Access to Jobs: Transportation Barriers Faced by Low-Skilled Autoless Workers in U.S. Metropolitan Areas

by

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ABSTRACT

One of the major concerns in today's urban labor market is spatial mismatch, the geographic separation between jobs and workers. Although numerous studies examine spatial mismatch, most of them focus on inner-city minorities, and the spatial mismatch problem for all autoless workers in a metropolitan area as a whole has not been well explored. Focusing on low-skilled workers and welfare recipients, this dissertation explores and quantifies the importance of job accessibility in employment outcomes for disadvantaged workers without autos in U.S. metropolitan areas.

Metropolitan areas studied are Boston, San Francisco, and Los Angeles for low-skilled workers and Los Angeles for welfare recipients. An essential component of the analysis is the calculation of improved job-access measures that take into account supply and demand sides of the labor market and travel modes. The resulting measures indicate that, contrary to the perception of many spatial mismatch studies, central-city areas still offer more of a geographical advantage in accessing employment opportunities than suburban areas, despite the substantial suburbanization of employment. In other words, spatial mismatch is greater in suburban areas than in central-city areas. The measures also indicate that the levels of spatially accessible job opportunities are considerably lower for transit users than for auto users. In other words, spatial mismatch is much greater for transit users than for auto users. This transit/auto disparity is much greater than the central-city/suburb disparity, suggesting that the mode of travel has greater importance in determining job accessibility than location. These findings suggest that spatial mismatch may pose a serious problem for autoless workers, particularly for those who live in suburban areas, although it may not be a problem for workers with autos.

By incorporating the improved job-access measures into multinomial logit (MNL) models and regression models with Heckman correction, I find that improving job accessibility for transit users significantly augments the employment probability and the probability of working full-time for low-skilled autoless workers in San Francisco and Los Angeles. Further, in all three areas the job-access effect is greater for low-skilled autoless workers than for low-skilled auto-owning workers. Applying the same analytical framework for welfare recipients in Los Angeles, I find consistent results. I also find that job accessibility for transit users plays a more important role in employment outcomes in San Francisco and Los Angeles, more highly auto-dependent areas, than in Boston, a more compact area with relatively well-developed transit

systems. The empirical findings together suggest that spatial mismatch is in fact the problem for autoless workers in suburban areas where jobs are dispersed and public transportation is poorly developed. The findings also suggest that spatial mismatch is more likely to be an employment barrier for those who live in suburban areas than for those who live in central-city areas, which contradicts the dominant view among spatial mismatch researchers.

The empirical findings hold important policy implications. Simulations of some policy scenarios indicate that for autoless workers in highly auto-dependent areas, a housing dispersal program would actually worsen their employment prospects, although for auto-owning workers such a program could be helpful, and that transportation mobility programs that improve mobility and job accessibility for transit users would enhance the employment outcomes for autoless as well as for auto-owning workers. Thus, this dissertation's empirical analysis of the combination of spatial and transportation mismatch contributes new information for the theory and policy debate surrounding the problem of spatial mismatch.

This research uses Geographic Information Systems (GIS) and statistical tools extensively. The analytical framework developed in this study can be applied for further research. For example, I plan to conduct a similar study using census 2000 data, which may indicate further exacerbated spatial mismatch for autoless workers.

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Chapter 1: Introduction

1.1 STATEMENT OF PROBLEM

Over the post-war period, U.S. metropolitan areas have undergone massive suburbanization of employment. Although all employment sectors have undergone this change, the most heavily suburbanized are the manufacturing and retailing sectors (O'Sullivan, 1993; Stanback, 1991). Since these sectors provide a large number of low-skilled jobs, and since suburban jobs are often beyond the reach of public transportation, this spatial job dispersion may put low-skilled workers without automobiles at a significant disadvantage.

The problem is related to one of the major concerns in today's urban labor market, spatial mismatch—the geographic separation between jobs and workers. Although numerous studies examine spatial mismatch, most of them focus on inner-city minorities, and the spatial mismatch problem for autolesss workers in a metropolitan area as a whole has not been well explored. The focus on inner-city minorities occurs largely because spatial mismatch was first recognized as one of the possible explanations for aggravated urban poverty. The notion of spatial mismatch has drawn increasing attention since John Kain introduced the spatial mismatch hypothesis in 1968. Kain's hypothesis states that a combination of housing segregation and job suburbanization creates spatial mismatch that reduces employment opportunities for African-Americans in inner cities and lowers their employment outcomes (Kain, 1968). Since the time of Kain's study, an extensive literature has examined the spatial mismatch hypothesis.[1]

While most early spatial mismatch studies pay little attention to travel modes, in recent years transportation has garnered growing recognition as one of the major barriers to employment

[1] Holzer (1991), Ihlanfeldt and Sjoquist (1998), and Kain (1992) present comprehensive reviews of spatial mismatch literature.

success, particularly on the part of welfare mothers (Lacombe, 1997; Sawicki and Moody, 2000; Wachs and Taylor, 1998). The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 requires welfare recipients to work as a condition of receiving public assistance, putting welfare recipients under strong pressure to make the transition from welfare to work.

Finding and keeping a job, however, is a severe challenge for people trying to achieve this transition. Most welfare recipients are single mothers who, besides working, have to perform diverse tasks including child and medical care, housework, and shopping. All these obligations must be handled by the sole adult in the household. Compared to the general population, the rate of auto ownership for welfare recipients is considerably lower, and vehicles owned by welfare recipients are often old and unreliable (Ong et al. 2001). For welfare recipients without reliable and flexible mobility, making multiple trips a day, traveling to and from childcare facilities, schools, workplaces, supermarkets, and so on, may be a formidable task.

Given the auto-oriented, spatially dispersed nature of urban development in the U.S., auto ownership is a key factor in determining spatial mobility. Despite the fact that households without autos are becoming increasingly scarce, many people still depend on public transportation, which severely limits their mobility. People without autos may face a considerable obstacle in accessing opportunities, and levels of accessible job opportunities with respect to residence may be significantly more important in obtaining and keeping jobs for workers without autos than for workers with autos.

Still, the importance of accessible job opportunities in employment outcomes has not been fully explored for autoless workers. Developing a refined measurement of job accessibility that differentiates among travel modes, Shen (1998, 2001) finds that job accessibility (a measure of the number of spatially accessible job openings per job seeker in a given zone) is significantly lower for transit users than for auto users. His studies, however, do not attempt to conduct an empirical analysis of the job access-employment relationship. Empirical analyses by Ong (1996) and Raphael and Rice (2000) show that auto ownership significantly increases employment outcomes for disadvantaged workers. These analyses, however, do not consider the levels of accessible job opportunities, which provide important location information about spatial mismatch. In this regard, these studies examine transportation mismatch rather than spatial mismatch.

Thus, this dissertation explores and quantifies the importance of accessible job opportunities in employment outcomes for workers without automobiles in U.S. metropolitan areas. In other words, it examines the combination of spatial mismatch and transportation mismatch, which sheds new light on the problem of spatial mismatch and the literature surrounding it.

Important concepts to be clarified are spatial mismatch and job accessibility, which sometimes are interpreted in different ways. In this dissertation, I define *spatial mismatch* simply as the geographic separation of workplaces and residences. The term *job accessibility* indicates a level of spatially accessible job opportunities in an area of residence. A job-access measure calculated in this thesis therefore indicates the level of spatial mismatch; a high job-access measure represents a low level of spatial mismatch, and a low job-access measure represents a high level of spatial mismatch. My study is not an examination of Kain's spatial mismatch hypothesis. While Kain's hypothesis addresses the spatial mismatch problem for inner-city minority workers, my research examines the spatial mismatch problem for all autoless workers in a metropolitan area as a whole. In fact, spatial mismatch for autoless workers is likely to be severer in suburban areas where jobs are dispersed and public transportation is poorly developed than in central-city areas with more concentrated jobs and more accessible transit services.

The focus groups of this dissertation are two of the most disadvantaged groups: general low-skilled workers and welfare recipients. The areas studied are the Boston metropolitan area, the nine-county San Francisco Bay Area, and Los Angeles County. While Boston is a relatively compact area with well-developed transit systems, the San Francisco Bay Area and Los Angeles County are much larger and more auto-dependent.[2] These three major metropolitan areas are selected in order to investigate whether the importance of job accessibility in

[2] For the nine-county San Francisco Bay Area, San Francisco County (the city of San Francisco) has well-developed transit networks, but transit networks in the other counties are more poorly developed.

employment outcomes for autoless workers varies substantially across metropolitan areas with different urban spatial structures. To date, almost no study systematically examines this metropolitan difference. For autoless workers, job accessibility may play a much more important role in employment outcomes in San Francisco and Los Angeles, highly auto-dependent areas, than in Boston, a more compact area with a relatively high level of transit usage. Additionally, the disparity in the importance of job accessibility between autoless and auto-owning workers may be greater in San Francisco and Los Angeles than in Boston.

This research uses Geographic Information Systems (GIS) and statistical tools extensively. No similar study has been done yet partly because of the difficulty in calculating job accessibility that differentiates among travel modes and partly because of the complexity of developing statistically sound models. One of the objectives of my dissertation is to develop an analytical framework that quantifies not only the job-access effect on employment outcomes for autoless workers but also the disparity in the job-access effect between autoless and auto-owning workers. Essential components to achieve this objective are the calculation of improved job-access measures that take into account the supply and demand sides of the labor market and differences in travel modes and the incorporation of the improved measures into statistical models. The analytical framework developed in this study can be applied for further research. For example, I plan to conduct a similar study using census 2000 data that are being gradually released, which may indicate exacerbated spatial mismatch for autoless workers.

1.2 OBJECTIVES AND RESEARCH QUESTIONS

The objectives of this dissertation are the following:

- to improve understanding of the relationships between urban spatial structure, transportation, and employment opportunities in the low-skilled urban labor market;

- to contribute to the spatial mismatch literature by examining the importance of job accessibility in employment outcomes for low-skilled workers and welfare recipients without automobiles in the major U.S. metropolitan areas;

- to develop an analytical framework that quantifies the job-access effect on employment outcomes for autoless workers and the disparity in the job-access effect between autoless and auto-owning workers; and

- to contribute new information for the theory and policy debate surrounding the problem of spatial mismatch.

To achieve these objectives, I attempt to answer the following specific research questions:

(1) What are the socioeconomic characteristics of low-skilled workers in general and low-skilled autoless workers in particular? To what extent are the characteristics of low-skilled workers different from those of higher-skilled workers? To what extent do the characteristicis of low-skilled workers without autos differ from those of low-skilled workers with autos? (Chapter 4)

(2) What are the geographies of low-skilled workers and jobs? To what extent do the geographies vary within and across the metropolitan areas? Is there a disparity in the geographies between the low-skilled and high-skilled groups? (Chapter 5)

(3) What are the spatial variations in job accessibility for low-skilled transit and auto commuters? To what extent do the spatial variations in job accessibility differ between low-skilled transit and auto commuters? (Chapter 6)

(4) Does improving job accessibility for transit users enhance employment outcomes for low-skilled workers without autos? Is the job-access effect for low-skilled workers greater for autoless workers than for auto-owning workers? Does the job-access effect for low-skilled autoless workers vary across metropolitan areas with different urban spatial structures? (Chapter 7)

(5) Does improving job accessibility for transit users augment employment outcomes for welfare recipients without autos? Is the job-access effect on employment outcomes greater for welfare recipients without autos than for welfare recipients with autos? (Chapter 8)

Policy implications will be discussed based on the empirical findings. This dissertation focuses on mobility policies that help spatially disadvantaged workers access employment opportunities. There is a widely-accepted view that spatial mobility should be encouraged for the disadvantaged workers (Ong and Blumenberg 1998; Shen 1998, 2001; Wachs and Taylor 1998). Each researcher or policy maker, however, favors a particular program over the other programs. Generally, the spatial mobility programs can be placed into three categories: (1) housing dispersal—helping workers move near jobs (e.g., Kain 1992; Rosenbaum and Popkin 1991); (2) economic development—creating jobs near workers (e.g., Giloth 1998; Porter 1997); and (3) transportation mobility—encouraging auto ownership or improving public transportation services (e.g., Hughes 1995; Sawicki and Moody 2000). The findings will be utilized for a further discussion of effective mobility programs.

1.3 OUTLINE OF DISSERTATION

To reflect the research questions listed above, this dissertation is organized as follows. Chapter 2 reviews the related literature to provide background information that motivated my research questions. Next, the research data, selection and description of the study areas, and methodology are described in Chapter 3. Chapter 4 investigates the socioeconomic and transportation characteristics of low-skilled workers in general and low-skilled workers without autos in particular. To identify the characteristics specific to low-skilled autoless workers, the characteristics of these workers are compared with those of the two comparison groups—higher-skilled workers and low-skilled workers with autos.

In Chapter 5, the geographies of low-skilled workers and jobs as opposed to the geographies of the high-skilled group are presented. This chapter indicates the limitation of the use of the simple jobs-to-workers ratio as a measurement of job accessibility and suggests the need to calculate the measures that better represent true job accessibility. The more representative measures are computed and mapped in Chapter 6. These improved measures capture the supply and demand sides of the labor market and the difference in travel modes; taking travel modes into account is critical in this study.

Incorporating the improved job-access measures into multinomial logit (MNL) models and regression models with Heckman correction, Chapter 7 develops the travel-mode sensitive approach to estimate the job-access effect on employment outcomes for low-skilled autoless workers. The chapter also demonstrates the disparity in the job-access effect between autoless and auto-owning workers. Employing the analytical framework developed in Chapter 7, Chapter 8 next investigates the job-access effect on employment outcomes for another disadvantaged group—welfare recipients without autos. Finally, in Chapter 9, the empirical findings are summarized and policy implications and future research directions are discussed.

Chapter 2: Related Literature

This chapter reviews literature that provides background information about the issues raised in this dissertation. The important related concepts, which have received a great deal of attention in the recent urban labor market, are skills mismatch and spatial mismatch. Skills mismatch indicates a gap between workers' skills and employers' skill demand, and spatial mismatch denotes the geographical separation of workers and jobs. I first introduce the important changes in urban spatial and economic structures in Section 2.1, and then in Section 2.2, I discuss the implications of such changes for disadvantaged people without automobiles, the focus group of this research.

2.1 CHANGES IN URBAN SPATIAL AND ECONOMIC STRUCTURES

The latter half of the 20^{th} century saw dramatic changes in spatial and economic structures in U.S. metropolitan areas. In this section, I review the following three critical changes that might significantly disadvantage low-skilled workers without autos: suburbanization, deindustrialization, and increasing demand for skills.

2.1.1 Suburbanization

America's urban development in the post-war period could be best characterized as the massive suburbanization of population and employment. The majority of metropolitan people once lived in central cities, but today, more and more people prefer living in suburban neighborhoods to living in central cities. Of metropolitan residents, 64% lived in central cities in 1948, but by 1980, the proportion dropped to 43% (O'Sullivan 1993). Between 1960 and 1990, the proportion of workers who lived in suburban counties in large metropolitan areas rose from 47% to 57% (Rossetti and Eversole 1993).

Between 1960 and 2000, the U.S. population grew by 52%, from 181 million to 275 million, and workers (persons in the civilian labor force) increased by 105%, from 66 million to 135 million (U.S. Census Bureau 2001). Much of the population growth in metropolitan areas was driven by suburban growth. During the period between 1970 and 1980, more than 95% of metropolitan population growth occurred in the suburbs, and among large metropolitan areas, population growth in the suburbs was more than 10 times faster than that in central cities between 1970 and 1994 (U.S. Department of Housing and Urban Development 1997, 1999). The outmigration from cities to suburban areas continued into the 1990s; in 1996, for example, 2.7 million people changed their residences from central cities to the suburbs, while only 800,000 people changed from the suburbs to central cities (U.S. Department of Housing and Urban Development 1998).

Employment has also suburbanized considerably during the post-war period, although it is less suburbanized than population. Between 1950 and 1980, the proportion of central city in metropolitan jobs dropped from 70% to 50% (Mills and Hamilton 1994). Kasarda (1995) notes that a great deal of metropolitan job growth took place in suburban downtown, or *edge cities*, and that many edge cities now have greater retail sales and office space than traditional downtowns.

Although suburbanization occurred in all employment sectors, the most heavily suburbanized are manufacturing and retailing sectors. O'Sullivan (1993) shows that during the period from 1948 to 1986, the proportion of manufacturing jobs in central cities fell from 67% to 46%. Following suburban consumers, retailing jobs have also suburbanized greatly; during the same period, the share of central cities in metropolitan retailing jobs declined from 75% to 49%. The most centralized sectors, on the other hand, are finance, insurance, and real estate (FIRE) sectors and other service sectors. Among the 60 largest metropolitan areas in 1986, 58% of jobs in these sectors still remained in central cities and 24% were in central business districts (O'Sullivan 1993).

One of the major driving forces for the mighty suburbanization of America is the increasing use of automobiles, which has come with cheap gasoline prices and rapid provision of road and highway infrastructures. Increased transportation mobility and decreased travel costs, together with government subsidies for mortgages, enabled many people, particularly middle-class and affluent families, to achieve the American dream of owning detached, single-family homes on spacious lots in suburban neighborhoods that offer better public services and less crime.

Increased mobility and reduced travel costs have also shifted locational advantages from central cities to suburban locations for many firms, particularly for manufacturing firms that take advantage of cheap and plentiful suburban land to establish single-story plants. After the enormous post-war suburbanization, many U.S. metropolitan areas are now characterized by sprawling low-density populations and employment. Kenworthy et al. (1999) show that U.S. cities (and Australian cities) have the lowest densities of population and employment among the world's major cities; for example, European cities are on average more than three times denser than typical American cities.

Dispersing population and employment have generated some social problems. A problem is the geographic separation between residence and workplace, known as spatial mismatch in academic literature. Spatial mismatch is likely to be an especially serious problem for people without automobiles, since many suburban jobs are not accessible by public transportation. Even when jobs and workers are connected by transit networks, many suburban jobs are not located within a reasonable amount of travel time from city centers. Additionally, the mass exodus of manufacturing and retailing jobs from central cities to the suburbs suggests that many low-skilled jobs are now in the dispersed suburbs, reducing accessible job opportunities for people who are both low-skilled and autoless.

The spatial mismatch problem for low-skilled autoless workers is the central issue in this dissertation. Most spatial mismatch studies examine Kain's (1968) spatial mismatch hypothesis that focuses on poor minority people in impoverished inner cities. However, my dissertation focuses on all disadvantaged workers without auto in metropolitan areas, regardless of location. Kain's spatial mismatch hypothesis is described in greater detail in Section 2.2.3.

2.1.2 Deindustrialization

One of the significant changes in urban economy in recent decades is deindustrialization, the structural shift from goods-producing sectors to service-producing sectors. The period from 1820 to 1960 experienced stable growth of manufacturing employment, but manufacturing jobs have declined ever since. In 1950, manufacturing constituted 34% of all non-agricultural employment, but by 1993, its share shrank to 17% (Mills and Hamilton 1994). The census statistics show that between 1980 and 2000, the proportion of manufacturing jobs in total employment dropped from 22% to 15% (U.S. Census Bureau 2001). Instead, the emerging growth industry is the service sector that increased its employment from 30% to 37% between 1980 and 2000 (U.S. Census Bureau 2001). The service sector is indeed the driving force of employment growth in urban America; between 1950 and 1985, the share of services in metropolitan employment rose from 29% to 46% (Mills and Hamilton 1994).

