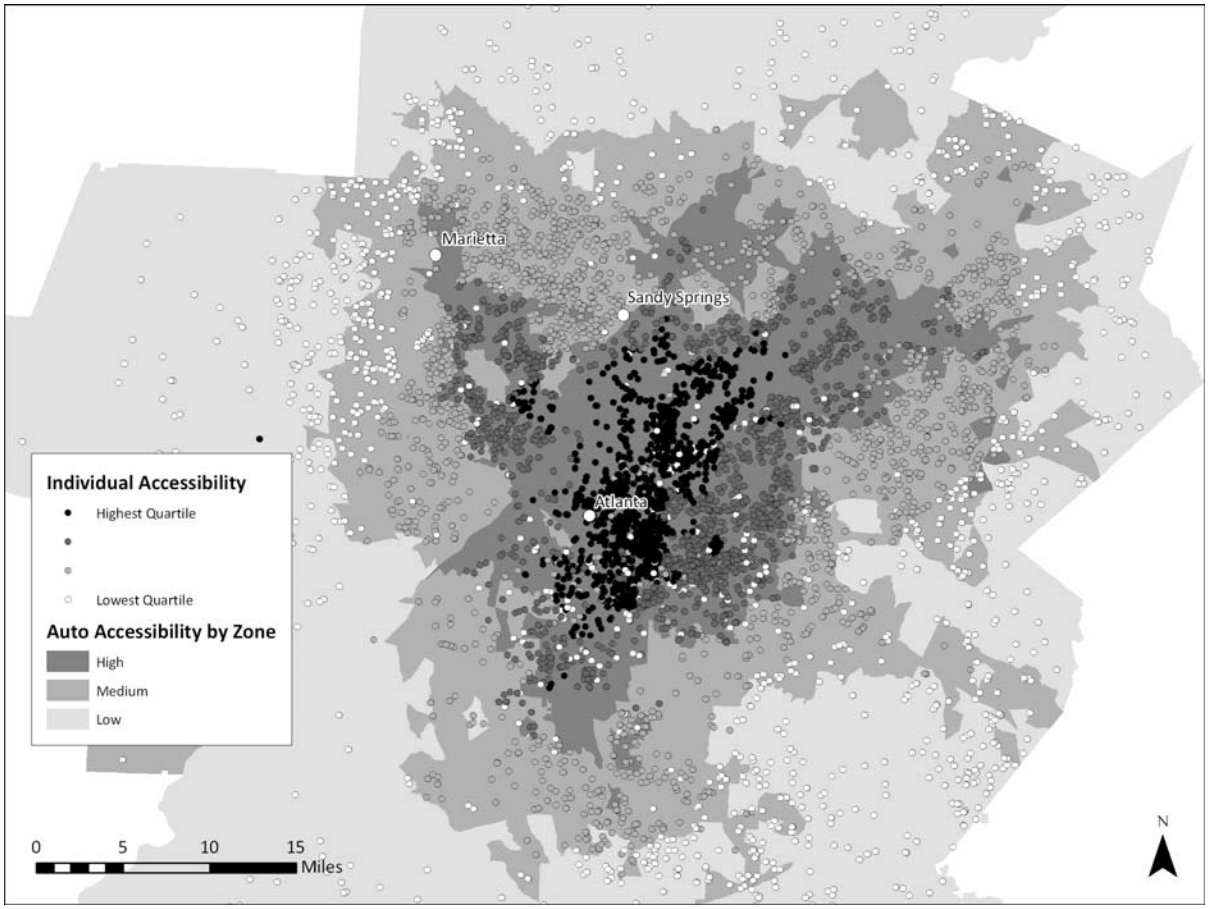

Figure 23: Individual and Zonal Accessibility, Atlanta

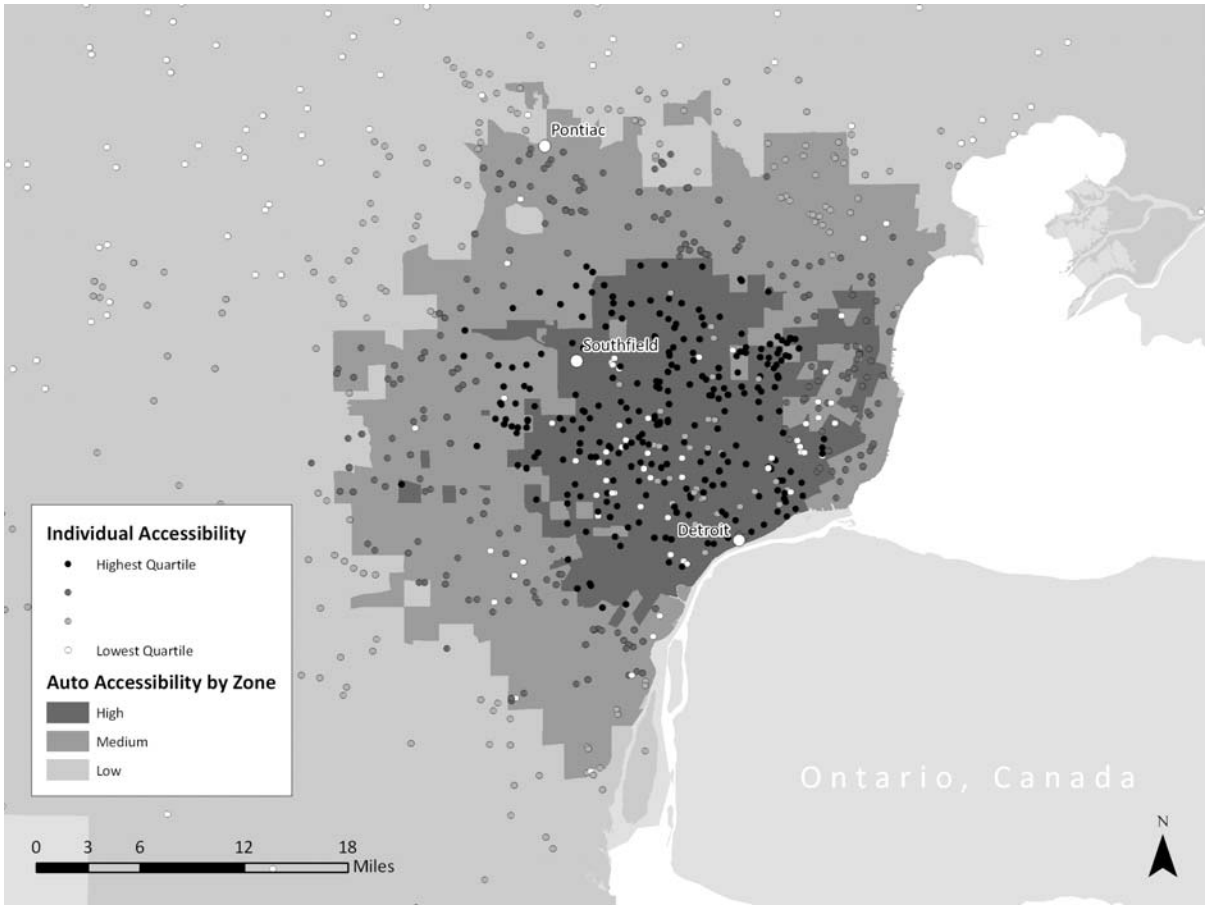

Figure 24: Individual and Zonal Accessibility, Detroit