Although national statistics indicate the strong trend of deindustrialization, the growth pattern of manufacturing varies considerably across regions. Enormous loss of manufacturing occurred in the Northeastern and Midwestern regions, but the loss did not occur in the Western and Southern regions. Kasarda (1995) shows that between 1970 and 1990, 1.5 million manufacturing jobs disappeared in the Northeast and 0.6 million disappeared in the Midwest. In the South and the West, however, manufacturing employment actually grew moderately, each region adding approximately 1.1 million jobs. It should be noted, however, that all regions gained far greater numbers of service and retail jobs. Since manufacturing jobs in general pay relatively high wages to blue-collar and low-skilled workers, researchers suggest that the deindustrialization movement might have contributed to the reduced employment opportunities and earnings for low-skilled workers (e.g., Holzer and Vroman 1992; Wilson 1987, 1996).

2.1.3 Increasing Skills Demand and Skills Mismatch

Over recent decades, the occupational structure has shifted from low-skilled jobs toward higher-skilled jobs. Between 1979 and 1998, the proportion of professional and technical jobs rose from 15% to 18%, and the proportion of managerial jobs increased from 10% to 14%, whereas the proportion of blue-collar jobs dropped from 33% to 24% (Osterman 1999).

One possible explanation for the decreased demand for low-skilled workers and the increased demand for high-skilled workers is increasing internationalization. Since the U.S. wage rates for low-skilled workers are relatively high, many American firms have moved their production facilities to less-developed countries where cheap labor is available. Such relocations of production facilities might have led to the reduced demand for low-skilled workers in the U.S., while the global demand for high-skilled American workers has increased (Blank 1997; Danziger and Gottschalk 1993).

Another possible explanation is that advancing technologies (e.g., the spread of computers) increased the demand for high-skilled workers and decreased the demand for low-skilled workers. Evidence for this explanation is mixed, however. For example, on the one hand, Howell (1994) argues that increasing competitive pressures from globalization and deregulation and a shift towards market-oriented ideology have a more significant impact. On the other hand, Johnson's study (1997) supports the assertion that technological change is an important factor for the increased relative demand for high-skilled workers.

The shift in the demand from low-skilled toward high-skilled workers generated a growing concern about skills mismatch, the mismatch between workers' skills and employers' skill requirements. Compared to spatial mismatch, skills mismatch is a relatively new concept, but it has received considerable attention in recent years. Note that spatial or skills mismatch occurs when the supply side of the labor market (workers) has difficulty adjusting to the demand side of the labor market (jobs). Indeed, studies suggest that skills mismatch has been growing not because workers' skills have been worsening, but because jobs have been demanding more skills (e.g., Blank 1997; Kasarda 1995).

Skills mismatch is especially noticeable in older and larger Northern cities that experienced substantial deindustrialization. In these cities, the manufacturing sector, which provided a large number of low-skilled jobs, has been replaced by the information-processing sector, which demands higher skills (Mills and Hamilton 1994; Kasarda 1995). For low-skilled workers in those areas, these high-skilled jobs may be spatially accessible, but they are not actually accessible. Many scholars argue that this skills mismatch has adversely affected the employment prospects of the inner-city poor, many of whom are low-skilled (e.g., Kasarda 1989, 1995; Wilson 1987, 1996).

2.2 SPATIAL MISMATCH, JOB ACCESS, AND TRANSPORTATION

2.2.1 Increasing Auto Dependence and Changing Commuting Patterns

As people and jobs have been dispersing into the suburbs, travel distance between residence and workplace has widened. According to the U.S. Census Bureau (1979), the average travel distance to work in 1975 was about 9 miles, but Pisarski's study (1992) indicates that the average distance to work was approximately 11 miles in 1990. Data from the Nationwide Personal Transportation Survey show that between 1983 and 1990 the average commuting distance increased from 8.3 miles to 10.1 miles (U.S. Department of Transportation, Federal Highway Administration. 1994). Increased inter-county travels reflect the lengthened travel distance. Rossetti and Eversol (1993) report that from 1960 to 1990, the number of workers who work outside their counties of residence increased by over 200%, from 9 million to 28 million. These results together suggest that mobility is becoming increasingly important for participating in work activity.

Indeed, auto dependence in the U.S. is extremely high. Two basic indicators of auto dependence are auto ownership and use. With increased household incomes and great expansion of roads and highways, America's auto ownership has grown rapidly. Between 1960 and 1990, the number of vehicles nearly tripled from 55 million to 152 million, and the average number of vehicles per household increased from 1.03 to 1.66. Notably, the fastest increasing household type during this period was a household with three or more vehicles, jumping from 1 million to 16 million, and much of the vehicle growth appeared in households with two or more vehicles (Rossetti and Eversole 1993). Between 1960 and 1990, the proportion of households with zero vehicles dropped from 22% to 12%, although the decreasing rate slowed between 1980 and 1990 with only about a 1% decline (U.S. Department of Transportation, 1997). A related figure is the increasing number of people who have driver's licenses. Of people over 16 years old, the proportion of licensed drivers rose from 72% to 88% (95% for men and 85% for women) during the period from 1960 to 1990 (U.S. Bureau of the Census, 1962, 1993b).

Given the great convenience, flexibility, and personal mobility afforded by automobiles, it is not surprising that auto use has increased dramatically, while transit use has declined. Between 1960 and 1990, the proportion of work trips that use private vehicles rose from 69% to 88%. During the same period, workers who use automobiles for commuting increased by about 135%, from 43 million to 101 million, although total workers increased by just 78%. The proportion of work trips that use public transit, on the other hand, dropped from 13% to 5%, and transit commuters decreased from 8 million to 6 million (Rossetti and Eversole 1993).

Indeed, America is the most auto-dependent country in the world. Kenworthy et al. (1999) provide a thorough international comparison of auto dependence. In 1990, non-auto modes accounted for only 14% of all work trips in 13 major U.S. cities, while the shares were much higher in other major cities in the world, for example, 57% for major European cities, and 80% for wealthy Asian cities.

America's strong preference for autos over public transit is also reflected in infrastructures, which actually enabled high auto dependence in the U.S. The provision of roads as opposed to transit in the U.S. is quite impressive. Kenworthy et al. (1999) show that American cities provide greater road coverage than do most other major cities in the world. The average road length per capita in 1990 was 7 meters for major American cities but much shorter, 2 meters, for European cities and for wealthy Asian cities, and 5 meters for Canadian cities. Conversely, transit service provision is scant in the U.S. In 1990, the average length of transit vehicle service per capita in the U.S. was 28 kilometers, which was much shorter than those in any other major cities in the world; for example, Canadian cities had the average length of 58 kilometers per capita, European cities had 92 kilometers, and wealthy Asian cities had 114 kilometers.

As population and employment grew, all forms of commuting—central-city-to-central-city, central-city-to-suburb, suburb-to-central-city, and suburb-to-suburb—increased from 1960 to

1990. As jobs have been dispersed into the suburbs, however, commuting patterns have changed considerably, and the fastest growing form has been suburb-to-suburb commuting. During this period, intra-suburban commuting almost quadrupled and has been the dominant form since 1980. In 1990, the number of suburb-to-suburb commuters was about 39 million, which was more than twice that of suburb-to-central-city commuters, 18 million, and more than 1.5 times that of central-city-to-central-city commuters, 25 million (Pisarski 1996). In Worcester, Massachusetts, for example, the proportion of suburban workers who commute to central cities declined from 42% to 27% between 1960 and 1990 (Hanson 1995). Examining commuting flows in 10 major U.S. metropolitan areas in 1990, Kasarda (1995) finds that the number of suburb-to-suburb commuters was more than twice that of suburb-to-central-city commuters.

Since transit systems were originally designed to transport people from suburban areas to central-city areas, they do not serve well the increasing needs of these non-traditional commuting patterns. The next section discusses transportation implications for disadvantaged workers without automobiles.

2.2.2 Transportation Barriers for Disadvantaged Workers without Autos

Today, the great majority of households own autos, but many people, most of whom are low-income, still remain autoless. Low auto ownership for welfare recipients, for example, is well documented. Green et al. (2000) report that about half of welfare recipients in Alameda County in California have automobiles available, and Ong et al. (2001) find a similar figure for welfare recipients in Los Angeles. These auto ownership rates may be unexpectedly high, but they are still much lower than those for the general populations.

Additionally, owning a car does not necessarily provide dependable mobility. Due to their limited financial budget, many low-income people have vehicles that are old and unreliable. Conducting a survey of welfare recipients in Los Angeles, Ong et al. (2001) find that of autos owned by welfare recipients, 69% are 10 years old or older and at high risk of maintenance and mechanical problems. Indeed, 55% of welfare recipients report having had at least one mechanical problem over the last three months, and 59% mention mechanical problems as among two of the major problems associated with auto ownership. Despite these problems, 17% of their autos are not covered by insurance.

People without dependable autos are likely to lack the mobility necessary to reach suburbanized employment. Public transportation systems are traditionally designed to transport people from the suburbs to cities in the morning and back from cities to the suburbs in the evening. Such traditional radial transportation systems, however, do not meet the increasing needs of non-traditional commuting patterns (e.g., suburb-to-suburb and city-to-suburb commuting). Suburban jobs that are easily accessible for people with autos may be completely inaccessible for people who depend on public transit. Even when suburban jobs are connected by transit networks, getting to these jobs may be impractical; transit routes may be indirect, trips to suburban jobs may require multiple transfers, waiting time as well as commuting time may be unworkably long, and transit schedules may not match with work schedules. Many low-skilled jobs have second and third shift schedules, but public transit generally does not operate in the late evening and early morning hours.

Given the fact that many low-skilled jobs are suburbanized as discussed earlier, people who are both low-skilled and autoless may have severely limited accessible job opportunities. For example, in Boston, where public transit systems are relatively well developed, 98% of welfare recipients live within one-quarter mile of a bus or transit station, a distance typically considered accessible. However, only 32% of potential entry-level jobs in the region's high-growth areas are located within one-quarter mile of transit (Lacombe 1998).

Indeed, transportation has been increasingly recognized as one of the major barriers to employment success for disadvantaged workers, particularly on the part of welfare mothers (e.g., Lacombe, 1997; Sawicki and Moody, 2000; Wachs and Taylor, 1998). In 1996, President Clinton enacted the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), which put welfare recipients under strong pressure to make the transition from welfare to work. Finding and keeping jobs, however, may be especially challenging for welfare mothers who do not have access to autos. Without the flexible and reliable mobility of automobiles, it may be extremely difficult to balance job demands with family responsibilities, which require multiple trips in daily life (e.g., trips to day care centers, schools, worksites, and grocery stores). Traditional transit systems are unlikely to meet these complex transportation needs.

For welfare recipients, most of whom are single mothers, access to childcare facilities is essential to make the welfare-to-work transition. A study by Ong et al. (2001) shows that of welfare recipients in Los Angeles, the percentage of persons who use childcare is 42% for recipients looking for jobs, but the figure is much higher, 84%, for working recipients. The study also shows that welfare recipients with young children are more likely to report that transportation is a major problem in obtaining jobs than recipients who do not have young children. For auto users, only 25% have difficulties with childcare trips, whereas for transit users, 50% report difficulties.

Lack of an automobile may also significantly hinder job search activities, which often involve considerable travels. Compared to workers with autos, workers who depend on public transportation are likely to be much less flexible in searching for jobs, and their search areas are limited to those areas served by transit networks. Job seekers often have to travel to unfamiliar areas where potential jobs are located, and finding appropriate bus routes and schedules to access these jobs can be a formidable task. Ong et al. (2001) find that welfare recipients who travel by public transportation are twice as likely to report that their job-search trips are somewhat or very difficult than recipients who travel by auto.

Moreover, workers without reliable autos may be more likely to have attendance problems, which increase the risk of job termination. The problem may be especially serious for those who have to make multiple transfers, for those who carpool to work, and for those whose cars are unreliable. Indeed, employers often prefer job applicants with reliable transportation, and some welfare recipients are not referred to job openings because they do not have autos (Ong et al. 2001).

Surprisingly, despite the problems associated with transit use and the great preference for autos over transit, 40% of welfare recipients in Los Angeles state that public transportation is a feasible trip option (Ong et al. 2001). Although autoless households are becoming increasingly scarce, many people's mobility still depends on public transportation. These people include not only workers without autos, but also workers in a household with multiple adults but only one car. Improving transportation mobility and job accessibility may enable these workers to advance in the labor market.

2.2.3 Spatial Mismatch and Labor Market Outcomes

Over the past few decades, concentrated poverty among inner-city minorities, particularly among less-educated African-Americans, has been a major concern in the urban labor market. Spatial mismatch was first recognized as one of the possible explanations for this concentrated urban poverty. In 1968, John Kain introduced the spatial mismatch hypothesis that the combination of job suburbanization and residential discrimination has contributed to deteriorating employment opportunities for African-Americans in inner-city neighborhoods. Using data from Detroit and Chicago in 1952 and 1956, respectively, Kain's study (1968) supports this hypothesis and suggests that further employment dispersal would worsen this situation.

Since Kain's study, an extensive body of literature has examined the spatial mismatch hypothesis, providing evidence both in favor of and against it. The general approach to testing the spatial mismatch hypothesis involves selecting or constructing job-access measures, and then incorporating the measures into a statistical model to examine to what extent job accessibility affects employment outcomes such as employment probability, wages, and earnings. Table 2.2.1 summarizes the spatial mismatch studies that focus on the spatial mismatch effect on employment. There are, however, numerous other spatial mismatch studies, and their methodological approaches vary considerably. Comprehensive reviews of the spatial mismatch literature are provided by Holzer (1991), Ihlanfeldt and Sjoquist (1998), and Kain (1992).

Table 2.2.1 Summary of spatial mismatch literature examining job-access effect on employment

Author	Data	Dependent Variable	Primary Independent Variables	Results	SPM
Kain (1968)	Detroit, 1952 and Chicago, 1956—Area Traffic Study surveys of places of work and residence.	Black share of total employment in a neighborhood.	Black share of residents in each neighborhood and distance of neighborhood from inner-city ghetto.	Fraction of blacks among the employed declines with distance from ghetto and rises with fraction of blacks in neighborhood. Black employment 3-8 percent lower than under uniform population distribution.	Y
Mooney (1969)	25 SMSAs, 1960—Census data on low-income tracts with half or more non-whites.	Employment probability of black males.	Fraction of jobs in manufacturing, trade, and services located in central city; fraction of employed central-city blacks working in suburbs.	Black employment in SMSA rises with job decentralization and with fraction of blacks working in suburbs, though overall SMSA unemployment has larger effect on black employment.	Y
Offner and Saks (1971)	Same as Kain.	Same as Kain.	Same as Kain.	Non-linear effects of fraction of blacks in neighborhood: mixed neighborhoods show few blacks among the employed.	Y
Friedlander (1972)	25 SMSAs, 1960—Census data merged with SMSA characteristics.	Central-city black unemployment rates.	Indices of residential segregation and fraction of jobs located in central city.	Segregation indices and fraction of employment in central cities have few significant effects on central-city black unemployment.	Y/N
Harrison (1974)	12 largest SMSAs, 1966—Survey of Economic Opportunity (males with work for at least 13 weeks).	Weeks worked by blacks in central-city and suburban areas.	Residence in central-city and suburban areas.	Distribution of weeks worked by blacks in central-city areas (poverty and non-poverty) not different from those in suburbs.	N
Hutchinson (1974)	Pittsburgh, 1967—Traffic Survey.	Employment probability of white and black males.	Numbers of jobs located at given distances (approximated by travel times) from homes.	Job proximity (number of jobs located at various distances) has positive effect on white male employment but negative effect on black male employment.	Y
Leonard (1985)	Los Angeles, 1980—Equal Employment Opportunity Survey on job locations merged with Census data.	Neighborhood employment probabilities.	Number of nearby jobs; import ratios; and average travel times.	Measures of job access have little effect on relation between percentage black and teen employment. Commute times are a little higher for majority black Census tracts.	Y/N
Ellwood (1986)	Chicago, 1970—Chicago Area Transportation Study survey merged with Census Employment Survey.	Youth employment probabilities.	Number of nearby jobs; import ratios (ratio of jobs to people); and average travel times for each neighborhood.	Measures of job access, neighborhoods and distance from commercial centers have no effects on the relation between percentage black and youth employment in neighborhood: higher commute times of blacks counteract the relative lack of jobs in their neighborhoods.	Y/N
Farley (1987)	SMSAs, 1980—Census of Population. SMSAs, 1977—Census of Industries.	Black and Hispanic unemployment rates.	Fraction of jobs in manufacturing, trade, and services located in central city.	Job decentralization raises relative unemployment rates of blacks and Hispanics.	Y

Table 2.2.1 Summary of spatial mismatch literature examining job-access effect on employment (cont'd)

Author	Data	Dependent Variable	Primary Independent Variables	Results	SPM
Ihlanfeldt and Sjoquist (1990)	Philadelphia, Chicago and Los Angeles, 1980—PUS.	Youth employment probabilities.	Average travel times for subcounty areas within SMSAs.	Average travel time has large effects on employment probabilities of black youth (and sometimes on those of whites as well), and explains about 30-50 percent of black-white employment difference among youth.	Y
Ihlanfeldt and Sjoquist (1991a)	43SMSAs, 1980—PUMS.	Youth employment probabilities.	Commuting time and individual and family characteristics.	Job access measured by commuting time has a significant effect on the employment probability of youth.	Y
Ihlanfeldt and Sjoquist (1991b)	9 MAs, 1980—PUMS.	Employment probability in each of the eight occupational groups.	Fraction of private sector jobs, fraction of black population, years of education, and potential labor market experience.	Disproportionate concentration of blacks in occupations paying lower average wages is not attributable to their higher frequency of working within central cities. However, the results suggest that the racial composition affects black employment.	Y/N
O'Regan and Quigley (1991)	47 MSAs, 1980—PUMS.	Youth employment probabilities.	Job concentration, isolation index for black poverty, isolation index for within race, and average one-way commute time.	Black youth employment is significantly related to job-access measures.	Y
Cooke (1993)	Morion county, Indiana, 1990—Census of Population and Housing. 1987— Economic Census.	Black male unemployment probabilities.	Jobs-to-workers ratios.	Job access has no significant effect on the black male unemployment.	N
Ihlanfeldt (1993)	10 SMSAs (with at least 10,000 Hispanic youth), 1980—PUMS.	Hispanic and white youth employment probabilities.	Intraurban job accessibility.	Job access has a significant effect on the employment probability of both racial groups. Hispanic youth have worse access to jobs than white youth, which explains about 25 to 30 percent of the difference in employment rates between whites and Hispanics.	Y
Holloway (1996)	50 largest MSAs, 1980, 1990—PUMS.	Youth employment probabilities.	Commuting time and individual and family characteristics.	The job-access effects on employment probabilities declined between 1980 and 1990, especially for black male youths not enrolled in schools.	Y
Holzer and Ihlanfeldt (1996)	Atlanta, Boston, Detroit, and Los Angels—Survey on 800 employers in each of MAs.	Fraction of a firm's black applicants.	Distance between a firm and the closest public transit stop, and the firm's average distance from the black, white, or Hispanic populations.	Employers' proximity both to black residences and to public transit increases the likelihood of hiring black employees.	Y
O'Regan and Quigley (1996a)	47 MSAs, 1980—PUMS. 73 MSAs, 1990—Census data.	Youth employment probabilities.	Individual and family characteristics, and MSA characteristics.	Minority youth residing in more segregated cities or cities in which minorities have less contact with nonpoor households have lower employment probabilities than otherwise comparable youth.	Y