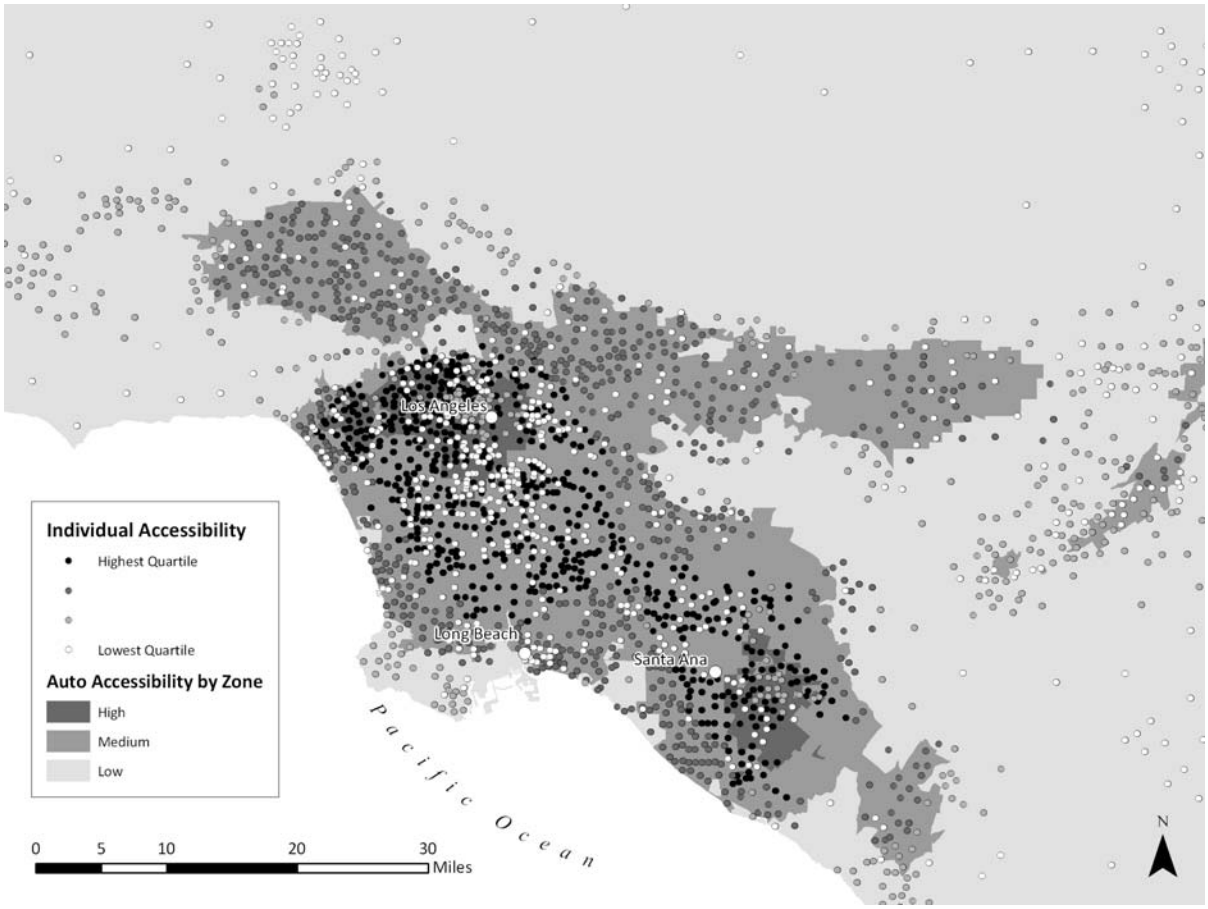

Figure 25: Individual and Zonal Accessibility, Los Angeles

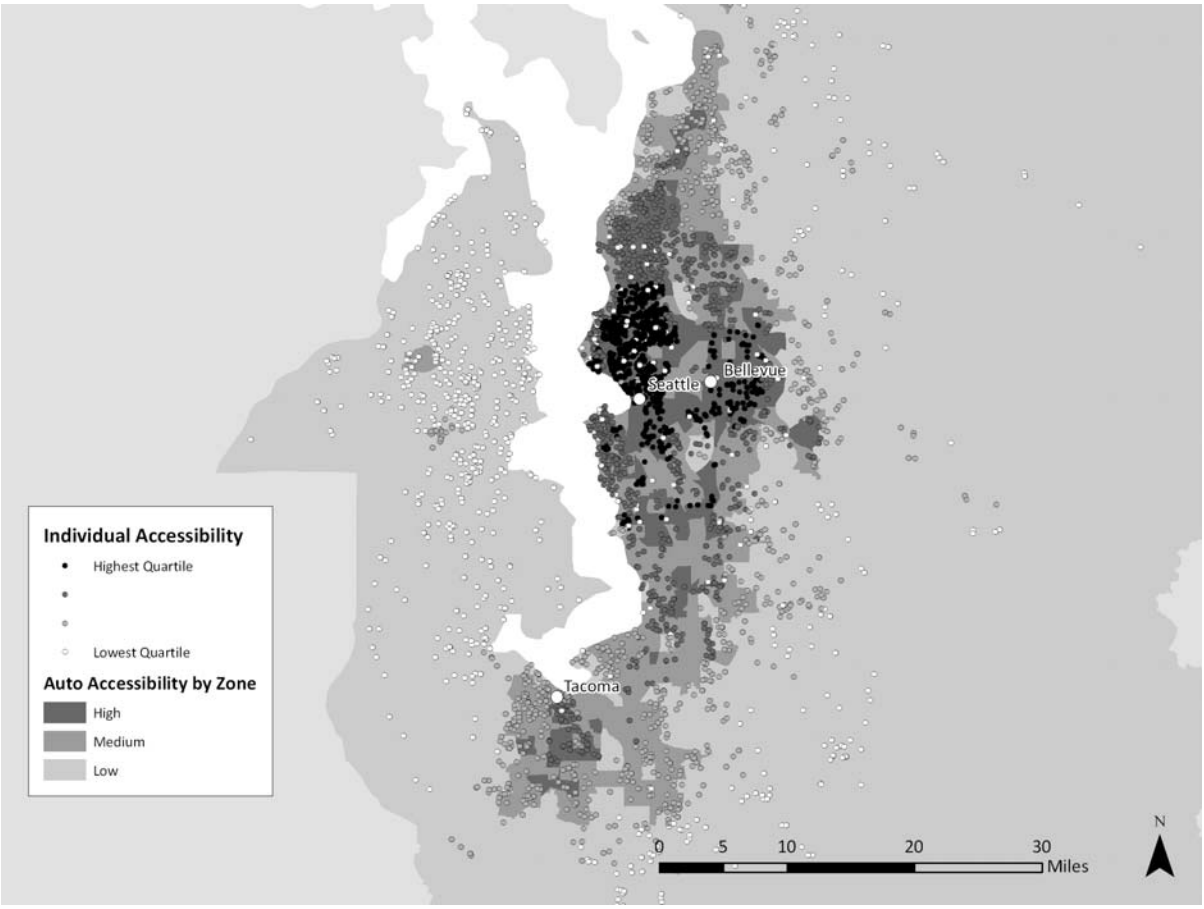

Figure 26: Individual and Zonal Accessibility, Seattle

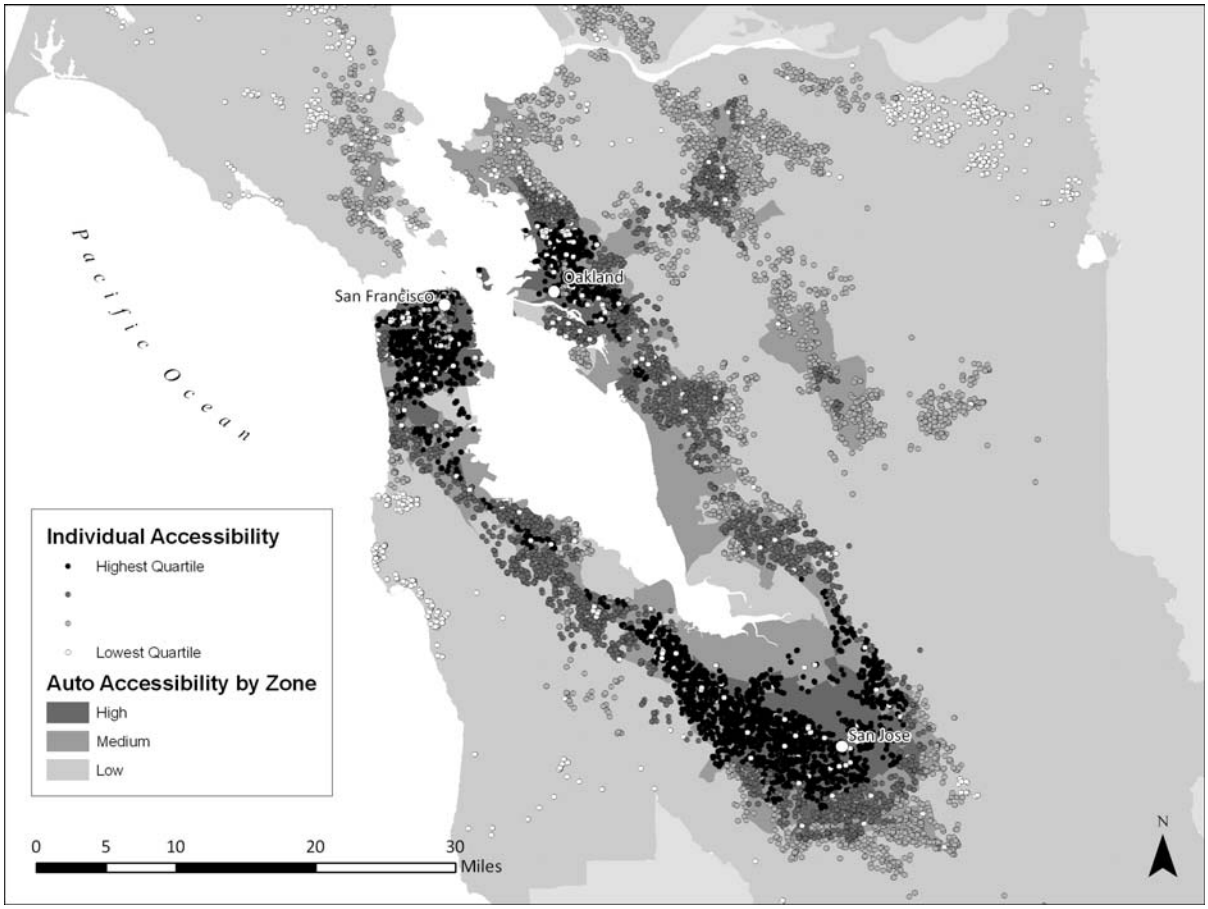

Figure 27: Individual and Zonal Accessibility, San Francisco

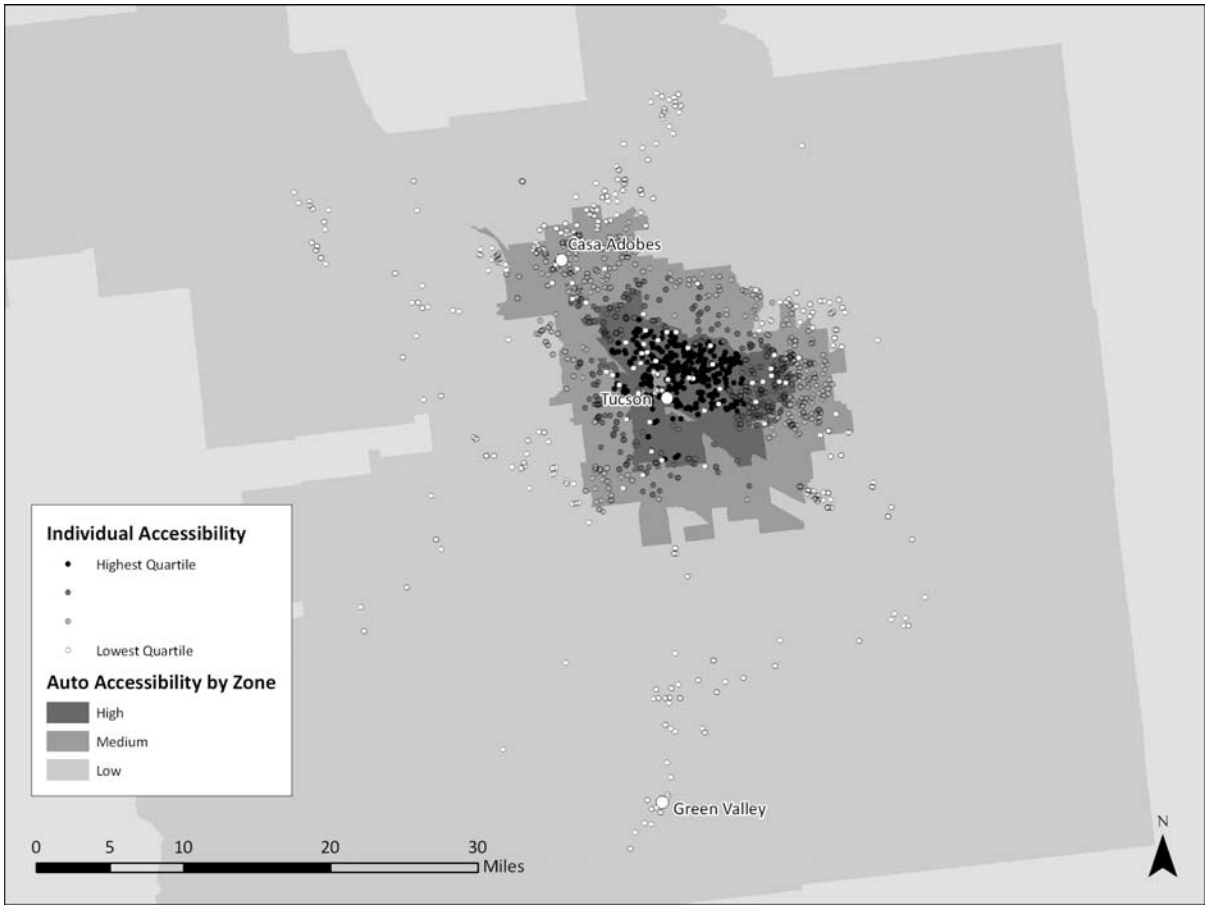