Table 2.2.1 Summary of spatial mismatch literature examining job-access effect on employment (cont'd)

Author	Data	Dependent Variable	Primary Independent Variables	Results	SPM
O'Regan and Quigley (1996b)	New Jersey (Newark, Bergen-Passaic, Middlesex, and Monmouth), 1990--Census data and CTPP.	Youth employment probabilities.	Individual and family characteristics, neighborhood characteristics, and job-access measures	Neighborhood composition and job access affect employment outcomes. Estimates differ by area and by outcome.	Y
Rogers (1997)	Pittsburgh, 1980-1986—municipal occupational privilege taxes' data, Southwestern Pennsylvania Regional Planning Commission's data, and CWBH data.	Unemployment duration probabilities.	Access index combining individual characteristics, municipal level employment, and a matrix of commuting times.	Access to employment growth is negatively and significantly related to unemployment duration.	Y
Cooke (1997)	Boston, 1990—PUMS.	Labor force participation.	Commuting time and individual and family characteristics.	Job access has no significant effect on the labor force participation rates of blacks, but it has a positive effect for white married mothers.	N
Thompson (1997)	Chicago, Philadelphia, Los Angeles, 1990—PUMS.	Female labor force participation probabilities.	Commuting time and individual and family characteristics.	Job access has a significant effect on the labor force participation rates of white, black, and Hispanic women in three MSAs.	Y
Raphael (1998)	San Francisco-Oakland-San Jose CMSA, 1990—STF3A, data from Bay Area Metropolitan Transportation Commission. 1980, 90—data from Association of Bay Area Governments.	Youth employment probabilities.	spatial accessibility measures using a gravity model, spatial measure of labor supply, and neighborhood variables.	Job accessibility has a significant effect on the youth employment rates. Differential accessibility explains 30 to 50 percent of the neighborhood employment rate differential between white and black male youths. Approximately one-fifth of the differential is attributable to differential access.	Y
Sanchez (1999)	Portland and Atlanta, 1990—STF3A, CTPP1990.	Average number of weeks worked in each census block group.	Relative access to service/retail jobs, distance to nearest rail/bus stops, average commuting time, public transit service frequency at nearest stop, auto ownership, and neighborhood characteristics.	Among access measures, auto ownership has the greatest impact on the average annual weeks worked. For the other access measures, the overall effects are significant but their magnitudes are small.	Y

Note: Literature review from 1968 to 1990 is based on the summary of literature review by Holzer (1991). PUS: public use sample. PUMS: public use micro samples. CTPP: census transportation planning package. STF: summary tape file. MSA: metropolitan statistical area. SMSA: standard metropolitan statistical areas.

There remains considerable controversy about the empirical results of Kain's spatial mismatch hypothesis, although recent studies provide results that are relatively consistent in supporting it. Major reasons for the controversy are the difficulty in creating job-access measures that well represent actual spatial accessibility to job opportunities and the complexity in developing statistically sound models. An example of the second difficulty is the possible endogeneity problem; that is, employment outcomes may affect residential choice and therefore job accessibility. If residential choice and employment outcomes are jointly endogenous, estimated job-access effects will be biased. To deal with this endogeneity problem, many existing spatial mismatch studies focus on youths since youths' residential locations are mostly predetermined by parents.

While most spatial mismatch studies pay little attention to travel modes, in recent years transportation has garnered growing recognition as one of the major barriers to employment success for disadvantaged people. Some studies, for example, examine the impact of auto ownership on employment outcomes. Using data from a survey of welfare recipients in California, Ong (1996) finds the significant and positive effects of auto ownership on employment and earnings. Estimating auto-ownership effects requires caution, however. As in the case of the possible endogeneity between residential choice and employment outcomes, auto ownership and employment outcomes are likely to be jointly endogenous; that is, greater employment outcomes are likely to increase auto ownership, yielding biased estimates.

To control for this endogeneity problem, Raphael and Rice (2000) estimate two-stage least squares (2SLS), using insurance and gasoline tax costs as instruments for car ownership. Their empirical results show that owning a car significantly increases employment probability and work hours, and that the estimated effects are quite similar for ordinary least-squares (OLS) and for 2SLS.

Shen (1998, 2001), on the other hand, shows the significant advantage for auto commuters in accessing employment opportunities. He develops refined job-access measures that use the gravity model and take into account the supply and demand sides of the labor market and travel modes. His results indicate that job accessibility for people who depend on public transportation is considerably lower than that for people who use autos.

Still, the importance of job accessibility in employment outcomes has not been fully explored for disadvantaged workers without autos. More specifically, whether job accessibility for transit users is an important factor in employment outcomes for autoless workers has not yet been examined. For autoless workers, more job opportunities accessible by public transportation may enable them to achieve higher employment outcomes. Further, no study quantifies the disparity between those who own autos and those who do not in this job-access effect on employment outcomes. This dissertation therefore attempts to provide new evidence on spatial mismatch by exploring and quantifying the importance of job accessibility in employment outcomes for autoless workers.

It is important to clarify that this dissertation is a part of the spatial mismatch research but not an examination of Kain's spatial mismatch hypothesis, which focuses on inner-city minority people. The target population of my dissertation, however, is disadvantaged people without autos in metropolitan areas as a whole. In fact, for autoless workers, the spatial mismatch problem is likely to be worse in suburban areas where jobs are dispersed and transit systems are poorly developed, than in central-city areas with relatively concentrated employment and better access to public transit services.

In the next section, I review job-access measurements that are widely used by existing spatial mismatch studies.

2.2.4 Variation in Measurements of Job Accessibility

As noted earlier, a major reason for the disagreement over the empirical results of the spatial mismatch studies is variation in measurements of job accessibility. The most commonly used measurements are: (1) the number of jobs in an area of residence—the jobs-per-area measurement; (2) the ratio of jobs to workers in an area of residence—the jobs-to-workers-per-area ratio; (3) the commuting time; and (4) the gravity-based measure of job accessibility.

The use of the first measurement—the jobs-per-area measurement—is problematic since it counts jobs but does not take into account the number of people seeking these jobs. For example, an area with a large number of jobs but with an even larger number of workers has a high jobs-per-area measurement, but the actual job accessibility is lower.

The second measurement—the jobs-to-workers-per-area ratio—could also be misleading because it does not incorporate jobs and workers in areas outside an area of residence. For example, the jobs-to-workers-per-area ratio is high in a central business district (CBD) that has a great number of jobs but few workers. However, since many suburban residents are likely to commute to fill these jobs, the jobs-to-workers-per-area ratio in this CBD is likely to overestimate true job accessibility. Another example is an area with few jobs but even fewer workers. For such an area, the jobs-to-workers-per-area ratio is high, but jobs are actually not plentiful.

The third measurement, commuting time, has been most widely used in the spatial mismatch literature. Researchers who use commuting time as a measurement of job accessibility assume that a longer commuting time is associated with lower job accessibility and shorter commuting time with higher accessibility. Several factors, however, indicate a need for caution in the application of commuting time as a measurement. Commuting time including all travel modes, or commuting time of only auto drivers, is often equated with job accessibility. It is, however, important to control for travel modes since it is known that commuting time for transit users is much longer than that for auto users (Kasarda, 1995; Shen, 2000; Taylor and Ong, 1995). The second reason for caution is that commuting time tends to be longer for higher-income workers (Shen, 2000; Taylor and Ong, 1995). A possible explanation for this factor is that higher-income workers are more likely to trade commuting time for more spacious housing units at a lower price, for better environmental amenities, and/or for better schools and government services. Income differences must therefore be controlled for. The third limiting factor is that commuting time is observed only for employed workers. Unless these factors are appropriately controlled for, commuting time may not serve well as an appropriate measurement of job accessibility.

An increasing but still limited number of studies attempts to use the fourth measurement, the gravity-based measure of job accessibility. It is desirable that this measurement be designed to take into account both the supply and demand sides of the labor market and differences in travel modes. When these factors are appropriately incorporated, the gravity-based measure is quite appealing as a measurement of job accessibility, since it more accurately captures the actual job opportunities that are accessible with respect to residence than do the other three measurements described above. Shen (1998, 2001) develops the gravity-based measures that take these factors into account. By showing a great discrepancy in job accessibility between auto users and transit users, he indicates the importance of differentiating between travel modes in the measurements of job accessibility. Shen also notes the necessity for using proper employment statistics in calculating job accessibility. His findings suggest that using employment growth only, ignoring employment levels, is likely to distort a picture of spatial distribution of job opportunities, since the number of job openings generated by job turnover is far greater than the number of openings created by job growth.

To date, however, no spatial mismatch studies consider all of these factors in the gravity-based measures to examine the job-access effect on employment outcomes. In particular, the differentiation of travel modes, which is an extremely important factor, is often ignored. In this dissertation, I therefore employ gravity-based job-access measures that take into account proper employment statistics and travel modes to examine the effect of job accessibility on employment outcomes for low-skilled workers without autos. The calculation of the gravity-based measures is presented in Chapter 6, and the empirical analysis of the access-employment relationships is reported in Chapters 7 and 8.

Chapter 3: Research Design

Having presented the research questions and theoretical background previously, I next describe research design to explore the questions outlined in Chapter 1. This chapter proceeds as follows: Sections 3.1 and 3.2 describe data sources and study areas, respectively, and Section 3.3 explains methodology employed in this research.

3.1 OVERVIEW OF DATA

A problem in spatial mismatch studies is difficulty in obtaining useful data sets. Ideal data are person-level data with exact residential locations, but such data are not publicly available to protect confidentiality. Aggregated data, on the other hand, are available for small geographic areas, because individual persons cannot be identified by aggregated data. Since my study requires differentiation of travel modes and extraction of specific labor market segments (e.g., low-skilled workers without autos), primary data sources need to be data on individual persons.

For individual low-skilled workers, I therefore use the five-percent Public Use Microdata Samples (PUMS) of the 1990 Census of Population and Housing. The five-percent PUMS data provide five percent samples of the housing units and the persons in them. Personal and household characteristics are stored separately in the housing unit record and person record, respectively. The two records are matched with serial numbers to obtain both personal and household characteristics.

The type of detailed geography provided by PUMS is the "Public Use Microdata Area (PUMA)." Each PUMA identified by the five-percent PUMS has at least 100,000 persons. In large metropolitan areas, PUMAs are usually larger than zip code areas but smaller than counties.

The use of PUMS has some advantages. Since PUMS are comprehensive census data, the metropolitan comparisons are feasible. Additionally, the results can be compared with the results from further research, for example, a study using census 2000 data that are being gradually released.

Individual data on welfare recipients come from a survey of CalWORKs Transportation Needs and Assessment (CTNA) that include over 1,500 adults on welfare in Los Angeles. The survey was conducted between late November 1999 and February 2000. The CTNA data are described in Section 8.1.

This research uses various other sets of data, including the Summary Tape File 3A (STF3A) of the 1990 Census, the PL94-171 data of the 2000 Census, the 1990 Census Transportation Planning Packages (CTPP), the 1980 Urban Transportation Planning Packages (UTPP), OD commuting time matrices, and GIS data. The data set used in the analysis is explained in detail in each chapter.

3.2 STUDY AREAS

3.2.1 Selection of Study Areas

For the analysis focusing on general low-skilled workers, this study selects the following three metropolitan areas as the study areas: the Boston Primary Metropolitan Statistical Area (PMSA), nine-county San Francisco Bay Area, and Los Angeles PMSA. The three study areas are indicated in Figure 3.2.1.

One reason for selecting these three areas is that my particular interest is in the comparison of the importance of job accessibility for autoless workers between metropolitan areas with different urban spatial structures. For example, while the Boston PMSA is a relatively compact metropolitan area with a comparatively high level of transit usage (14% are transit commuters), the San Francisco Bay Area and Los Angeles PMSA are larger metropolitan areas with lower levels of transit usage (9% and 7%, respectively, are transit commuters). Another reason that this study focuses on these areas is the availability of data. These three are the only metropolitan areas where all the necessary data are obtainable. The only study area for the analysis focusing on welfare recipients is the Los Angeles PMSA, for which the survey data on welfare recipients are available.

3.2.1 Description of Study Areas

The Boston PMSA completely or partially overlaps with the following seven counties in Eastern Massachusetts: Bristol, Essex, Middlesex, Norfolk, Plymouth, Suffolk, and Worcester Counties.[3] The nine counties in the San Francisco Bay Area are Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties. Note that the census geography of the San Francisco—Oakland—San Jose Consolidated Metropolitan Statistical Area (CMSA) additionally includes Santa Cruz County, having a total of 10 counties.[4] I choose the nine instead of 10 counties since the regional planning and transportation agencies in the Bay Area—the Association of Bay Area Governments (ABAG) and the Metropolitan Transportation Commission (MTC)—define their regions as nine counties. The Los Angeles PMSA is equivalent to Los Angeles County.

This research uses three different geographic levels: the census tract, traffic analysis zone (TAZ), and Public Use Microdata Area (PUMA). Census tracts are relatively small areas with generally between 2,500 and 8,000 persons. Tracts are delineated by the U.S. Bureau of the Census to have similar socioeconomic characteristics. Traffic analysis zones, which vary in size depending on density and homogeneity of land uses, are used mostly in the field of transportation and are designated by local transportation agencies. Public Use Microdata Areas are geographic areas used solely by PUMS and are described in detail in Section 3.1.

The three geographic levels are used according to the type of the data. Each of the succeeding chapters employs different data that best suit the purpose of the analysis. Census tracts are used mainly with the 1990 Summary Tape File 3A (STF3A), TAZs are used with the 1990 Census Transportation Planning Packages (CTPP) or the 1980 Urban Transportation Planning Packages (UTPP), and PUMAs are used with the 1990 PUMS.

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[3] The Boston—Worcester—Lawrence Consolidated Metropolitan Statistical Area (CMSA), which is larger than the Boston PMSA, has two additional counties: Hillsborough and Rockingham Counties in New Hampshire.

Table 3.2.1 Land characteristics of study areas

	Boston		San Francisco		Los Angeles	
	PMSA	Boston city	Nine-county Bay Area	San Francisco city	PMSA	Los Angeles city
Land area (sq. mile)	1,760	48	6,923	47	4,060	469
Number of census tracts	628	165	1,382	152	1,652	530
Number of TAZs	775/790	193	1,099	126	849	342
Number of PUMAs	21	5	48	6	58	21

Note: The land area of 775/790 is larger (2383/2834 sq. miles) than that of the Boston PMSA. The land area of 12 PUMAs (1,400 sq. miles) is smaller than the Boston PMSA since PUMAs that are partially and not completely within the Boston PMSA were excluded. Santa Catalina Island and San Clemente Island are excluded from TAZs in Los Angeles County. Zones in central cities are those that are completely within the cities.

Table 3.2.1 shows the land characteristics of the study areas. The three metropolitan areas vary in size substantially. The land area of the nine-county San Francisco Bay Area is markedly large, 6,900 square miles, while the Boston PMSA is more compact, having 1,800 square miles of land. The Los Angeles PMSA stands around the middle with 4,100 square miles of land.

The size of the central city differs considerably between Los Angeles and the other two areas. In this study, I define the central city as the city of Boston for the Boston PMSA, the city of San Francisco for the San Francisco Bay Area, and the city of Los Angeles for the Los Angeles PMSA. The city of Los Angeles is much larger (496 square miles) than the cities of Boston and San Francisco (48 and 47 square miles, respectively). Consequently, the percentage of the central-city area in the metropolitan area is much higher in Los Angeles (12%) than in Boston and San Francisco (3% and 1%, respectively). The difference in land areas should be kept in mind since this study sometimes presents statistics for total metropolitan areas and the central-city areas.

As the numbers of the geographic units in Table 3.2.1 indicate, census tracts are the most spatially disaggregated areas among the three geographic levels, and PUMAs are the most aggregated areas. Traffic analysis zones (TAZs) are similar to census tracts but are slightly more aggregated. The geographic boundaries in the three study areas are depicted in Figures 3.2.2 to 3.2.4. Note that the land area of 775/790 TAZs is larger than the Boston PMSA, and the land area of 21 PUMAs is smaller than the Boston PMSA, as indicated in Figure 3.2.2.

[4] The San Francisco PMSA includes only three counties: Marin, San Francisco, and San Mateo Counties.

Figure 3.2.2 presents the two different TAZ coverages for the Boston PMSA; the 775 zones are used for the calculation of job accessibility, and the 790 zones are utilized for Chapter 5, which uses the 1990 CTPP. The 775-zone system was originally developed in 1975 based on 1970 census geography. It was expanded to 787 zones in 1980 with the addition of 12 communities south of Boston and disaggregated to 790 zones in 1990 to isolate the Boston Harbor Islands (zones 900-902) from the mainland zones to which they had originally been attached. Some of these zones were modified slightly in 1990, but the original 775 zones are generally unchanged since 1975.

The coverage of 21 PUMAs is smaller than the Boston PMSA since these 21 PUMAs are completely within the Boston PMSA, and PUMAs that are partially but not completely within the Boston PMSA are excluded. The excluded zones that partially overlap with the Boston PMSA are five PUMAs identified by as 01000, 01300, 03800, 04100, and 04200.

Table 3.2.2 Some socioeconomic characteristics of study areas

	Boston		San Francisco		Los Angeles	
	PMSA	Boston city	Nine-county Bay Area	San Francisco city	PMSA	Los Angeles city
Population	2,870,650	574,283	6,023,577	723,959	8,863,164	3,485,398
25+ years old < HS diplomas (%)	16	24	17	22	30	33
White (%)	85	59	61	47	41	37
African-American (%)	7	24	9	11	11	13
Hispanic (%)	4	10	15	13	37	39
Asian (%)	3	5	15	29	10	9
Other race (%)	0	1	1	1	1	1
Unemployment rate	6.2	8.3	5.2	6.3	7.4	8.4
Median household income*	$40,491	$29,180	$41,459	$33,414	$34,965	$30,925
Poverty (%)	8	19	9	13	15	19
Household without auto (%)	17	38	11	31	11	15
Commute by auto (%)*	76	51	81	50	86	81
Commute by public transportation* (%)	14	32	9	34	7	11
Mean travel-time work (minute)*	24.5	24.9	25.6	26.9	26.5	26.5

Note: Data source: STF3A of the 1990 U.S. Census. White, African-American, Asian, and other race are non-Hispanic. *Statistics for the Bay Area are for the San Francisco—Oakland—San Jose Consolidated Metropolitan Statistical Area (CMSA) that adds Santa Cruz County.