Figure 28: Individual and Zonal Accessibility, Tucson

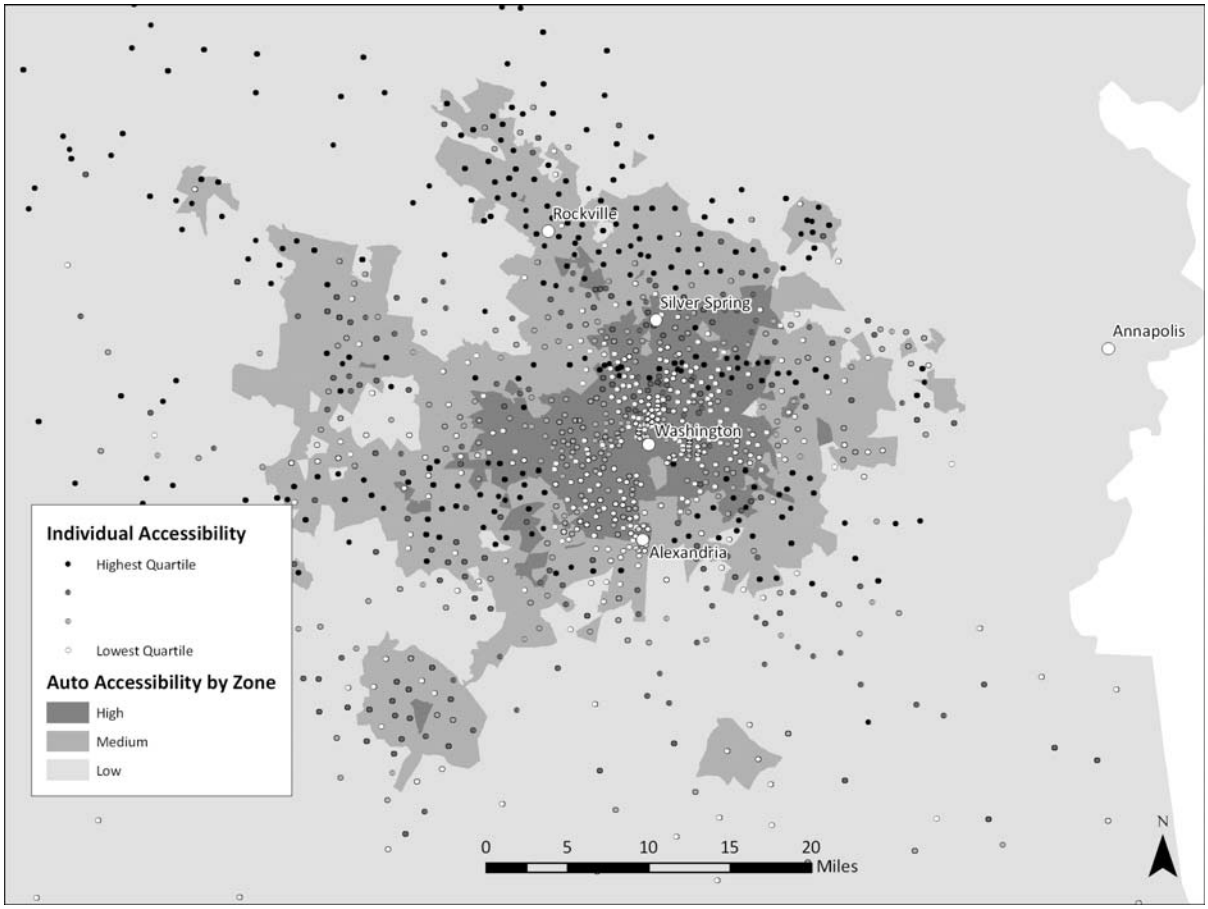

Figure 29: Individual and Zonal Accessibility, Washington, D.C.

Metropolitan Area	Gini Coefficient of Nonwork Accessibility Distribution	Percent of Sample with Auto Availability
Atlanta	0.658	86.5%
Detroit	0.666	85.8%
Los Angeles	0.483	80.5%
San Francisco	0.694	87.1%
Seattle	0.520	90.0%
Tucson	0.214	84.4%
Washington, D.C.	0.727	87.7%

Table 4: Gini Coefficients of Accessibility Distribution

(lower coefficient: more equitable distribution)

Regardless of the level of transit accessibility provided in a region, carless individuals can always increase their transit accessibility by locating in zones of higher transit accessibility. Ideally, the modal disadvantage of the transit-dependent population would be compensated by their location advantage if they reside in high transit accessibility zones, and these people would still have reasonable accessibility. In other words, their traveling modes

"match" their home locations. However, for the transit-dependent population who live in low transit accessibility zones, their accessibility would be extremely poor because of both location disadvantage and mode disadvantage. In this way, there is a "mismatch" between their traveling mode and home locations.

Figure 30 illustrates the severity of this mismatch for seniors aged 75 and older. To detect the mismatch problem, all TAZs in each metropolitan area are grouped into four zones based on their nonwork accessibility scores by transit. The first quartile zone includes the TAZs whose transit accessibility is lower than 25 percent population of that metro; the second quartile zone includes the TAZs whose transit accessibility is higher than 25 percent yet lower than 50 percent population in the metro; and so on. The quartiles are thus determined internally to the metropolitan region, and differ in their levels of accessibility between regions.

The mismatch—i.e. the share of older individuals without cars living in zones of poor transit accessibility — appears most severe in San Francisco and Los Angeles. In these areas, at least 20 percent of carless older adults reside in areas of the poorest transit accessibility for their regions. And around 40 percent of the carless older-adult population of the California regions lives in areas of lower-than-median transit accessibility for their regions. By contrast, fewer than 20% of the carless older population of metropolitan Washington, D.C. lives in areas of lower-than-median transit accessibility. With only seven cases studied, it is beyond the scope of this project to determine the causes of these variations. It may be, however, that the high transit accessibility of Washington. D.C. both attracts carless populations and enables even those who might be able to afford cars to choose a car-free lifestyle.

The fact that the two California regions display the greatest mismatch—carless older adults on low-transit-accessibility territory—may stem from obstacles to relocate to higher accessibility zones. One of those obstacles may be the property tax regime put in place in California under Proposition 13, under which property taxes are held relatively constant as long as owners remain in their homes, but are reassessed at the time of sale. For older Californians who have owned homes for many years, a move to a more transit-accessible neighborhood invariably results in a large increase in property taxes paid. In this way, this tax regime may impede locational decisions based on transit accessibility, effectively encouraging carless older adults to remain in areas that are a poor fit for their current transportation capacities.

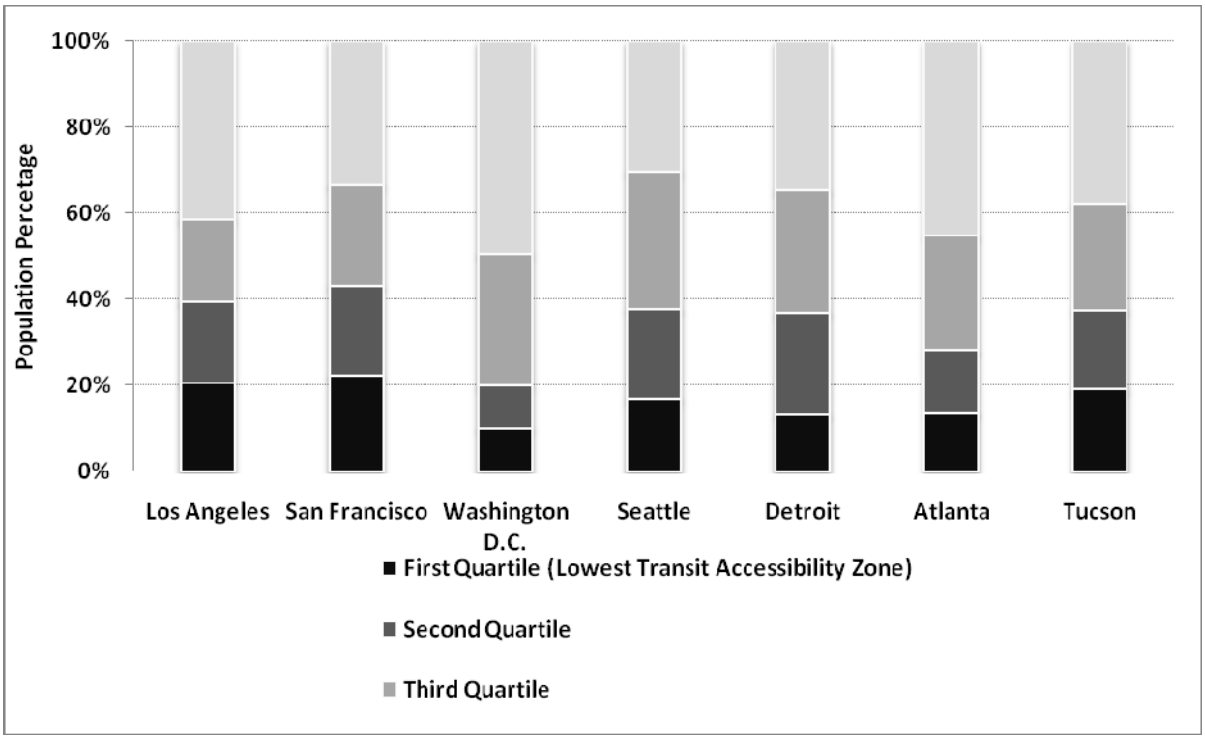

Figure 30: Share of Transit-Dependent People Aged 75-98 Living in Four Transit Accessibility Zones

6. Conclusion

This study was designed to demonstrate the feasibility and relevance of applying accessibility-based metrics to transportation policy questions pertaining to older and younger populations. The accessibility framework is a direct outgrowth of the observation that the demand for travel is derived from the demand to reach destinations; viewed in this way, mobility is merely a means toward the ends of accessibility—ends that are also promoted through proximity and remote connectivity. This study analyzed accessibility differences between metropolitan regions, breaking those differences down into a speed effect, modal effect, and proximity effect. It focused on speed and proximity as components of accessibility, and did not consider connectivity.