Table 3.2.2 reports some socioeconomic characteristics that are relevant to this study. The Los Angeles PMSA is the most populated area, having about 9 million people. The nine-county San

Francisco Bay Area accommodates approximately 6 million people, and the Boston PMSA has about 3 million.

The characteristics vary across the three metropolitan areas, particularly between Los Angeles and the other two areas. The socioeconomic status in Los Angeles is overall lower than that in Boston and San Francisco. Low-skilled persons (persons 25 years or older without high school diplomas) are more common in Los Angeles, where 30% are low-skilled, while in Boston and San Francisco, the figures are much lower, 16% and 17%, respectively. The unemployment rate and the proportion of persons in poverty are higher in Los Angeles (7.4% and 15%, respectively) than in Boston (6.2% and 8%, respectively) and San Francisco (5.2% and 9%, respectively). Furthermore, the median household income of Los Angeles ($34,965) is lower than that of Boston ($40,491) and San Francisco ($41,459).

Los Angeles is a highly multiethnic area with a 59% nonwhite population. The Hispanic population is particularly large in Los Angeles, accounting for 37% of the total population. In San Francisco, 39% are minority members, and compared to the other two metropolitan areas the percentage of Asian persons is noticeably high, 15%. In Boston, the great majority (85%) of residents are white persons.

In terms of transportation, Boston shows uniqueness. Although in all three areas the great majority of people rely on autos, Boston is a more transit-dependent area than the other two areas. The percentage of households without autos in Boston is 17%, which is higher than San Francisco and Los Angeles' 11% (the same percentage for both). In Boston, 14% use public transportation to work and 76% use autos. San Francisco and Los Angeles are more auto dependent, having 81% and 86% auto commuters, respectively, and only 9% and 7% transit commuters, respectively. Note that even though the San Francisco Bay Area is a heavily auto-dependent area, its central city, San Francisco City, has high proportions of autoless persons and transit users (31% and 34%, respectively). This is because the city of San Francisco has well-developed transit networks, but the transit coverage is poor in most suburban areas in the Bay Area.

The travel time for public transportation is usually considerably longer than that for autos. Interestingly, however, the mean commuting time is shortest in Boston (24.5 minutes), which has the highest proportion of transit users (14%), and the mean commuting time is longest in Los Angeles, which has the lowest proportion of transit commuters (7%). San Francisco's mean commuting time is around the middle, 25.6 minutes. The shorter commuting time in Boston may reflect its compactness, and the longer commuting time in Los Angeles is perhaps related to its sprawling urban structure and well-known congestion.

The socioeconomic profiles are consistently lower in the central cities than in suburban areas. Low-skilled persons, minority races, unemployed persons, and poverty are more prevalent in the central cities, and the median household incomes are lower there.

The geographies of population, median household income, low-skilled persons, and autoless persons are presented in Figures 3.2.5 to 3.2.7 Note that the Santa Catalina Island and San Clemente Island in the Los Angeles PMSA are not shown in the maps. In Boston, areas with high population density are found around the city of Boston and few outer suburban areas including Lawrence and Lowell. In the San Francisco Bay, densely-populated areas include zones around the city of San Francisco, Oakland, San Jose, and scattered zones near the San Francisco Bay Area. Areas with high concentrations of population in Los Angeles are located around the south central parts of Los Angeles County, including downtown Los Angeles. These well-populated areas largely overlap with areas with lower income and higher percentages of low-skilled persons and autoless persons.

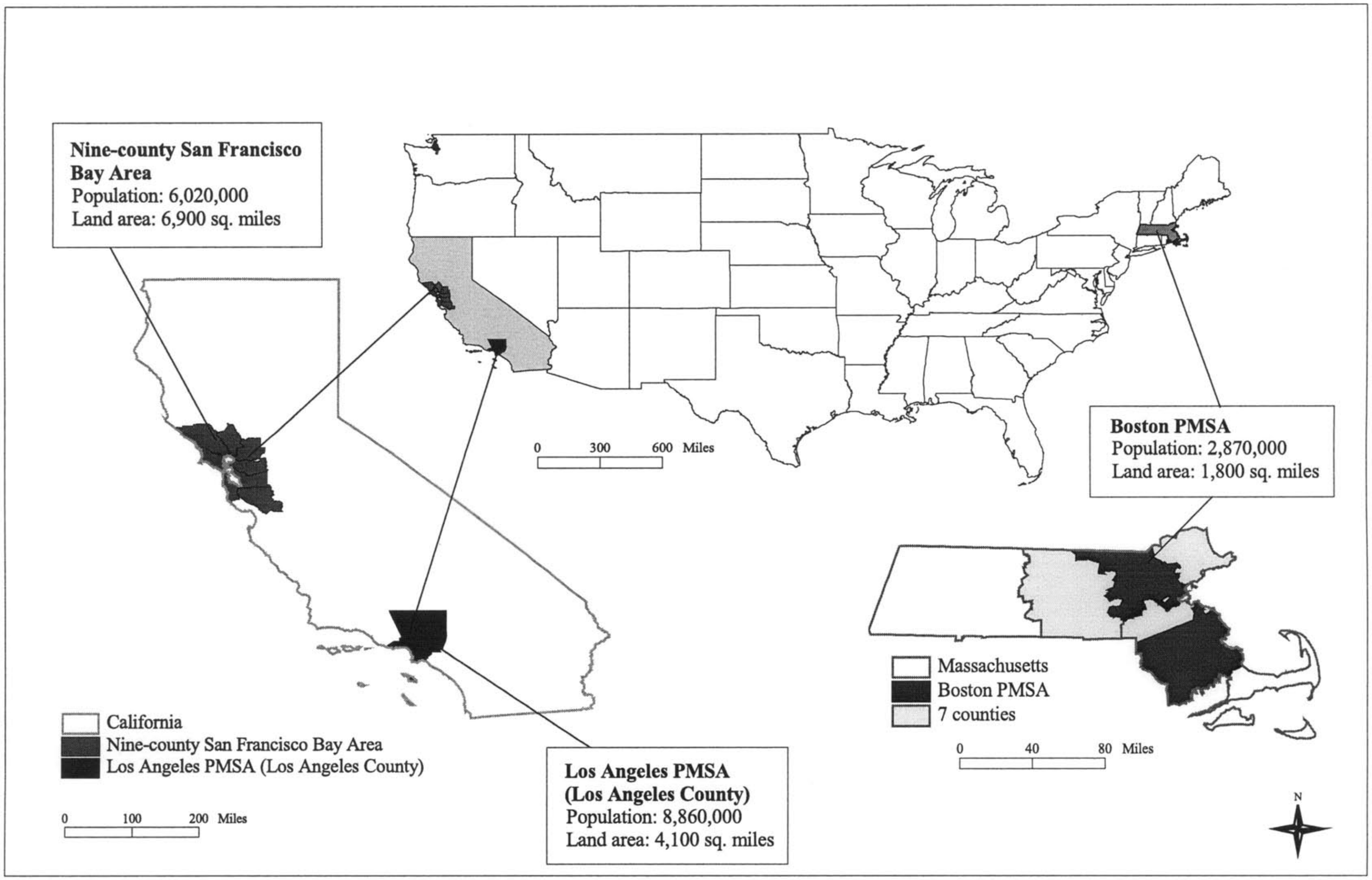

Figure 3.2.1 Study areas: Boston, San Francisco, and Los Angeles metropolitan areas