Overall, accessibility is significantly correlated with age, with lower accessibility observed at the younger and older ends of the lifespan. Transportation policy broadly has tended to focus on problems of roadway congestion, which is strictly a speed-based definition of the transportation problem. Low travel speeds clearly reduce accessibility in some of our study areas, with Seattle being the most prominent case. But the importance of travel speed tends to decline as a component of accessibility at higher ages.

Much of transportation policy toward older adults has focused on modal characteristics, particularly the extent of access to driving. But results presented here suggest that the role of car availability in producing accessibility also declines as a component of accessibility differences at the older end of the lifespan. Clearly, accessibility differences between drivers

and non-drivers are very large, but with very high rates of auto availability, most of the variability in accessibility is among the drivers, not between the drivers and non-drivers.

This leads to proximity-based differences in accessibility, which are large and appear to grow with advancing age. Even among older people who retain the ability to drive, location-based accessibility differences can be great. Residing in a remote part of the metropolitan region can constitute accessibility challenges even for the driving elderly. This can be exacerbated by the fact that many older people curtail driving under certain circumstances; residence in a higher accessibility area may give them the opportunity to more easily restrict driving to the conditions that best suit them.

The non-driving population faces a different set of challenges. The current quality of transit service frequently leaves transit-dependent populations with poor accessibility, even when they live in the most accessible territory in their region. And the regions studied offer a wide range in the extent of their "match" or "mismatch" between locations of the non-driving older population and zones of transit accessibility.

Transportation evaluation of the young and old remains largely mobility-based, failing to acknowledge the fundamental implications of the derived nature of transportation demand: mobility is a means and accessibility is an end. The accessibility concept accounts for mobility, but also for the central role of proximity in shaping the accessibility of cities and metropolitan regions. By accounting for this central role of proximity, urban planners, policy-makers, and public officials open up a much broader set of solutions for improving the transportation experiences of younger and older travelers.

Appendix 1: Gravity-Based Calculation of Work and Non-Work Accessibility

The basic form of the gravity model is the following:

$$(A_i)^{p,m} = \sum_j O_j^{\ p} F(c_{ij})^{p,m} \qquad (1)$$

Where, $(A_i)^{p,m}$ is the accessibility index for people living in zone *i*, for trip purpose *p* (work and nonwork), and for travel mode *m* (auto or transit); O_j^p is the number of opportunities in destination zone *j* based on a set of destinations determined by trip purpose *p*; for work travel the value is the sum of jobs in a zone, for nonwork travel the value is given by the variable NWA in Equations 4 and 5 below; $F(c_{ij})^{p,m}$ is a composite impedance function capturing travel conditions across multiple metropolitan areas, associated with the cost of travel *c* for travel between zones *i* and *j*, for trip purpose *p*, and for travel by mode *m*; defined in Equation 2 below. For metropolitan regions with a total of N zones, *i, j* = 1, 2, …, N.

The composite impedance function is given by:

$$F(C_{ij})^{p,m} = e^{-\beta^p T_{ij}^m} \qquad (2)$$

Where, *e* is the base of the natural logarithm; T_{ij}^m is the travel time (minutes) between zones *i* and *j* for travel mode *m*; β^p is a parameter empirically derived to maximize the fit between predictions of the gravity model and observed distributions of travel times for trip purpose p. For all the metropolitan regions in our research, we developed one shared β parameter for work travel and one shared β parameter for nonwork travel. We first estimated individual work and nonwork β values for each of the 16 metropolitan regions for which we had complete data. Values of the parameter were negatively correlated with metropolitan population, then we estimated a regression with individual values β dependent and metropolitan population independent. For work travel, the best-fitting regression is:

estimated $\beta = 0.109*\exp(-3.52*10^{-8}*\text{Population})$.

For nonwork travel, the best-fitting regression is:

estimated $\beta = 0.24*\exp(-3.52*10^{-8}*\text{Population})$.

These two equations were then used to predict the work and nonwork β values, respectively, for each of the 38 metropolitan regions for which we had population data. The β values for the 20th largest metropolitan region, roughly the median in our sample in size terms were then used as the unitary β values for accessibility calculation in our research (0.10157 for work and 0.2307 for nonwork).

The following equation can readily be transformed into a linear format for ordinary least squares regression:

$$N_{ij} = k v_i^{\mu} w_j^{\alpha} c_{ij}^{-\beta} \qquad (3)$$

Where, N_{ij} is the number of trips from origin zone i to destination zone j; v_i^{μ} is a measure of the propensity of trips to be generated at zone i; w_j^{α} is a measure of the attractiveness of zone j; c_{ij} is a measure of the spatial separation of i and j; and k, μ, α, and β are parameters to be estimated by regression.

To weight jobs according to their trip-attracting capacity requires several steps. First, we assumed that the distribution of nonwork trips in a given metropolitan area matches the nationwide distribution of trips in the NHTS. We know that work trips make up 17.7 percent of all national person trips, and that nonwork trips make up 82.3 percent of all national person trips. Then, by using the total number of jobs in a metropolitan region, we can calculate the nonwork "trip draws" – a term we use to capture the attractive capacity of a job at a nonwork destination – as follows:

$$TD_m = J_m\left(\frac{0.823}{0.177}\right) \tag{4}$$

Where, TD_m is the number of trip draws for metropolitan region m; J_m is the number of jobs in metropolitan region m; and the fraction is the ratio of the national share of nonwork to work trips.