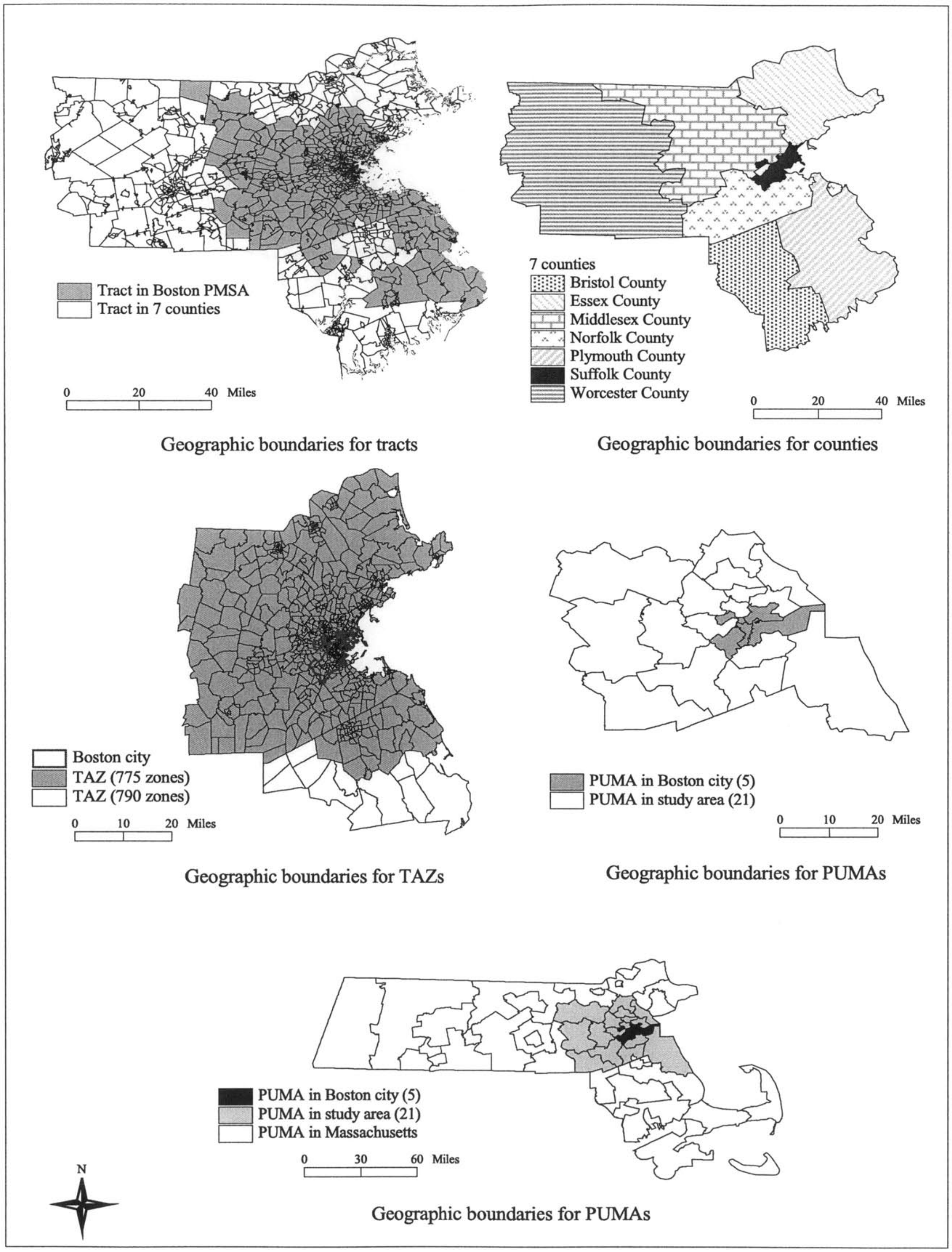

Figure 3.2.2 Geographic boundaries in Boston metropolitan area

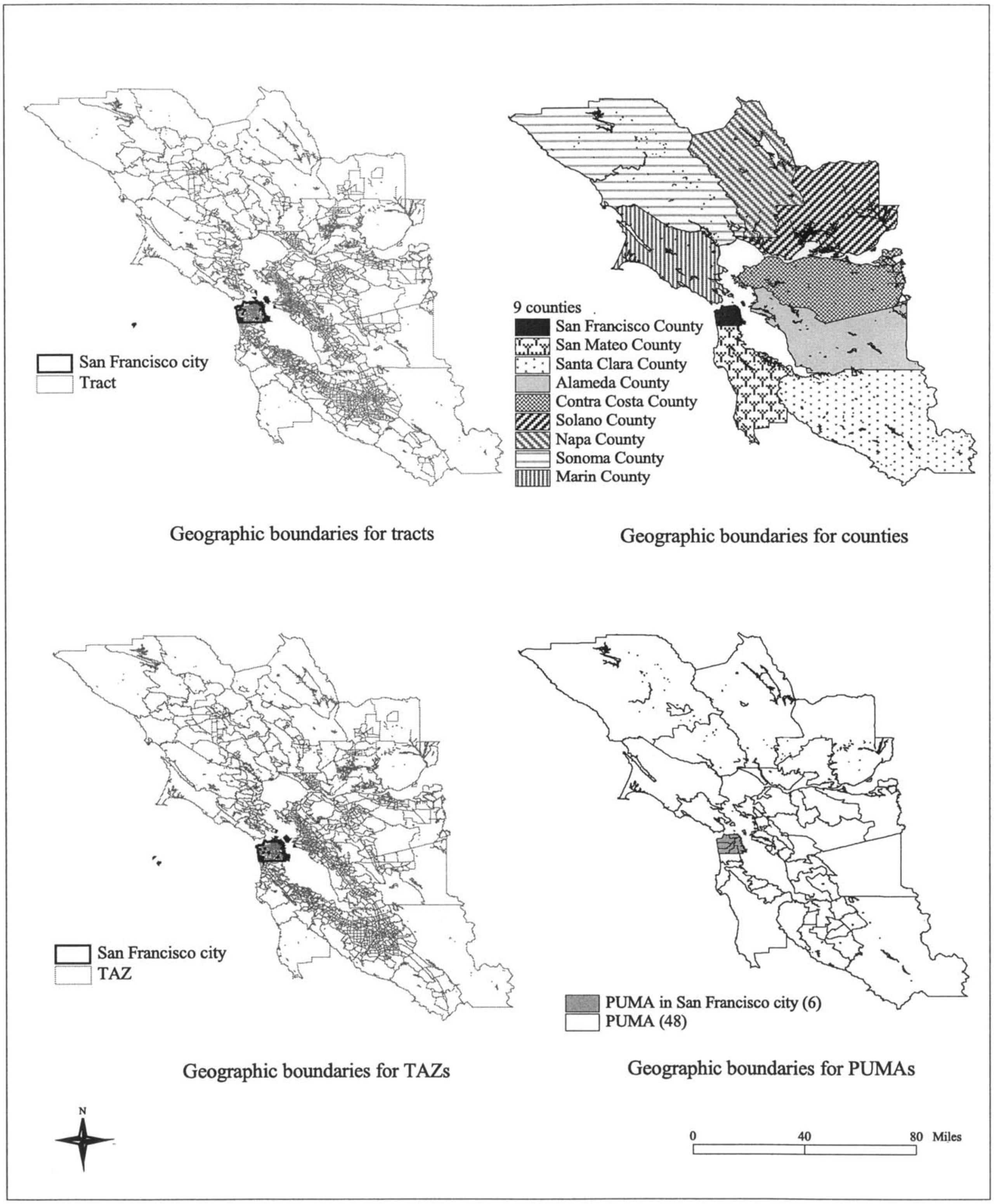

Figure 3.2.3 Geographic boundaries in nine-county San Francisco Bay Area

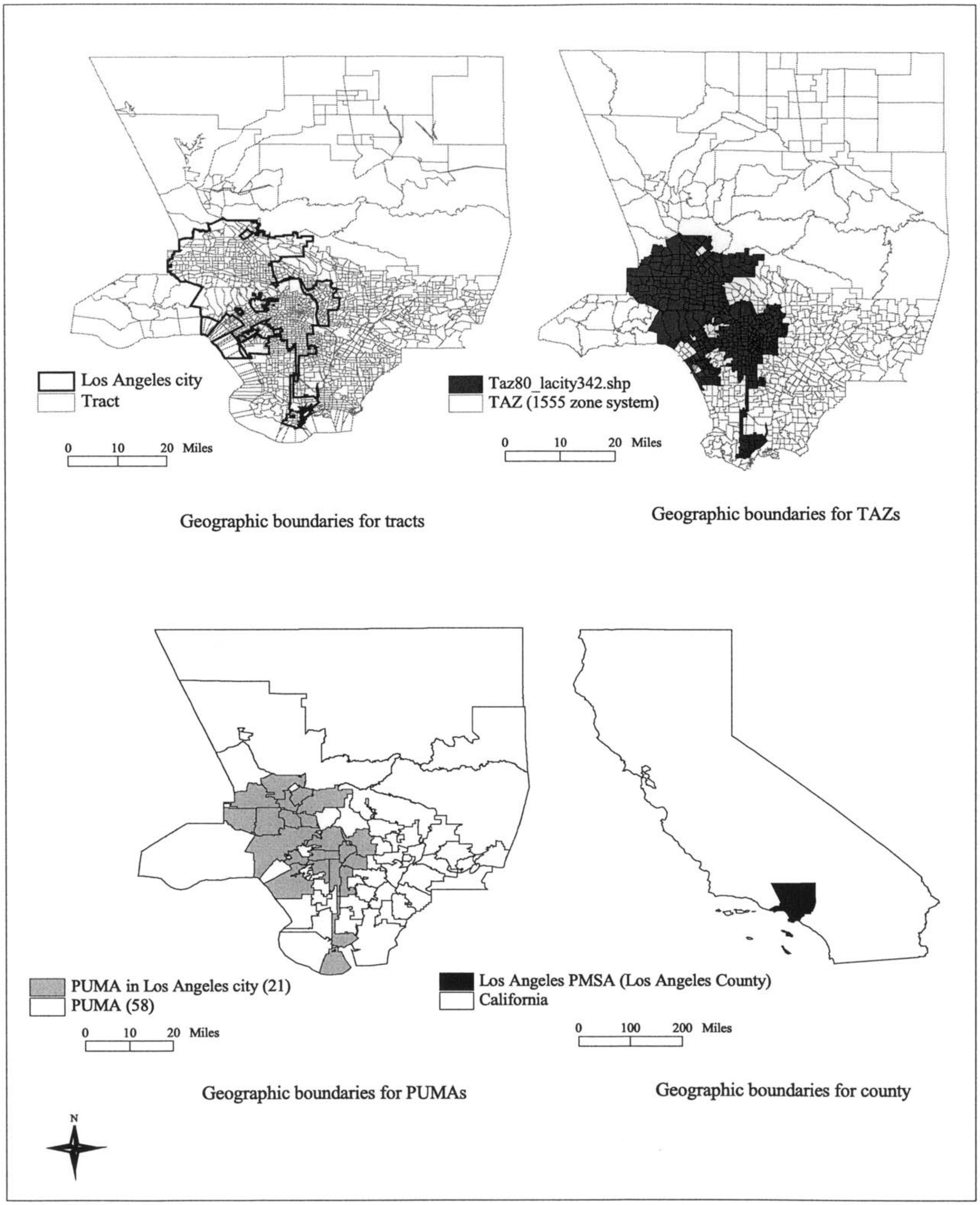

Figure 3.2.4 Geographic boundaries in Los Angeles metropolitan area

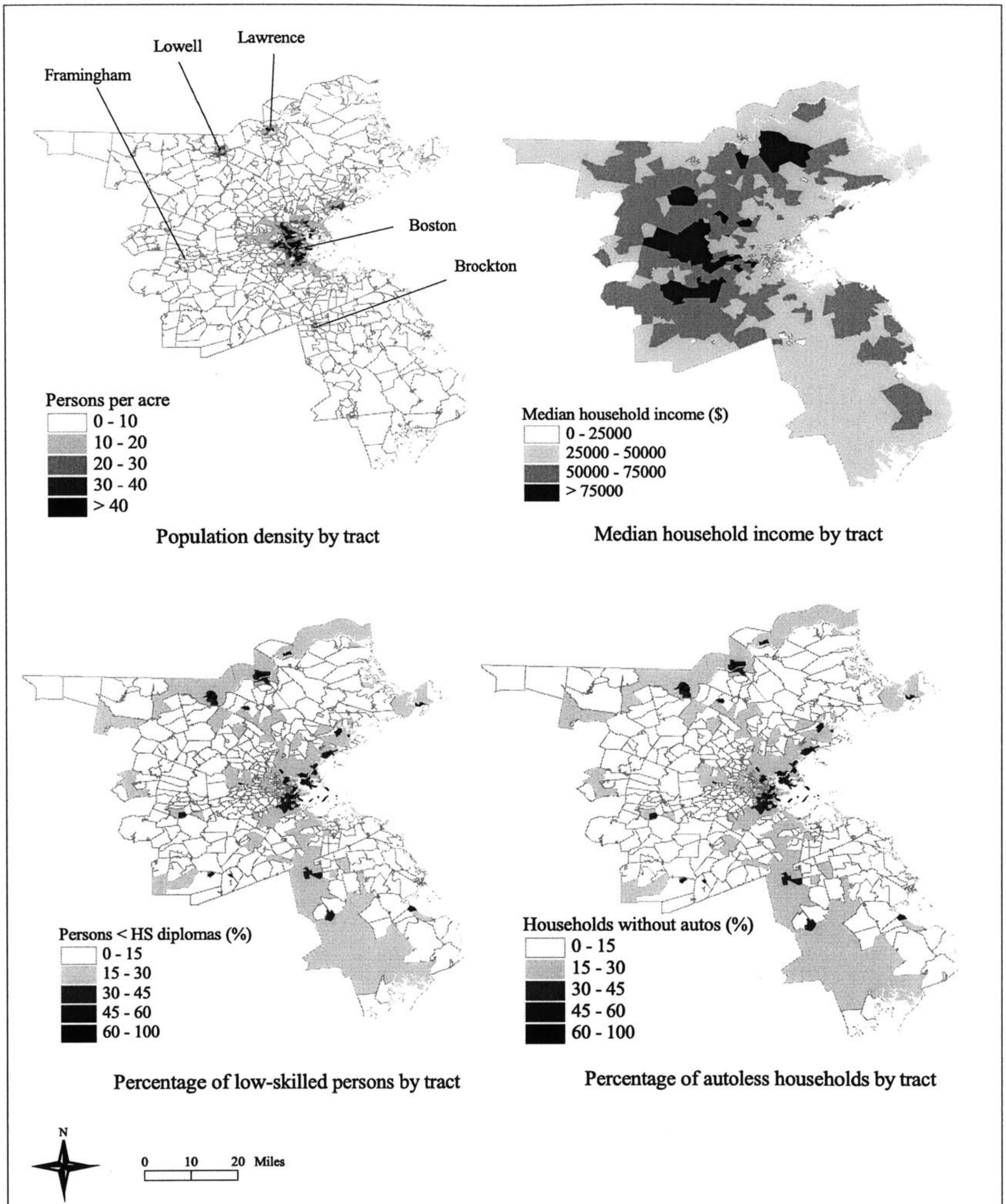

Figure 3.2.5 Some socioeconomic characteristics of Boston metropolitan area (5 counties)

(Source: 1990 STF3A)

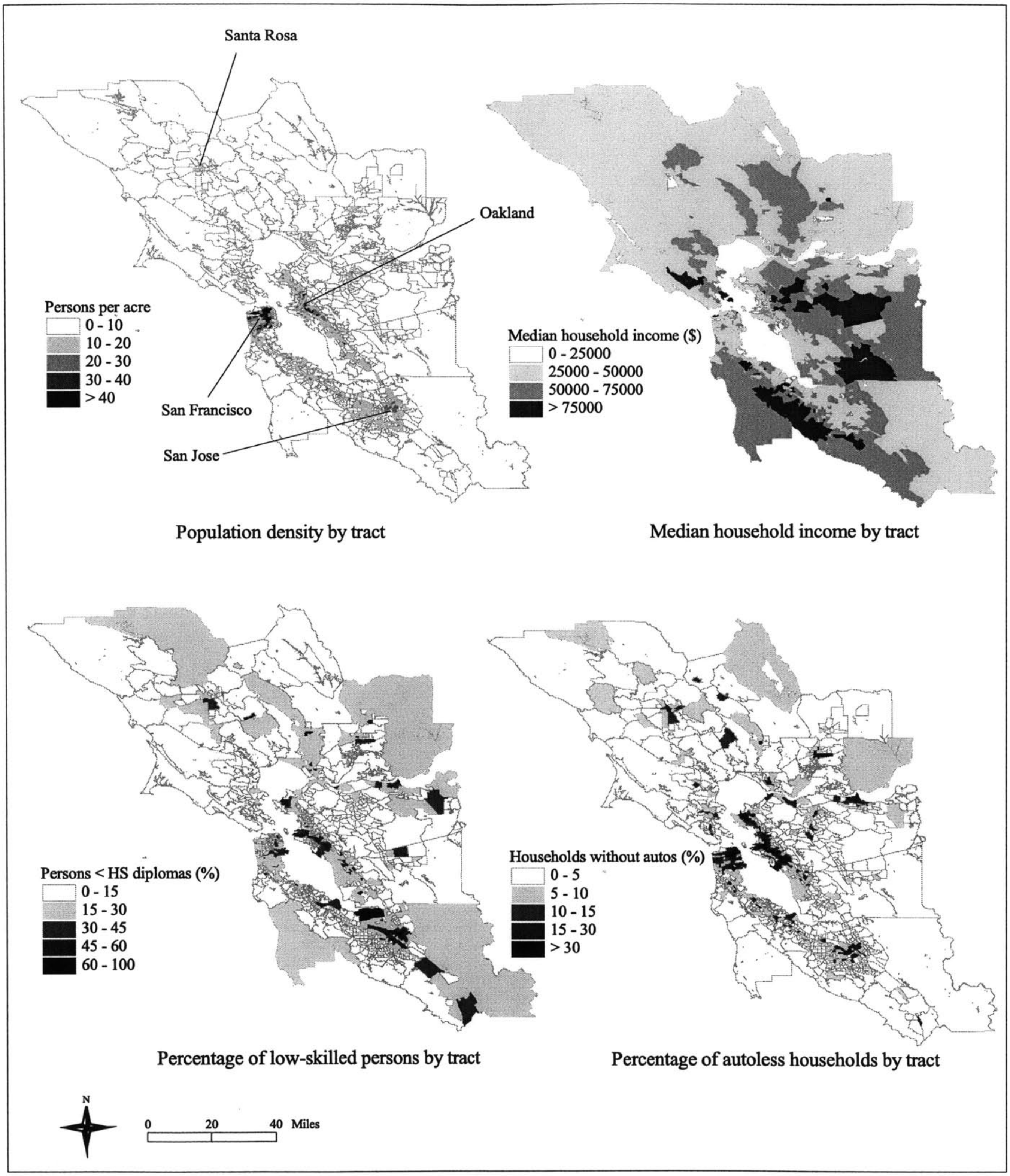

Figure 3.2.6 Some socioeconomic characteristics of nine-county San Francisco Bay Area

(Source: 1990 STF3A)

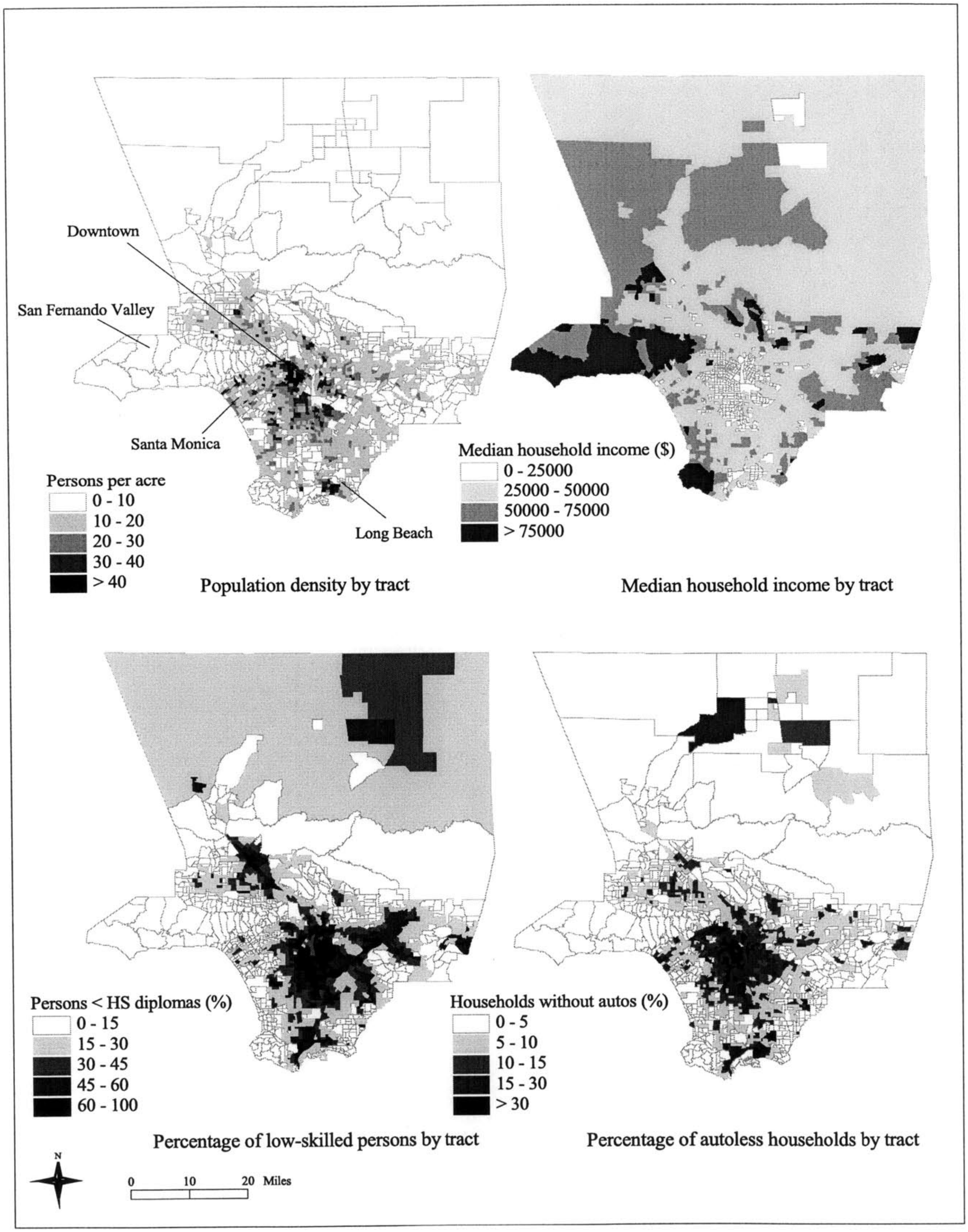

Figure 3.2.7 Some socioeconomic characteristics of Los Angeles metropolitan area
(Source: 1990 STF3A)

3.3 OVERVIEW OF METHODOLOGY

This section provides a quick overview of methodology employed in this dissertation. Since each chapter takes a unique approach to answering the research questions outlined in Chapter 1, a thorough description of data and methodology is presented in each chapter.

I first clarify the basic terminology. As stated already, the focus groups in this research are low-skilled workers and welfare recipients, two of the most disadvantaged groups in today's urban labor market. The term "workers" indicates persons who are 16 years and over and in the labor force, which corresponds to the general definition in labor statistics. The category of workers therefore excludes persons "not in the labor force," which mainly consists of students, homemakers, retired workers, seasonal workers enumerated in unpaid family work (less than 15 hours during the reference week).

I define low-skilled workers as workers without high school diplomas, generally the lowest educational category. Note that the results may be sensitive to the definitions of low-skilled workers; for instance, if low-skilled workers are defined as workers with high school diplomas but no advanced degrees, the results may change significantly. Since the focus groups of this study are those who are most disadvantaged, the different definitions are not explored in this dissertation, but are of interest to my future research. Welfare recipients analyzed are adults on welfare in Los Angeles County.

The analysis starts with Chapter 4, which investigates the demographic, economic, and transportation characteristics of low-skilled workers in general and low-skilled autoless workers in particular. This chapter uses the individual-level 1990 PUMS data, which allow users to create any tabulation of interest. To identify the characteristics specific to low-skilled autoless workers, the characteristics of this worker group are compared with those of the two comparison groups—higher-skilled workers and low-skilled workers with autos. The demographic characteristics examined are age, gender, household structure, race, and poverty, while the economic characteristics include employment status, income, earnings, and occupation. The transportation characteristics involve auto ownership, travel modes, and commuting time. These characteristics are compared across the three study areas: Boston, San Francisco, and Los Angeles.

The second part of the analysis looks into the spatial distributions of low-skilled workers and jobs in Chapter 5. Understanding how workers and jobs are distributed within and across the metropolitan areas is important, before examining spatial accessibility to job opportunities. Data are from 1990 CTPP, which provide data on jobs as well as on workers for small geographic areas. To examine whether the spatial distributions of workers and jobs are unique to the low-skilled group, the distributions are compared with those of its counterpart, the high-skilled group. The distributions are first presented in a table that shows workers and jobs by skill and by aggregated location—central city versus suburbs. Tabulated statistics for the central city versus suburban division convey rather aggregated pictures of the spatial distributions, but they are useful in gaining a quick understanding of the overall spatial patterns. More disaggregated pictures of the spatial patterns are then visualized in maps, which are presented in three dimensions to show great spatial variability.

The computation of refined job-access measures in Chapter 6 is the third part of the analysis. The job-access measures are calculated based on the formulas that capture the two important factors—supply and demand of the labor market and travel modes. These measures represent the ratios of job openings to job seekers, but unlike the simple jobs-to-workers-per-area ratio, the measures take into account job openings and job seekers not only within an area of residence but also in areas beyond that area of residence, depending on travel modes and travel costs. The measures therefore better represent true accessibility to job opportunities. A comprehensive review of various job-access measurements is presented in Section 2.2. Main data for the computation are the 1980 Urban Transportation Planning Packages (UTPP), 1990 CTPP, and OD commuting time matrices. Resulting measures are mapped in two geographic levels—TAZ and PUMA—to show the spatial variations in job accessibility within and across the study areas, and are presented separately for transit users and auto users to exhibit a great discrepancy between the two groups.

The analysis proceeds to one of the major parts of this dissertation, Chapter 7. Incorporating the refined job-access measures differentiated by travel mode into statistical models, in this chapter I develop a statistical framework to examine whether improving job accessibility of transit (relative to autos) enhances employment outcomes for low-skilled autoless workers. The framework is also designed to investigate the disparity in the job-access effect between low-skilled autoless and auto-owning workers. This chapter combines three data sources—individual low-skilled workers from 1990 PUMS, the computed job-access measures, and neighborhood data from the Summary Tape File 3A (STF3A) of the 1990 Census. The chapter analyzes three typical employment outcomes: the probability of employment, the probability of working 30 or more hours per week, and earnings. To deal with the sample selection problem, I apply multinomial logit (MNL) and the Heckman correction method for the models. The results are used to examine whether the job-access effect for autoless workers varies across the three metropolitan areas with different urban spatial structures.

The final part of the analysis is Chapter 8, another major part of this dissertation. In this chapter, I employ the analytical framework developed in Chapter 7 to examine the job-access effect on employment outcomes for another disadvantaged group—welfare recipients in Los Angeles. Data are from individual adults on welfare from the survey of CalWORKs Transportation Needs and Assessment (CTNA) conducted between late 1999 and February 2000. In this chapter, new job-access measures are calculated using the 1998 American Business Information (ABI) data and OD commuting time matrices for 2000. Theseaccess measures are incorporated into MNL models to estimate the job-access effect on two employment outcomes: the probability of employment and earnings. As in the case of the analysis in Chapter 7, I also investigate the disparity in the job-access effect between autoless and auto-owning welfare recipients.

Chapter 4: Socioeconomic Characteristics of Low-Skilled Workers

The focus group of this research is low-skilled workers without automobiles. This chapter examines the socioeconomic characteristics of low-skilled workers in general and low-skilled autoless workers in particular. The characteristics are presented for the three study areas: the Boston Primary Statistical Area (PMSA), the nine-county San Francisco Bay Area, and Los Angeles PMSA (i.e., Los Angeles County).

The data are from the five-percent Public Use Microdata Samples (PUMS) of the 1990 Census of Population and Housing. Since PUMS are person-level data with almost all the records from census's long-form questionnaires, a variety of tabulations interrelating any set of variables can be constructed.

The samples include persons who are 16 years and over and in the labor force. Note that the samples exclude persons not in the labor force, most of whom are students, housewives, retired workers, and seasonal workers enumerated in unpaid family work (less than 15 hours during the reference week). Low-skilled workers in this research are defined as workers without high school degrees.

In order to clarify the socioeconomic characteristics specific to low-skilled workers and low-skilled workers without autos, I first compare the characteristics of low-skilled workers with the characteristics of higher-skilled workers, defined as workers with high school degrees or higher. As a reference, I also show the statistics for total workers. Concentrating on low-skilled workers, I then compare the characteristics of autoless persons with the characteristics of auto-owning persons.

Note that observations with missing values are excluded from the statistics, and the excluded observations account for about 1% in each sample. For example, due to missing values in the auto-ownership variable, the total number of low-skilled workers is not equal to the sum of the number of low-skilled autoless workers and the number of low-skilled auto-owning workers. Also note that numbers are rounded, and variables therefore may generate the sum of the percentages for a category (e.g., race) not equal to 100%. Since PUMS data are weighted, the population size listed in the tables is estimated by adding the weights of all persons that possess the characteristics of interest.

Sections 4.1, 4.2, and 4.3 describe the demographic, economic, and transportation characteristics, respectively, and Section 4.4 summarizes the results.

4.1 DEMOGRAPHIC CHARACTERISTICS

Table 4.1.1 shows the demographic characteristics for low-skilled workers (i.e., workers without high school degrees) in the three metropolitan areas, comparing them with higher skilled workers (i.e., workers with high school degrees or higher).