The second step was to distribute the total trip draws among our 24 categories of trip purposes, assuming that the share of all trips for any trip purpose is the same in a metropolitan region as it is nationwide:

$$TD_t = TD_m(F_t) \tag{5}$$

Where, TD_t is the number of trip draws in a metropolitan region for trip purpose t; F_t is the trip purpose weighting factor for a set of k nonwork trip purposes, representing the proportion of all national trips that are made for trip purpose k, such that $F_1 + F_2 + \ldots + F_k = 0.823$ = the proportion of all national trips that are made for nonwork purposes.

A third step is to express the trip draws for each trip purpose on a per job basis:

$$TDPJ_t = \frac{TD_t}{J_t} \tag{6}$$

Where, $TDPJ_t$ is the trip draws per job for trip purpose t; J_t is the number of jobs in the metropolitan region associated with trip purpose t; for the trip purpose "visiting friends and relatives," the indicator is not jobs but population, so J_t for this trip purpose is the residential population in the metropolitan region.

The fourth and final step is to calculate the nonwork attractiveness of each zone:

$$NWA_i = \sum_{t=1}^{k}(TDPJ_t)J_{it} \tag{7}$$

Where, NWA_i is the nonwork attractiveness index at zone i; $TDPJ_t$ is as defined in Equation 6; J_{it} is the number of jobs in zone i associated with trip purpose t; for the trip purpose "visiting friends and relatives," the indicator is not jobs but population, so J_{it} for this trip purpose is the residential population in zone i. k is the number of categories of nonwork trip purposes, equal to 24.

We observed that travel speeds between TAZs within a metro are approximately normally distributed. The transformation was accomplished by calculating the z-score of each value in a zone-to-zone travel speed matrix from metro A. This z-score matrix, the values of which have a standard normal distribution, was then applied to the mean and standard deviation of speeds from metro B in order to transform the speed distribution of metro A into that of metro B. The transformed travel speeds of metro A are normally distributed with the same mean and the same standard deviation of metro B.

This is consistent with our expectations because the empirically derived β parameter used in the impedance function of Equation 2 is substantially higher for nonwork trips than it is for work trips (0.2307 for nonwork compared to 0.10157 for work), reflecting a tendency for travelers to take shorter trips for nonwork purposes, which in turn drives down the accessibility index.

Appendix 2: Decomposing Intermetropolitan Accessibility Differences by Age

This appendix illustrates the mathematical derivation of the three effects in the decomposition of the difference in composite nonwork accessibility between two MPOs X and Y. The same procedure applies to the decomposition of the difference in composite work accessibility, except that the nonworking people are excluded from the samples.

1. Derivation of Mode Effect

Mode effect contains two parts, the effect of the share of people with driving access, and the effect of spatial distribution of those people. To derive the mode effect, several steps are taken. First, the original set of composite accessibility for the ith age cohort in the two MPOs would be calculated as:

$$C^1_{x,i} = \frac{1}{N_{x,i}}\left[\sum_{j=1}^{N_{x,i}} A_{x,j} \cdot W_{x,j} \cdot D_{x,j} + \sum_{j=1}^{N_{x,i}} T_{x,j} \cdot W_{x,j} \cdot (1 - D_{x,j})\right]$$

$$C^1_{y,i} = \frac{1}{N_{y,i}}\left[\sum_{j=1}^{N_{y,i}} A_{y,j} \cdot W_{y,j} \cdot D_{y,j} + \sum_{j=1}^{N_{y,i}} T_{y,j} \cdot W_{y,j} \cdot (1 - D_{y,j})\right]$$

Where: $C^1_{x,i}$ and $C^1_{y,i}$ denote the composite accessibility scores of the ith age cohort in MPO X and Y, respectively;

$N_{x,i}$ and $N_{y,i}$ denote the number of sampled persons in the ith age cohort;

$A_{x,j}$ and $A_{y,j}$ denote the accessibility scores by auto for the jth person in the ith age cohort;

$D_{x,j}$ and $D_{y,j}$ denote whether the jth person in the ith age cohort has access to driving; the value would be 1 if this person has both a valid driver's license and at least one vehicle in the household and 0 otherwise;

$W_{x,j}$ and $W_{y,j}$ denote the weighting applied to the jth person in the ith age cohort, based on the sampling method specified by the survey agency;

T_{xij} and T_{yij} denote the accessibility scores by transit for the jth person in the ith age cohort. Next, a second set of composite accessibility is computed for both MPO X and MPO Y, assuming that access to driving is randomly assigned to people in each age cohort, while holding the average share of people with driving access the same as the actual value. Such altered composite accessibility is calculated as:

$$C_{xit}^{2} = \frac{1}{N_{xit}}\left[\sum_{j=1}^{N_{xit}} A_{xij} \cdot W_{xij} \cdot \left(\frac{1}{N_{xit}}\sum_{j=1}^{N_{xit}} D_{xij}\right) + \sum_{j=1}^{N_{xit}} T_{xij} \cdot W_{xij} \cdot \left(1 - \frac{1}{N_{xit}}\sum_{j=1}^{N_{xit}} D_{xij}\right)\right]$$

$$C_{yit}^{2} = \frac{1}{N_{yit}}\left[\sum_{j=1}^{N_{yit}} A_{yij} \cdot W_{yij} \cdot \left(\frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right) + \sum_{j=1}^{N_{yit}} T_{yij} \cdot W_{yij} \cdot \left(1 - \frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right)\right]$$

Where: C_{xit}^{2} and C_{yit}^{2} denote the altered composite accessibility scores of the ith age cohort in MPO X and Y, respectively; and the rest notations are the same as explained above. The difference between the original set of composite accessibility and the second set of composite accessibility is considered as the effect of spatial distribution of the people with driving access in the two MPOs. That is:

$$E_{t,m,spatial} = \left(C_{xit}^{1} - C_{xit}^{2}\right) + \left(C_{yit}^{2} - C_{yit}^{1}\right)$$

Then, based on the altered composite accessibility computed above, a third set of composite accessibility is calculated for MPO X, with an additional assumption that the share of people with driving access in the ith age cohort in MPO X is the same as that of the same age cohort in MPO Y. The formula is as below:

$$C_{xit}^{3} = \frac{1}{N_{xit}}\left[\sum_{j=1}^{N_{xit}} A_{xij} \cdot W_{xij} \cdot \left(\frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right) + \sum_{j=1}^{N_{xit}} T_{xij} \cdot W_{xij} \cdot \left(1 - \frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right)\right]$$

The difference between the second set of composite accessibility and the third set of composite accessibility is considered as the effect of availability of driving access among people. That is:

$$E_{t,m,share} = C_{xit}^{2} - C_{xit}^{3}$$

Therefore, the total mode effect could be calculated as:

$$E_{t,m} = \left(C_{xit}^{1} - C_{xit}^{2}\right) + \left(C_{xit}^{2} - C_{xit}^{3}\right) + \left(C_{yit}^{2} - C_{yit}^{1}\right)$$

2. Derivation of Speed Effect

The derivation of speed effect is a continuation of the work above. Speed effect also has two parts: the auto speed effect and the transit speed effect.