Table 4.1.1 Demographic characteristics of workers by education in study areas

	Boston			San Francisco			Los Angeles		
	Total workers	<HS degrees	>= HS degrees	Total workers	<HS degrees	>= HS degrees	Total workers	<HS degrees	>= HS degrees
Number of observations	72,283	8,362	63,921	159,555	21,388	138,167	218,869	58,981	159,888
Population size	1,516,489	178,106	1,338,383	3,311,455	447,225	2,864,230	4,547,476	1,207,035	3,340,441
% of total workers	100%	12%	88%	100%	14%	86%	100%	27%	73%
Average age	38	38	38	38	36	38	37	35	38
% Female	47%	43%	48%	45%	40%	46%	43%	38%	45%
% Female-headed household	18%	23%	23%	21%	20%	21%	21%	19%	22%
% Non-Hispanic white	87%	73%	89%	69%	52%	72%	56%	38%	63%
% Non-Hispanic black	7%	12%	6%	7%	7%	7%	10%	6%	11%
% Hispanic	2%	7%	2%	4%	9%	4%	9%	18%	5%
% Non-Hispanic Asian or Pacific	3%	5%	3%	14%	16%	14%	11%	5%	13%
% Other race	1%	3%	1%	5%	15%	3%	15%	32%	8%
% Poor	4%	9%	4%	5%	12%	4%	9%	19%	6%

Note: Data source: 1990 PUMS. Universe: persons 16 years or older in the labor force.

The estimated population of low-skilled workers is 178,000 (8,400 observations) in the Boston PMSA, and about two and half times of that, 447,000 (21,400 observations), in the nine-county San Francisco Bay Area. Los Angeles has the largest low-skilled population, 1,207,000 (59,000 observations), roughly seven times that of Boston and three times that of San Francisco. The proportions of low-skilled workers in Boston and San Francisco are similar, 12% and 14% respectively, but the proportion is considerably higher in Los Angeles, 27%.

While the average age and the percentage of workers in female-headed households vary only slightly between low-skilled workers and higher-skilled workers, noticeable differences are discerned for the gender, race, and poverty compositions.

Low-skilled workers are more likely to be men than are higher-skilled workers. In all three areas, the percentages of female persons are lower for low-skilled workers (38%-43%) than for higher-skilled workers (45%-48%).

The share of minority population is consistently greater for low-skilled workers than for higher-skilled workers in the three areas, but the racial composition is quite different. In Boston, even for low-skilled workers the great majority, 73%, are white, and among the minority groups African-American persons make up the highest proportion, 12%. The other minority groups in Boston have lower proportions: 7% for Hispanics, 5% for Asians, and 3% for other-race persons (minority members other than African-Americans, Hispanics, and Asians). In San Francisco, white persons account for about half of low-skilled workers, and among minority members Asian persons and other-race persons account for great proportions, 16% and 15%, respectively.

Los Angeles is quite a hetero-racial area. For low-skilled workers in Los Angeles, white persons are no longer the majority, making up only 38%, roughly half of Boston's 73%. Among the minority groups, other-race workers account for the largest proportion, 32%, followed by Hispanic workers' 18%. For workers with high school degrees or higher, on the other hand, the proportions of other-race persons and Hispanic persons in Los Angeles sharply drop to 8% and 5%, respectively, while the proportions of African-American persons and Asian persons rise to 11% and 13%, respectively. The proportions of other-race persons and Hispanic persons also become much lower for higher-skilled workers in San Francisco.

These results are not surprising, given the fact that California has a large number of immigrants from Mexico, and that many Hispanic persons have no high school degrees. Indeed, in 1990, 58% of Hispanic residents whose country of origin is Mexico lived in the Western region, whereas only 1% lived in the Northeastern region. In the West, California has the largest number of Hispanic immigrants, admitting 63,221 Mexicans in 1993 (U.S. Census Bureau 1995). Hispanic workers are highly concentrated in the low-skill cohort. The proportion of persons with less than high school diplomas is 47% for the Hispanic population, which is much higher than 18% for whites, 27% for African-Americans, and 15% for Asians (U.S. Census Bureau 1995).

Low-skilled workers are more likely to be poor than are high school graduates, as one would expect. For low-skilled workers, Los Angeles has a remarkably higher proportion (19%) of poor persons (persons below the census's poverty threshold) than do Boston and San Francisco (9% and 12%, respectively).

Table 4.1.2 Demographic characteristics of low-skilled workers by auto ownership in study areas

	Boston		San Francisco		Los Angeles	
	No auto	Own auto	No auto	Own auto	No auto	Own auto
Number of observations	1,234	7,052	1,869	19,241	6,979	51,678
Population size	28,511	147,644	40,940	399,345	145,826	1,055,539
% of total workers	2%	10%	1%	12%	3%	23%
Average age	39	38	38	36	34	35
% Female	49%	42%	45%	40%	41%	37%
% Female-headed household	50%	18%	39%	18%	37%	17%
% Non-Hispanic white	46%	78%	31%	54%	28%	40%
% Non-Hispanic black	25%	10%	16%	7%	8%	6%
% Hispanic	14%	6%	13%	8%	26%	17%
% Non-Hispanic Asian or Pacific	7%	5%	27%	15%	4%	5%
% Other race	7%	2%	14%	16%	33%	32%
% Poor	24%	6%	28%	10%	39%	16%

Note: Data source: 1990 PUMS. Universe: persons 16 years or older in the labor force, without high school degrees.

Table 4.1.2 summarizes the demographic characteristics of low-skilled workers by auto ownership. The estimated population of low-skilled autoless workers is approximately 29,000 in Boston, 41,000 in San Francisco, and 146,000 in Los Angeles. The average ages for autoless workers and auto-owning workers are similar across the three metropolitan areas, but the other statistics show noticeable differences.

Autoless workers are somewhat more likely to be female than are auto-owning workers, and they are far more likely to be in female-headed households. This trend is particularly strong in Boston. Among low-skilled autoless workers in Boston, the proportions of women and persons in female-headed households are 49% and 50%, respectively, whereas for low-skilled workers with autos, the proportions are lower, 42% and 18%, respectively.

The minority population is considerably larger for autoless workers than for auto-owning workers. For low-skilled workers without autos, white persons account for less than half in all study areas, even in Boston, where white persons make up a high proportion, 73% of low-skilled workers and 87% of total workers. Of low-skilled autoless workers in Los Angeles, a highly multiethnic area, only 28% are white, and Hispanic and other-race persons compose great proportions, 26% and 33%, respectively.

Autoless workers are more likely to be in poverty than are auto-owning workers. Among autoless workers, the proportions of poor persons are quite high, ranging from 24% to 39%, which are remarkably higher than those for auto-owning workers, 6% to 16%.

4.2 ECONOMIC CHARACTERISTICS

Table 4.2.1 reports the economic characteristics of low-skilled workers, comparing them with those of higher-skilled workers. The table also presents the statistics for total workers as a reference.

As expected, the economic status of low-skilled workers is lower than that of higher-skilled workers. The unemployment rates for low-skilled workers (12%-13%) are higher than those for higher-skilled workers (4%-5%), and the median household incomes and the median person's earnings are less for low-skilled workers (approximately $33,000-$44,000 and $11,000-$12,000, respectively) than for workers with high school degrees or higher ($52,000-$59,000 and $24,000-$25,000, respectively).

The table also presents information on the distribution of workers by occupation. The proportions of workers in potentially high-skill occupations, which include the executive, administrative, and managerial occupation (occupation 1), professional specialty occupation (occupation 2), and technical and related support occupation (occupation 3), are lower for low-skilled workers than for higher-skilled workers.

The occupations for which many low-skilled workers would be qualified are the private household service occupation (occupation 6), farming, forestry, fishing occupation (occupation 7), precision, production, craft repair occupation (occupation 8), and operator, fabricator, laborer occupation (occupation 9). The proportion of low-skilled workers in each of these occupations is consistently higher for low-skilled workers than for higher-skilled workers. One may argue that the sales occupation (occupation 4) is in the low-skilled category. The sales category, however, includes relatively high-skill occupations, such as sales representatives and finance and business services.

Table 4.2.1 Economic characteristics of workers by education in study areas

	Boston			San Francisco			Los Angeles		
	Total workers	<HS degrees	>= HS degrees	Total workers	<HS degrees	>= HS degrees	Total workers	<HS degrees	>= HS degrees
% Unemployed	6%	13%	5%	5%	12%	4%	7%	13%	5%
Median household income	$56,779	$44,000	$58,500	$54,500	$42,450	$56,500	$46,227	$33,318	$52,000
Median person's earnings	$23,000	$12,000	$24,356	$24,000	$12,000	$25,000	$19,600	$11,000	$24,000
Occupations (%)									
1: Executive, Administrative, Managerial	16%	4%	18%	16%	4%	17%	13%	4%	16%
2: Professional specialty	19%	2%	22%	17%	2%	19%	14%	2%	18%
3: Technical and related support	5%	1%	5%	5%	1%	5%	3%	1%	4%
4: Sales	11%	13%	11%	12%	11%	12%	12%	9%	12%
5: Administrative support/ clerical	18%	13%	19%	17%	10%	18%	17%	9%	20%
6: Private household service	12%	28%	10%	12%	27%	9%	12%	21%	9%
7: Farming, forestry, fishing	1%	1%	1%	1%	5%	1%	1%	3%	1%
8: Precision, production, craft repair	8%	13%	8%	10%	15%	10%	11%	17%	9%
9: Operator, fabricator, laborer	9%	24%	7%	11%	24%	8%	16%	35%	10%
10: Military	0%	0%	0%	0%	0%	0%	0%	0%	0%

Note: Data source: 1990 PUMS. Universe: persons 16 years or older in the labor force.

Table 4.2.2 Economic characteristics of low-skilled workers by auto ownership in study areas

	Boston		San Francisco		Los Angeles	
	No auto	Own auto	No auto	Own auto	No auto	Own auto
% Unemployed	23%	11%	19%	11%	18%	12%
Median household income	$23,000	$47,110	$22,100	$44,600	$19,200	$35,607
Median person's earnings	$10,750	$12,480	$9,600	$12,000	$8,640	$12,000
Occupations (%)						
1: Executive, Administrative, Managerial	3%	4%	3%	4%	2%	4%
2: Professional specialty	4%	2%	2%	1%	1%	2%
3: Technical and related support	1%	1%	1%	1%	1%	1%
4: Sales	9%	14%	9%	11%	7%	9%
5: Administrative support/ clerical	12%	13%	9%	10%	6%	9%
6: Private household service	39%	26%	39%	26%	28%	21%
7: Farming, forestry, fishing	0%	1%	4%	5%	3%	3%
8: Precision, production, craft repair	8%	14%	12%	16%	15%	17%
9: Operator, fabricator, laborer	24%	24%	21%	25%	37%	34%
10: Military	0%	0%	0%	0%	0%	0%

Note: Data source: 1990 PUMS. Universe: persons 16 years or older in the labor force, without high school degrees.

The economic characteristics of low-skilled workers by auto ownership are presented in Table 4.2.2. Within the low-skilled group, further differences are found between autoless and auto-owning workers; the economic profile of autoless workers is even worse than that of workers with autos. The unemployment rates of autoless workers are markedly high, 18%-23%, whereas for auto-owning workers the rates are lower, 11%-12%. The median household incomes and the median person's earnings are much lower for autoless workers ($19,000-$23,000 and $9,000-$11,000, respectively) than for those who own autos ($36,000-$47,000 and $12,000, respectively).

While for both autoless and auto-owning workers the proportions of persons in the potentially high-skill occupations (occupations 1, 2, and 3) remain low, noticeable differences in some of the lower-skill occupations are found between the two worker groups. The proportion of persons in the precision, production, craft repair occupation (occupation 8) is somewhat lower for autoless workers (8%-15%) than for auto-owning workers (14%-17%). The proportions of persons in the private household service occupation (occupation 6) are, on the other hand, higher for autoless workers (28%-39%) than for auto-owning workers (21%-26%). This result is probably related to the fact that the autoless groups have higher proportions of women (41%-49%) than the auto-owning groups (37%-42%), as indicated in Table 4.1.2. A closer look at the data reveals that while the proportions of low-skilled workers who work in the precision, production, craft repair occupation are higher for men (20%-23%) than for women (4%-6%), the proportions of low-skilled workers who work in the private household service occupation are higher for women (29%-34%) than for men (17%-26%).

4.3 TRANSPORTATION CHARACTERISTICS

This section summarizes the transportation characteristics, including auto ownership, means of transportation to work, and the average travel time to work. The category of "public transportation" includes bus, trolley bus, streetcar, trolley car, subway, elevated rail, railroad, ferryboat, and taxicab. This categorization is consistent with the one used by Rossetti and Eversole (1993). The "other means" include motorcycle, bicycle, and other methods.

Table 4.3.1 Transportation characteristics of workers by education in study areas

	Boston			San Francisco			Los Angeles		
	Total workers	<HS degrees	>= HS degrees	Total workers	<HS degrees	>= HS degrees	Total workers	<HS degrees	>= HS degrees
% Autoless	8%	16%	7%	5%	9%	4%	6%	12%	4%
% Own 1 vehicle	27%	31%	27%	22%	24%	22%	25%	30%	23%
% Own 2 vehicles	41%	30%	42%	41%	33%	42%	39%	32%	42%
% Own 3+ vehicles	24%	22%	24%	32%	33%	32%	30%	26%	31%
Means of transportation to work									
% Commute by auto	75%	69%	75%	81%	77%	82%	86%	76%	89%
% Commute by public transportation	15%	18%	14%	9%	12%	9%	6%	14%	4%
% Commute by walk	7%	10%	7%	4%	6%	3%	3%	6%	3%
% Work at home	3%	2%	3%	3%	2%	4%	3%	2%	3%
% Commute by other means	1%	2%	1%	2%	3%	2%	2%	3%	2%
Average travel time to work (min)	24	22	25	26	24	26	23	22	24

Note: Data source: 1990 PUMS. Universe: persons 16 years or older in the labor force.

Table 4.3.1 looks at the transportation characteristics by education. The statistics indicate the great auto dependency in the U.S. The percentages of persons without autos are much higher for low-skilled workers (9%-16%) than those for higher-skilled workers (4%-7%). Nevertheless, even for low-skilled workers, whose incomes and earnings are low as described above, the great majority own autos and more than half have at least two cars. Even though the autoless population is small, however, this disadvantaged group should not be ignored by planners.

When the three areas are compared, San Francisco is the most auto-dependent metropolitan area, and Boston is the least auto-dependent. Among low-skilled workers, the proportion of autoless persons is only 9% in San Francisco, but much higher, 16%, in Boston. Los Angeles stands around the middle, having 12% autoless workers.

Despite the fact that low-skilled workers are more likely to use public transportation than are higher-skilled workers, the automobile predominates as a mean of commuting, accounting for 69%-76% of total modes of travel for low-skilled workers. The second choice of a mode for low-skilled workers is public transportation, which account for 12%-18% of travel modes. The two modes—auto and public transportation—together account for roughly 90% of the means of transportation to work.

Low-skilled workers on average commute for shorter times than do higher-skilled workers. In the three metropolitan areas, the average commuting times are 22-24 minutes for low-skilled workers and 24-26 minutes for higher-skilled workers.

Table 4.3.2 Transportation characteristics of low-skilled workers by auto ownership in study areas

	Boston		San Francisco		Los Angeles	
	No auto	Own auto	No auto	Own auto	No auto	Own auto
Means of transportation to work						
% Commute by auto	27%	77%	31%	81%	27%	77%
% Commute by public transportation	50%	12%	44%	9%	50%	12%
% Commute by walk	19%	8%	18%	5%	19%	8%
% Work at home	1%	2%	3%	2%	1%	2%
% Commute by other means	3%	1%	4%	3%	3%	1%
Average travel time to work (min)	28	20	29	23	28	20

Note: Data source: 1990 PUMS. Universe: persons 16 years or older in the labor force, without high school degrees.

The statistics for low-skilled workers by auto ownership are reported in Table 4.3.2. The estimated populations of low-skilled autoless workers are 29,000 in Boston, 41,000 in San

Francisco, and 146,000 in Los Angeles. For low-skilled autoless workers, the dominant mode of travel is public transportation, and 44%-50% of them are transit users. It is interesting to find that even for those who do not own autos, 27%-31% commute by auto. A closer look at the data reveals that of low-skilled autoless workers who commute by auto, about half in Boston and Los Angeles and 40% in San Francisco carpool to work. For low-skilled workers with autos, on the other hand, the majority (77%-81%) use autos for commuting as expected, but 9%-12% use public transportation to get to work.

The average commuting times for autoless workers (28-29 minutes) are much longer than those for auto-owning workers (20-23 minutes). This is highly likely owing to the greater proportion of transit commuters among autoless workers, since in most cases commuting time for transit users is considerably longer than that for auto users.

4.4 CHAPTER SUMMARY

The statistics for the three metropolitan areas indicated that the socioeconomic status of low-skilled workers (workers without high school degrees) is considerably lower than that of higher-skilled workers (workers with high school degrees or higher), and that within the low-skilled group, the socioeconomic profile of persons without autos is even worse than that of persons with autos.

Compared to the other general populations, low-skilled workers without autos are far more likely to be members of female-headed households, minority members, poor, and unemployed; and their household incomes and personal earnings are markedly low. Of low-skilled autoless workers in the study areas, 37%-50% are in female-headed households; 54%-72% belong to minority groups; 24%-39% are in poverty; and 18%-23% are unemployed. For low-skilled autoless workers, the median household incomes and the median personal earnings are, respectively, approximately $19,000-$23,000 and $9,000-$11,000, which are extremely lower than those of general workers. For instance, workers with high school degrees or higher, who consist of 73%-88% of total workers, have median household incomes of $52,000-$59,000 and median person's earnings of $24,000-$25,000. The results indicate clearly that workers who are both low skilled and autoless experience significant disadvantages in today's urban labor market.

Low-skilled autoless workers constitute a small proportions, however. Indeed, even for low-skilled workers, the great majority own autos and more than half have two or more cars. Autoless persons account for only 9%-16% of low-skilled workers, and persons who are both low skilled and autoless make up tiny proportions of total workers, 1%-3%. Even though the proportions of low-skilled autoless workers are small, however, the estimated population of these workers is sizable: 29,000 in the Boston PMSA, 41,000 in the nine-county San Francisco Bay Area, and 146,000 in the Los Angeles PMSA.

Among low-skilled workers without autos, the dominant mode of travel is public transportation, and 44%-50% commute by transit. Interestingly, however, 27%-31% of low-skilled autoless workers commute by auto, and roughly half of them carpool to work. For low-skilled workers with autos, on the other hand, although 9%-12% use public transportation, the great majority, 77%-81%, use autos to get to work. These figures suggest the great auto dependency and the difficulty of using public transportation as a mean of commuting.

When the three metropolitan areas are compared, the auto dependency is highest in San Francisco, second highest in Los Angeles, and lowest in Boston. Of low-skilled workers, the proportion of autoless persons is only 9% in San Francisco and 12% in Los Angeles, while the proportion in Boston is relatively high, 16%. Among those who are low-skilled, 77% and 75% commute by auto in San Francisco and Los Angeles, respectively, whereas a much lower proportion, 69%, are auto commuters in Boston.

The other noticeable metropolitan differences include the low-skilled population and the racial composition. Los Angeles has a markedly higher proportion (27%) of low-skilled workers than do Boston and San Francisco (12% and 14%, respectively), having an estimated population of about 1,207,000 low-skilled workers. Los Angeles is also an exceptionally hetero-racial area. For low-skilled workers in Los Angeles, a quite high proportion, 62%, are minority members, and Hispanic persons and other-race persons (minorities other than African-Americans, Hispanics, and Asians) account for great proportions, 18% and 32%, respectively. Boston, on the other hand, is a predominantly white area. Only 27% of low-skilled workers in Boston are nonwhite, and among the minority groups, African-Americans have the highest proportion, 7%. San Francisco stands around the middle, having 48% minority low-skilled workers. Among the minority groups in San Francisco, Asian persons and other-race persons account for high proportions of low-skilled workers, 16% and 15%, respectively.

Chapter 5: Geographies of Workers and Jobs by Skill

Before examining job accessibility for low-skilled workers, it is important to understand how workers and jobs are spatially distributed within and across the metropolitan areas. In this chapter, I investigate the geographies of low-skilled workers and jobs for the three study areas of the Boston, San Francisco, and Los Angeles metropolitan areas. To investigate whether the distributions of workers and jobs are unique to the low-skilled group, I also examine the distributions for their counterparts, the high-skilled group, and compare the results for the two worker groups. The questions asked in this chapter are: (1) What are the spatial distributions of low-skilled workers and jobs?; (2) To what extent do the distributions vary within and across the metropolitan areas?; and (3) Is there a disparity in the geography of workers and jobs between the low-skilled and high-skilled groups?

5.1 DATA

The primary data are from the Urban Element of the 1990 Census Transportation Planning Packages (CTPP). The CTPP data are sponsored by the Department of Transportation in each state to provide a set of special tabulations for the needs of transportation planners. The reason for selecting CTPP is because its data provide information about jobs as well as about workers for small geographic areas. Part 1 of CTPP contains data for workers by *area of residence*, which I use as workers, and Part 2 provides data for workers by *area of work*, which I use as jobs.

The study areas are the Boston, San Francisco, and Los Angeles metropolitan areas. The Urban Element of CTPP is created for each Metropolitan Planning Organization (MPO), and the MPO defines its area, called a CTPP region. The CTPP region for Boston is somewhat larger than the Boston Primary Metropolitan Statistical Area (PMSA), covering 790 traffic analysis zones

(TAZs) for the 790 zone system.[5] San Francisco's CTPP region, on the other hand, completely overlaps with the nine-county San Francisco Bay Area and contains 1,099 TAZs for the 1099 zone system.

Los Angeles has a CTPP region with 1,555 TAZs for the 1555 zone system, which covers Los Angeles County (without islands), Orange County, Ventura County, and some western areas of Riverside County and San Bernardino County. For the Los Angeles metropolitan area, I use areas only within Los Angeles County (excluding islands) to make the area consistent with the areas in the other chapters. The geographic boundaries for the three metropolitan areas are depicted in Figure 5.1.1.

The type of detailed geography provided by CTPP is different for the three areas: the block group (BG) for Boston, TAZ for San Francisco, and tract for Los Angeles. For comparison, I first make the type consistent to the TAZ by converting the BG-level data in Boston and the tract-level data in Los Angeles to the TAZ-level data.

The next step is the calculation of workers and jobs for the low-skilled and high-skilled groups. Workers are defined as persons 16 years and over in the labor force. I define low-skilled workers as workers without high school degrees and low-skilled jobs as jobs that are filled by these low-skilled workers. I define high-skilled workers as workers who have at least bachelor's degrees and high-skilled jobs as jobs that are filled by these high-skilled workers.

Note that the results may be sensitive to the definitions of low skills and high skills. If the low-skill category is defined as having a high school diploma or less, and if the high-skill category is defined as having an associate degree or higher, the distributions of workers and jobs may significantly differ. The focus group of this study, however, is those who do not have high school degrees, one of the most disadvantaged groups, and their counterparts are highly skilled workers. I therefore do not examine the different definitions in this study but plan to explore them in my future research.

[5] A different zone system uses a different number of TAZs for the same area.

For the calculation of low-skilled (or high-skilled) workers in zone i (W_i^{skill}), I propose the following formulas, utilizing the tabulations available in Part 1 of CTPP:

$$W_i^{skill} = W_i^{skill,\ employed} + W_i^{skill,\ unemployed}, \tag{5.1}$$

where

$$W_i^{skill,\ employed} = \sum_o \left(W_{io} \times p_o^{skill}\right), \tag{5.2}$$

$$W_i^{skill,\ unemployed} = U_i \times p_i^{skill}, \tag{5.3}$$

$$p_i^{skill} = \frac{W_i^{skill,\ employed}}{W_i^{employed}}. \tag{5.4}$$

$W_i^{skill,\ employed}$ is the number of employed low-skilled (or high-skilled) workers who live in zone i, and $W_i^{skill,\ unemployed}$ is the number of unemployed low-skilled (or high-skilled) workers who live in zone i. W_{io} is the number of workers who live in zone i and work in occupation o, and p_o^{skill} indicates the proportion of low-skilled (or high-skilled) workers in occupation o. U_i represents the number of unemployed workers living in zone i; and p_i^{skill} is the proportion of low-skilled (or high-skilled) workers in zone i. $W_i^{employed}$ is the total number of employed workers who live in zone i.

For the calculation of low-skilled (or high-skilled) jobs in zone i (E_i^{skill}), I propose the following formula, using a tabulation from Part 2 of CTPP:

$$E_i^{skill} = \sum_o \left(E_{io} \times p_o^{skill}\right). \tag{5.5}$$

E_{io} is the number of workers who work in zone i and in occupation o, and p_o^{skill} indicates the proportion of low-skilled (or high-skilled) workers in occupation o. Note that zone i in Equation (5.5) is the area of work and not the area of residence.

Since the proportion of low-skilled (or high-skilled) workers in each occupation (p_o^{skill}) is not available for small geographic areas, I use the five-percent Public Use Microdata Samples (PUMS) of the 1990 Census to estimate the proportion. Unlike the aggregated CTPP data, the individual-level PUMS data allow users to create a tabulation of interest (but they do not provide data for small geographic areas like TAZs). The estimated proportions are shown in Table 5.1.1 and correspond to the 13 occupational categories (excluding the armed force occupation) provided by CTPP.

Table5.1.1 Proportion of workers by skill and by occupation in study areas

		Proportion of workers < high school degrees			Proportion of workers >= bachelor's degrees		
Occupation	SOC code*	BOS	SF	LA	BOS	SF	LA
1 Executive, administrative, and managerial	003 - 042	3%	4%	8%	60%	53%	44%
2 Professional specialty	043 - 202	1%	1%	3%	79%	76%	67%
3 Technicians and related support	203 - 242	4%	4%	7%	48%	43%	35%
4 Sales	243 - 302	14%	12%	20%	36%	31%	23%
5 Administrative support occupations, including clerical	303 - 402	8%	8%	14%	18%	19%	14%
6 Private household service	403 - 412	31%	44%	70%	10%	7%	3%
7 Protective service	413 - 432	10%	8%	15%	19%	22%	17%
8 Service, except protective and household	433 - 472	30%	33%	47%	11%	9%	6%
9 Farming, forestry, and fishing	473 - 502	23%	47%	62%	12%	11%	5%
10 Precision production, craft, and repair	503 - 702	18%	20%	39%	10%	10%	6%
11 Operators, fabricators, and laborers	703 - 802	35%	33%	64%	7%	9%	4%
12 Transportation and material Moving	803 - 863	24%	22%	40%	6%	8%	4%
13 Handlers Equipment cleaners, helpers, and laborers	864 - 902	32%	35%	55%	6%	6%	4%

Note: *SOC code represents the Standard Occupational Classification code. The armed forces occupation is excluded.

In the above equations, the proportion of low-skilled (or high skilled) workers in each occupation (p_o^{skill}) is assumed to be spatially homogeneous, which may be questioned. The proportions, however, are calculated for each metropolitan area, taking into account the regional variation. If the proportions vary substantially within the metropolitan area, the estimated absolute values of workers and jobs could be distorted. The distortion, however, is likely to be visible only around urban cores with high concentrations of workers and jobs and is likely to be much less visible in most suburban areas with low densities of workers and jobs. Additionally, since the focus of this study is more on the relative values than on the absolute values, the assumption is unlikely to affect the interpretations of the results. If the proportions vary substantially but are representative for the proportions in areas with high concentrations of workers and jobs, the distortion becomes invisible even for such areas.

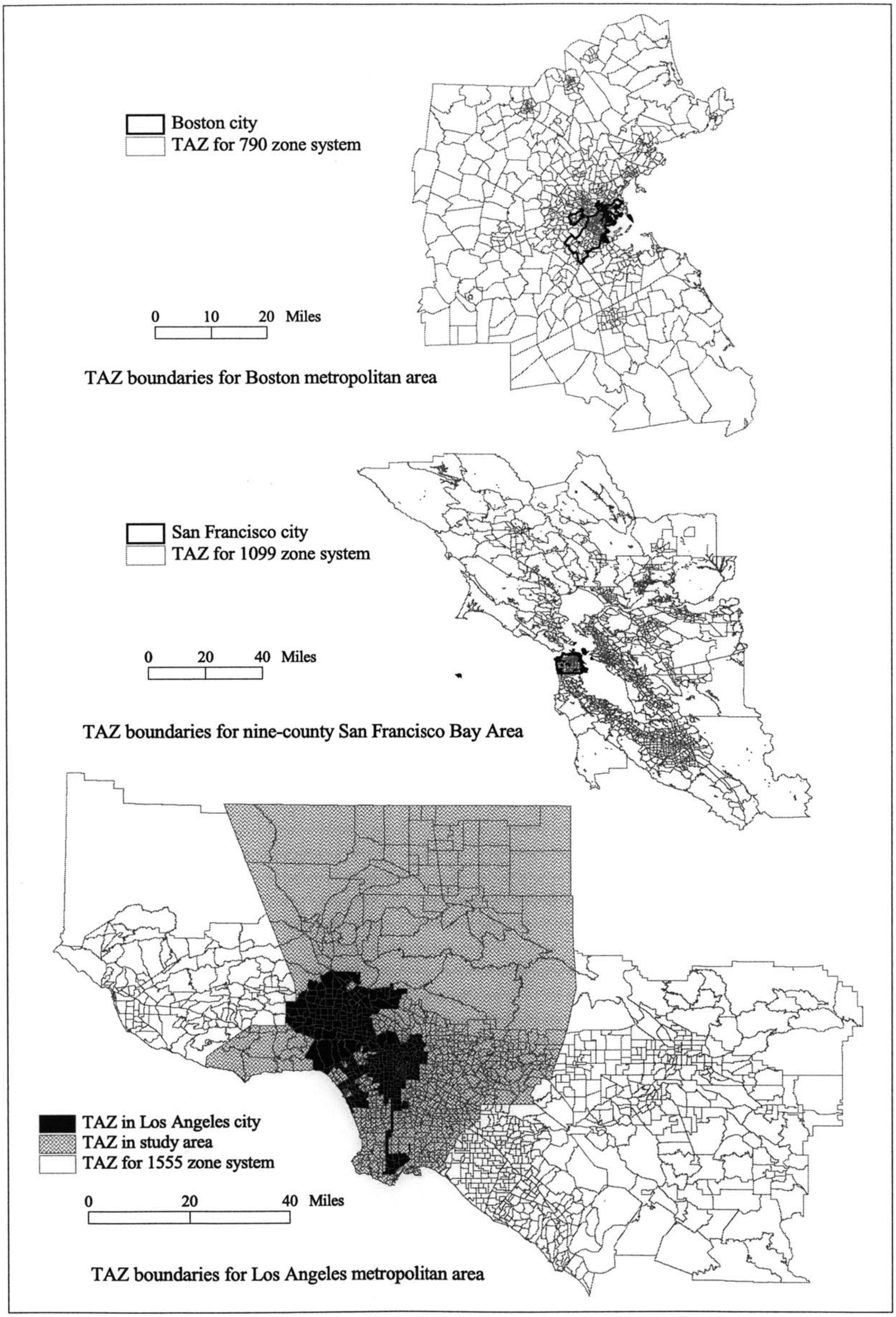

Figure 5.1.1 TAZ boundaries for three metropolitan areas

5.2 METHODOLOGY

The calculated workers and jobs are presented as follows. First, I provide overall pictures of the geographies of workers and jobs by tabulating them by skill and aggregated location.

To show more detailed pictures, I next create maps that show the densities of workers and jobs and the jobs-to-workers ratios, using ArcView 3.2a, a popular GIS package. Since the spatial distributions of workers and jobs vary considerably, I present the maps in three dimensions to clarify the variations. A problem arose when I created the 3D maps, however; some TAZs are very small, making the densities of workers or jobs unrealistically high even though the neighboring areas have much less densities. Utilizing GIS, I employ a unique smoothing technique to solve this problem, which is summarized as follows.

1) First, I convert the TAZ coverages of the densities of workers and jobs to the grid coverages. I decided to set each cell size in the grid coverages to 250m × 250m after exploring the data. The value in each cell is assigned such that the central point of the cell has the value of the overlapping TAZ.
2) Second, using the neighborhood statistics function in ArcView 3.2a, for each cell I calculate the mean of the values in surrounding 4x4 cells (i.e., 1 square kilometer); again, I decided the neighborhood area after exploring the data. The resulting grid coverages are presented in the maps labeled the geography of low-skilled (or high-skilled) workers and jobs in Section 5.3.
3) Lastly, to make the maps for the jobs-to-workers ratios, I employ the map calculator function in ArcView 3.2a to compute the ratios using the two separate grid coverages for the densities of workers and the densities of jobs created in the second step. The resulting maps are presented in Section 5.3.

5.3 GEOGRAPHIES OF WORKERS AND JOBS BY SKILL

5.3.1 Overview of Spatial Distributions of Workers and Jobs by Skill

The overall pictures of the spatial distributions of workers and jobs are presented in Table 5.3.1. This table shows workers, jobs, and jobs-to-workers ratios by skill for three geographic areas: the entire metropolitan area, central city, and suburbs. The central cities of the Boston, San Francisco, and Los Angeles metropolitan areas are defined as the cities of Boston, San Francisco, and Los Angeles, respectively. The central city versus suburban division tells little about the detailed spatial variations, though it provides a quick understanding of the overall pictures of the distributions.

Table 5.3.1 Spatial distribution of workers and jobs in study areas in 1990

	Boston			San Francisco			Los Angeles		
	Entire metro	Central city	Suburbs	Entire metro	Central city	Suburbs	Entire metro	Central city	Suburbs
Workers									
Total	2,220,299	308,823 (14%)	1,911,476 (86%)	3,255,879	408,164 (13%)	2,847,715 (87%)	4,438,701	1,763,494 (40%)	2,684,602 (60%)
Low-skill	264,765	38,728 (15%)	226,037 (85%)	420,176	52,564 (13%)	367,612 (87%)	1,153,380	476,208 (41%)	680,002 (59%)
High-skill	808,866	108,828 (13%)	700,038 (87%)	1,077,704	138,307 (13%)	939,397 (87%)	1,056,138	414,501 (39%)	643,631 (61%)
Jobs									
Total	2,201,478	497,654 (23%)	1,703,824 (77%)	2,936,721	564,272 (19%)	2,372,449 (81%)	4,333,417	1,843,602 (43%)	2,492,591 (58%)
Low-skill	260,798	51,210 (20%)	209,588 (80%)	375,256	66,163 (18%)	309,093 (82%)	1,094,780	457,463 (42%)	637,936 (58%)
High-skill	804,182	197,832 (25%)	606,351 (75%)	974,999	196,389 (20%)	778,610 (80%)	1,058,166	459,837 (43%)	599,108 (57%)
Jobs-to-Workers Ratios									
Total	0.99	1.61	0.89	0.90	1.38	0.83	0.98	1.05	0.93
Low-skill	0.99	1.32	0.93	0.89	1.26	0.84	0.95	0.96	0.94
High-skill	0.99	1.82	0.87	0.90	1.42	0.83	1.00	1.11	0.93

Note: Workers include employed and unemployed workers. The central cities of the Boston, San Francisco, and Los Angeles metropolitan areas are defined as the cities of Boston, San Francisco, and Los Angeles, respectively.

It is important to note that when interpreting the statistics, differences in the size of metropolitan areas and in the size of the central cities should be kept in mind. As indicated in Section 3.2, the metropolitan area is largest in San Francisco (6,900 square miles) and second largest in Los Angeles (4,100 square miles for Los Angeles County). Compared to these two areas, Boston is a much more compact area (2,800 square miles for 790 TAZs). The city of Los Angeles has approximately 470 square miles of land, which is much larger than that of the city of Boston (60 square miles) and the city of San Francisco (50 square miles). The proportion of the central city in the metropolitan area is therefore considerably higher in Los Angeles (11%) than in Boston (2%) and San Francisco (1%). Thus, we need to be careful in interpreting the values and percentages in the absolute meaning, and the statistics in the relative meaning are better indicators.

The Boston metropolitan area (the 790-TAZ area) has a total of about 2.2 million jobs and workers each. Among them, an estimated 265,000 and 261,000 are low-skilled workers and jobs, respectively, while 809,000 and 804,000 are high-skilled workers and jobs, respectively. The nine-county San Francisco Bay Area accommodates approximately 3.3 million workers and 2.9 million jobs, of which an estimated 420,000 and 375,000 are low-skilled workers and jobs, respectively, and 1,078,000 and 975,000 are high-skilled workers and jobs, respectively. The Los Angeles metropolitan area (Los Angeles County excluding islands) has about 4.4 million workers and 4.3 million jobs. The estimated numbers of low-skilled workers and jobs are 1,153,000 and 1,095,000, respectively, and the estimated numbers of high-skilled workers and jobs are 1,056,000 and 1,058,000, respectively.

It is apparent from the above statistics that while high-skilled workers and jobs far outnumber low-skilled workers and jobs in Boston and San Francisco, in Los Angeles, the figures for the low-skilled group slightly exceed those for the high-skilled group. Note that there are more workers than jobs since workers includes both employed and unemployed workers, while jobs include only employed workers.

In all three areas, workers are more suburbanized than jobs. The proportions of workers who live in the suburbs in Boston, San Francisco, and Los Angeles are 86%, 87%, and 60%, respectively, while the proportions of jobs that are in the suburbs are 77%, 81%, and 58%, respectively. Note that the lower percentages for Los Angeles are largely owing to its large central city (i.e., the low proportion of suburban areas in the Los Angeles metropolitan area), as noted earlier.

In San Francisco, the proportions of low-skilled workers and high-skilled workers who are in the central city are the same, 13%, but in Boston and Los Angeles, low-skilled workers are slightly more concentrated in the central cities than are high-skilled workers. In Boston, 15% of low-skilled workers live in the central city, whereas 13% of high-skilled workers live in the central city. Likewise, in Los Angeles, 41% of low-skilled workers are central-city residents, while 39% of high-skilled workers are central-city residents.

Conversely, low-skilled jobs are more decentralized than are high-skilled jobs, particularly in Boston. The proportions of low-skilled jobs that are in the central cities in Boston, San Francisco, and Los Angeles are, respectively, 20%, 18%, and 42%, while the proportions of high-skilled jobs that are in the central cities are, respectively, 25%, 20%, and 43%, respectively. These results suggest that for both low-skilled and high-skilled workers, job opportunities are greater in the central cities than in the suburbs, but within the central cities, low-skilled workers have less job opportunities than do high-skilled workers.