To compute the auto speed effect, a fourth set of composite accessibility for each age cohort in MPO X is calculated, with a new assumption that the auto traveling speed in MPO X is the same as that in MPO Y. To approximately meet that assumption, the zone-to-zone auto traveling speed in MPO X is transformed to be normally distributed with the mean and standard deviation of the distribution is identical with the corresponding values in MPO Y. Such transformation is done by first computing the z-score of each zone-to-zone traveling speed in MPO X and then applying the mean and standard deviation of MPO Y to the z-scores to derive the transformed speed. The transformed auto traveling times for MPO X are

then calculated based on such transformed traveling speed and the transformed accessibility by auto in MPO X are computed accordingly.
Thus, the fourth set of composite accessibility for the ith age cohort in MPO X is calculated as:

$$C_{xit}^{4} = \frac{1}{N_{xit}}\left[\sum_{j=1}^{N_{xit}} A_{xij}^{T} \cdot W_{xij} \cdot \left(\frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right) + \sum_{j=1}^{N_{xit}} T_{xij} \cdot W_{xij} \cdot \left(1 - \frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right)\right]$$

Where: A_{xij}^{T} is the transformed accessibility by auto for the ith age cohort in MPO X; everything else is the same as in C_{xit}^{3}. The difference between the third set of composite accessibility and the fourth set of composite accessibility is then the auto speed effect. That is:

$$E_{t,s,auto} = C_{xit}^{3} - C_{xit}^{4}$$

Similarly, to capture the transit speed effect, the transit travel speeds in MPO Y are then transformed in a way that the distribution would be normal, with the mean and the standard deviation of the travel speed in MPO Y. The transformed transit traveling times and accessibility by transit in MPO X are calculated based on the transformed transit travel speeds. And a fifth set of composite accessibility for the ith age cohort in MPO X is calculated as:

$$C_{xit}^{5} = \frac{1}{N_{xit}}\left[\sum_{j=1}^{N_{xit}} A_{xij}^{T} \cdot W_{xij} \cdot \left(\frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right) + \sum_{j=1}^{N_{xit}} T_{xij}^{T} \cdot W_{xij} \cdot \left(1 - \frac{1}{N_{yit}}\sum_{j=1}^{N_{yit}} D_{yij}\right)\right]$$

Where: T_{xij}^{T} is the transformed accessibility by transit for the ith age cohort in MPO X; everything else is the same as in C_{xit}^{4}. The difference between the fourth set of composite accessibility and the fifth set of composite accessibility is then the transit speed effect. That is:

$$E_{t,s,transit} = C_{xit}^{4} - C_{xit}^{5}$$

Therefore, the total speed effect could be calculated as:

$$E_{t,s} = \left(C_{xit}^{3} - C_{xit}^{4}\right) + \left(C_{xit}^{4} - C_{xit}^{5}\right)$$

3. Derivation of Proximity Effect

Finally, the remaining difference between the fifth set of composite accessibility of MPO X and the second set of composite accessibility of MPO Y would be considered as the proximity Effect.

$$E_{t,p} = C_{xit}^{5} - C_{yit}^{2}$$

Therefore, the total difference between the composite accessibility of the ith age cohort in MPO X and MPO Y is divided into three parts:

$$\begin{aligned}
&Total\ Difference \\
&= E_{t,m} + E_{t,s} + E_{t,p} \\
&= \left(C_{xit}^{1} - C_{xit}^{2}\right) + \left(C_{xit}^{2} - C_{xit}^{3}\right) + \left(C_{yit}^{2} - C_{yit}^{1}\right)\left(C_{xit}^{3} - C_{xit}^{4}\right) + \left(C_{xit}^{4} - C_{xit}^{5}\right) + \left(C_{xit}^{5} - C_{yit}^{2}\right) \\
&= C_{xit}^{1} - C_{xit}^{2}
\end{aligned}$$

Appendix 3: Methodology for senior over/under-representation maps

Block group data from the US Census Bureau, Census 2000, provide population and demographic data for each metropolitan area. Using a GIS, a centroid is derived for each block group, with its gross population count and its population age 65 or older.
Next, a kernel density raster is computed using these block group centroids as input data. This method produces a smoothed grid of population density values across the entire extent of the metropolitan area by passing a defined kernel over it and calculating density at regular intervals. Here, the kernel used is quadratic with a 10km diameter, and its value is sampled at the nodes of a 500m grid.
This method is carried out twice: once with the gross population of block groups, and again with the senior population only. Descriptive statistics for each grid are used to convert each cell value to a z-score, defined as

$$z_i = \frac{x_i - \mu}{\sigma}$$

where:

x_i is the observed kernel density x at grid cell i;
μ is the mean of all observations;
σ is the standard deviation of all observations.

Two standardized grids are thus produced: one containing z-scores of gross population, and another containing z-scores of the senior population.
In the next step, these two raster grids are subtracted, such that the values of the difference grid are

$$z_{di} = z_{si} - z_{pi}$$

where:

z_{di} is the value of the difference of z-scores at cell i
z_{si} is the z-score of the senior population density at cell i
z_{pi} is the z-score of the gross population density at cell i.

The difference raster is then mapped with cells classified into three groups:

1: $z_{di} < -0.5$, defined as *underrepresentation of seniors;*
2: $z_{di} \geq -0.5$ *and* $z_{di} \leq 0.5$, where seniors are close to average density, and
3: $z_{di} > 0.5$, defined as *overrepresentation of seniors*.

Because these values show significant spatial autocorrelation, they are displayed on maps as boundaries containing contiguous cells of group 1 or 3; all other areas are made up of group 2 cells.

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