The same patterns are indicated by the jobs-to-workers ratios. The ratios are consistently higher in the central cities than in the suburbs, reflecting greater job opportunities for the central cities. The jobs-to-workers ratios in the central cities are lower for the low-skilled group than for the high-skilled group, which suggests that for the central-city residents, job opportunities are greater for high-skilled workers than for low-skilled workers. In the suburbs, on the other hand, the jobs-to-workers ratios are higher for low-skilled workers than for high-skilled workers, but the difference is relatively small with the exception of Boston. Compared to the other two areas, Boston's difference in the ratios between the two worker groups is large both within the central city and within the suburbs, reflecting the Boston's distinctive and compact central city with highly centralized high-skilled jobs.

5.3.2 Visualizing Spatial Distributions of Workers and Jobs by Skill

The table above provided rather aggregated pictures of the spatial distributions of workers and jobs. In this section, I create maps that display more disaggregated pictures. Since some areas have extremely high concentrations of workers and jobs, I present the maps in three dimensions to clarify the large variability, which tables or 2D maps cannot express effectively. Figures 5.3.1a-5.3.3c illustrate the spatial distributions; figures with suffix 'a' show the geographies of workers and jobs for the low-skilled group, figures with suffix 'b' present the geographies for the high-skilled group, and figures with suffix 'c' illustrate the ratios of jobs to workers.

To make the maps comparable, the legends for the maps use the same equal interval classifications. Additionally, I make the following consistent in each metropolitan area: the value used to extrude features for workers and jobs, and the value used to extrude features for the jobs-to-workers ratios. For each area, therefore, the extruded lengths are comparable between the four maps for the geographies of low-skilled and high-skilled workers and jobs (figures with suffix 'a' and 'b'), and the extruded lengths in the two maps for the jobs-to-workers ratios (figure with suffix 'c') are comparable.

Boston

Figures 5.3.1a and 5.3.1b display the maps for the distributions of workers and jobs in Boston. The maps indicate that Boston has a distinctive urban center with high concentrations of workers and jobs in areas around the city of Boston, including Cambridge, Everett, and Somerville. Jobs are, however, far more centralized than are workers, clustering around the Central Business District (CBD). Note that even within the city of Boston, South Boston (which includes Boston's low-income neighborhoods) has moderately high densities of workers but low densities of jobs. Clusters of workers and jobs—although less conspicuous than those around the central city—are also found in some suburban areas (e.g., Brockton, Framingham, Lawrence, Lowell, and Lynn). The extruded features are higher overall for the high-skilled cohort than for the low-skilled cohort, which reflects the greater number of workers and jobs for the high-skilled cohort as shown in Table 5.3.1. The spatial patterns of workers and jobs for the two cohorts are, however, quite similar.

Figure 5.3.1c shows the jobs-to-workers ratios. Areas around the CBD have strikingly high ratios of jobs to workers for both the low-skilled and high-skilled groups, but the ratios are higher for the high-skilled group than for the low-skilled group. Interestingly, areas with high jobs-to-workers ratios are limited to the areas around the CBD, and many inner suburban areas with relatively high concentrations of jobs, such as Cambridge and Somerville, have jobs-to-workers ratios of less than one.

Caution is required in interpreting these ratios. The high jobs-to-workers ratios in the CBD does not necessarily mean that the CBD has such great accessibility to job opportunities; conversely, the low jobs-to-workers ratios in the inner suburban areas do not indicate such low accessibility to job opportunities. Since it is likely that a large body of residents in the inner suburban ring commute to fill the jobs in the CBD, the actual accessibility to jobs in the CBD is likely to be lower, and the actual accessibility in the inner suburban areas is likely to be higher. This is an example of the limitation of the use of the simple jobs-to-workers ratio to represent job accessibility for small geographic areas.

Note that moderately high ratios of jobs to workers are located in some suburban areas including Bedford, Braintree, Burlington, Dedham, and Waltham. Interestingly, these areas are located near Route 128, Boston's major inner belt highway. Indeed, outer suburban areas with relatively high levels of jobs and the jobs-to-workers ratios are mostly located near the major highways, such as Route 90 and Route 495. The result suggests that firms prefer to locate near highways to gain greater transportation (auto) mobility.

San Francisco

The distributions of workers and jobs for San Francisco are shown in Figures 5.3.2a and 5.3.2b. In San Francisco, areas around the city of San Francisco have high concentrations of workers and jobs, but the jobs are more heavily concentrated than are workers. In particular, the northeastern areas of the city of San Francisco (e.g., Financial District, Fisherman's Wharf, Telegraph Hill, and Union Square) have higher concentrations of jobs than workers, while the western and southern areas of the city have higher concentrations of workers than jobs.

Workers and jobs are also clustered—although not as much as in the areas above—in areas surrounding the San Francisco Bay and in some outer suburbs (e.g., Concord, Gilroy, Napa, and Santa Rosa). As the maps indicate, the major suburban centers (e.g., downtown Oakland and downtown San Jose) attract more jobs than workers. As in the case of Boston, the higher extruded features for the high-skilled group than for the low-skilled group reflect the greater numbers of workers and jobs for the high-skilled group, and the spatial patterns for the two worker groups are similar.

The ratios of jobs-to-workers in San Francisco are presented in Figure 5.3.2c. As expected, the areas with high ratios are located in such areas as the northeastern part of the city of San Francisco (e.g., Union Square and Financial District) and downtown Oakland, but areas around downtown San Jose have unexpectedly high ratios. Similar to the situation of the Boston's CBD, interpreting these high ratios as such great job accessibility is misleading, since many workers outside the areas commute to the jobs in downtown San Jose. This is a caveat in using the simple jobs-to-workers ratio for a small geographic unit.

Another caveat in using the simple ratio is indicated by the area with a small number of jobs but even a smaller number of workers. For example, the large area to the east of Livermore and the area in South San Jose have relatively high ratios of jobs to workers even though workers and jobs are scarce. In such areas, job opportunities are actually not plenty.

Los Angeles

In Los Angles, workers and jobs are more spread out, and urban centers are less prominent. Note that as Table 5.3.1 indicates, the numbers of workers and jobs for the low-skilled group are similar to those for the high-skilled group in Los Angeles; therefore the extruded lengths of the features are visually quite comparable between the low-skilled and high-skilled group.

Figures 5.3.3a and 5.3.3b show that both low-skilled and high-skilled workers are widely distributed in the southern sections of Los Angeles County, but the neighborhoods between downtown Los Angeles and Beverly Hills have relatively high concentrations of low-skilled workers.

Jobs are also widely distributed in southern Los Angeles County, but downtown Los Angeles has noticeably high concentrations of both low-skilled and high-skilled jobs. Relatively large clusters of jobs are found in the areas near Wilshire Boulevard, including Santa Monica and Century City.

Figure 5.3.3c shows the jobs-to-workers ratios in Los Angeles, but again interpretation of the ratios in some areas needs caution. For example, areas around the Terminal Island, Long Beach

Airport, and Los Angeles International Airport have moderate levels of jobs but few residents; therefore, the job-to-workers ratios are high in these areas. The actual ratios to represent job accessibility, however, should be lower, since many workers outside the areas work in those areas. Areas at the southern part of Angeles National Forest have also high ratios, but in fact, these areas have few jobs and even fewer workers. The areas that have reasonably high numbers of workers but much higher numbers of jobs (i.e., high jobs-to-workers ratios) are found in such areas as downtown Los Angeles, Century City, Pasadena, and Santa Monica.

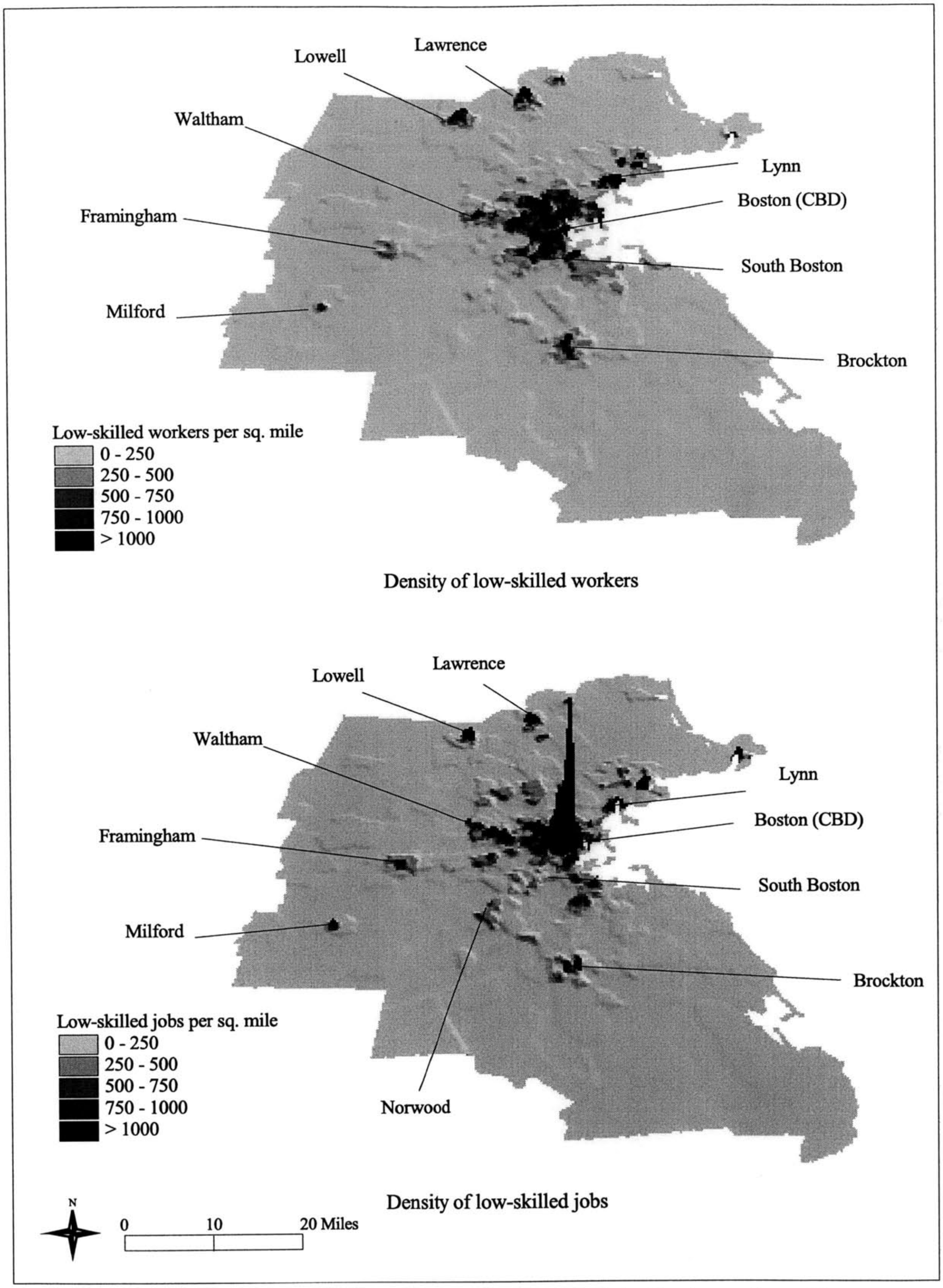

Figure 5.3.1a Geography of low-skilled workers and jobs in Boston metropolitan area

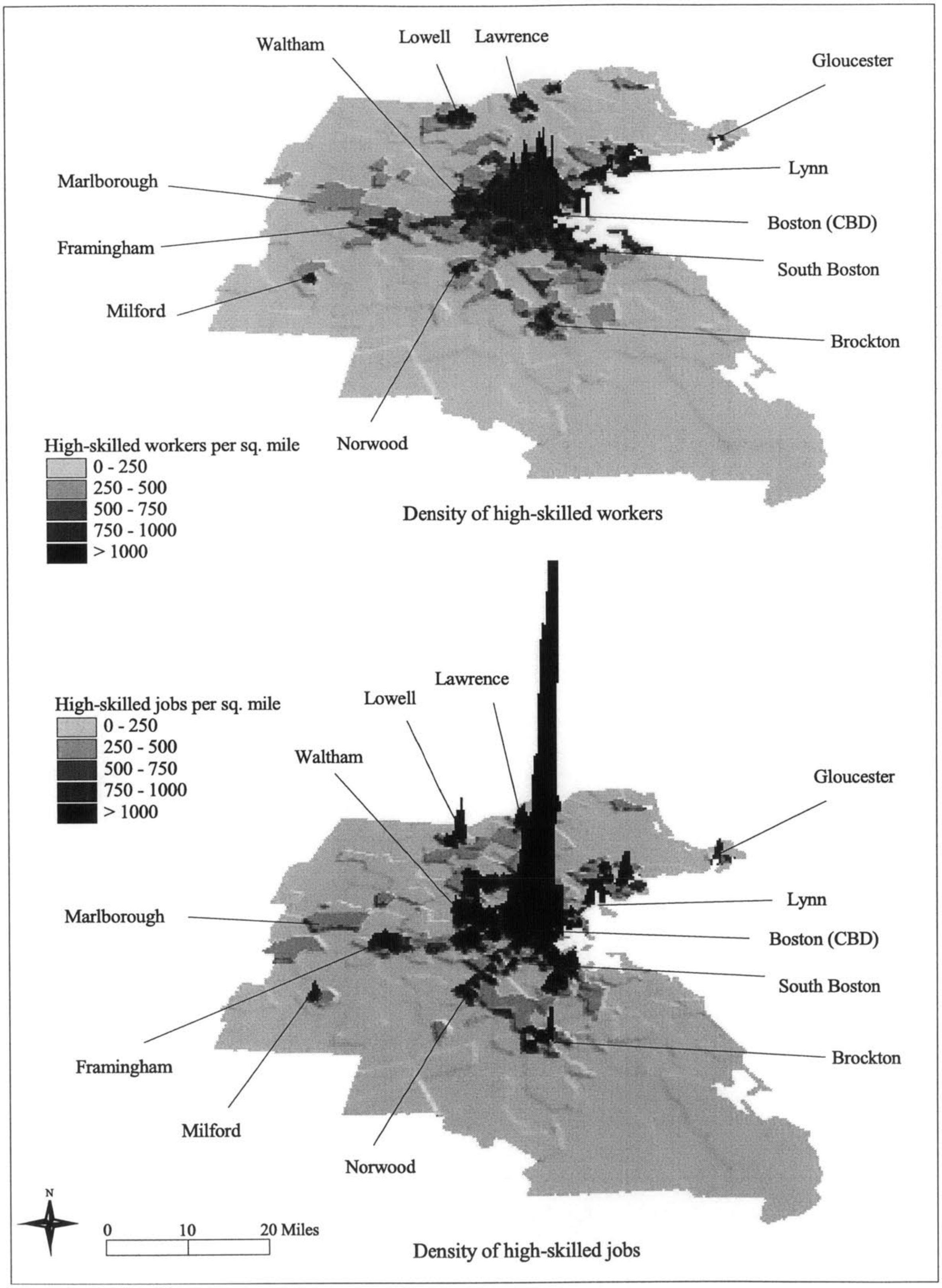

Figure 5.3.1b Geography of high-skilled workers and jobs in Boston metropolitan area

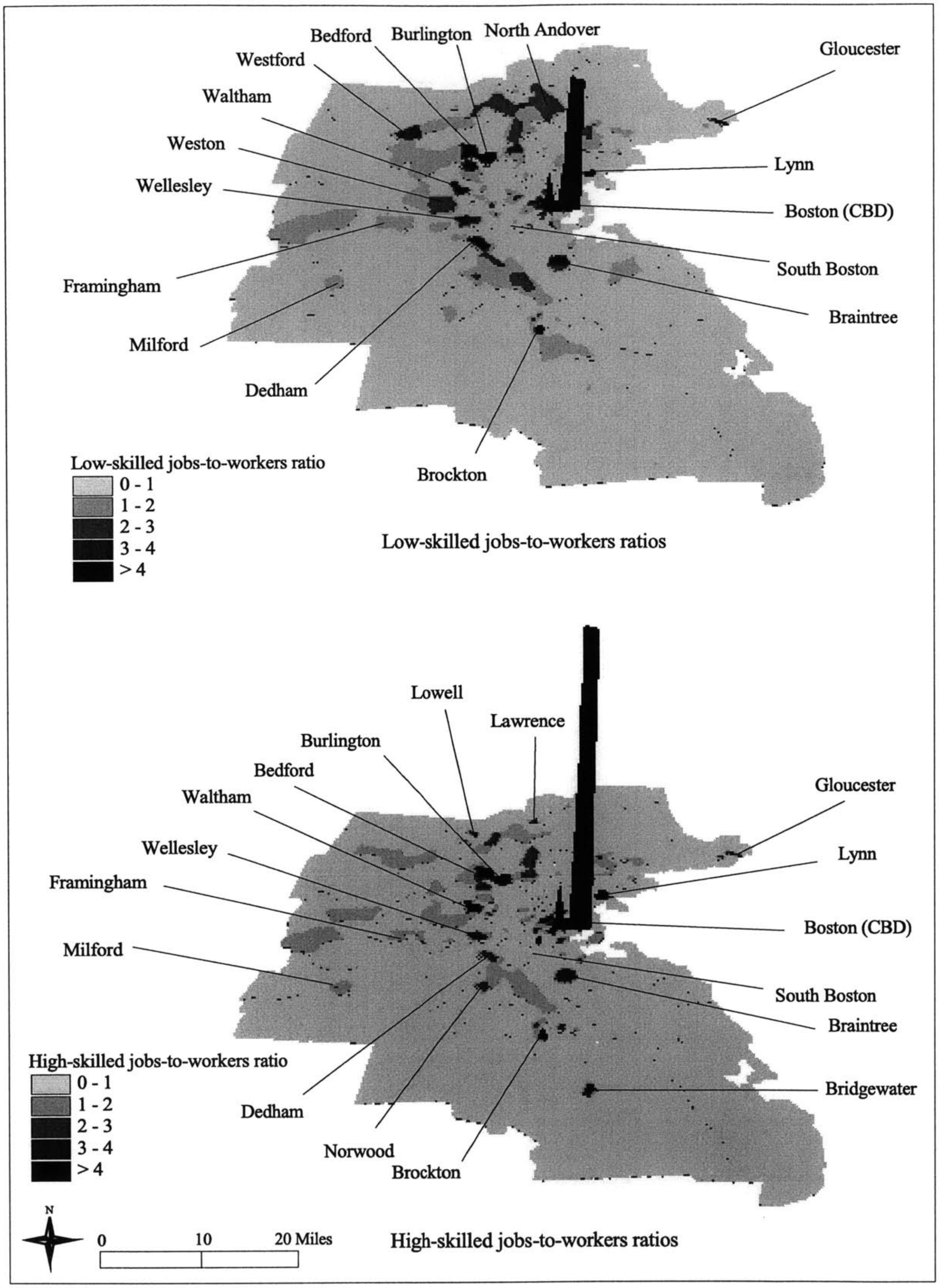

Figure 5.3.1c Jobs-to-workers ratio in Boston metropolitan area

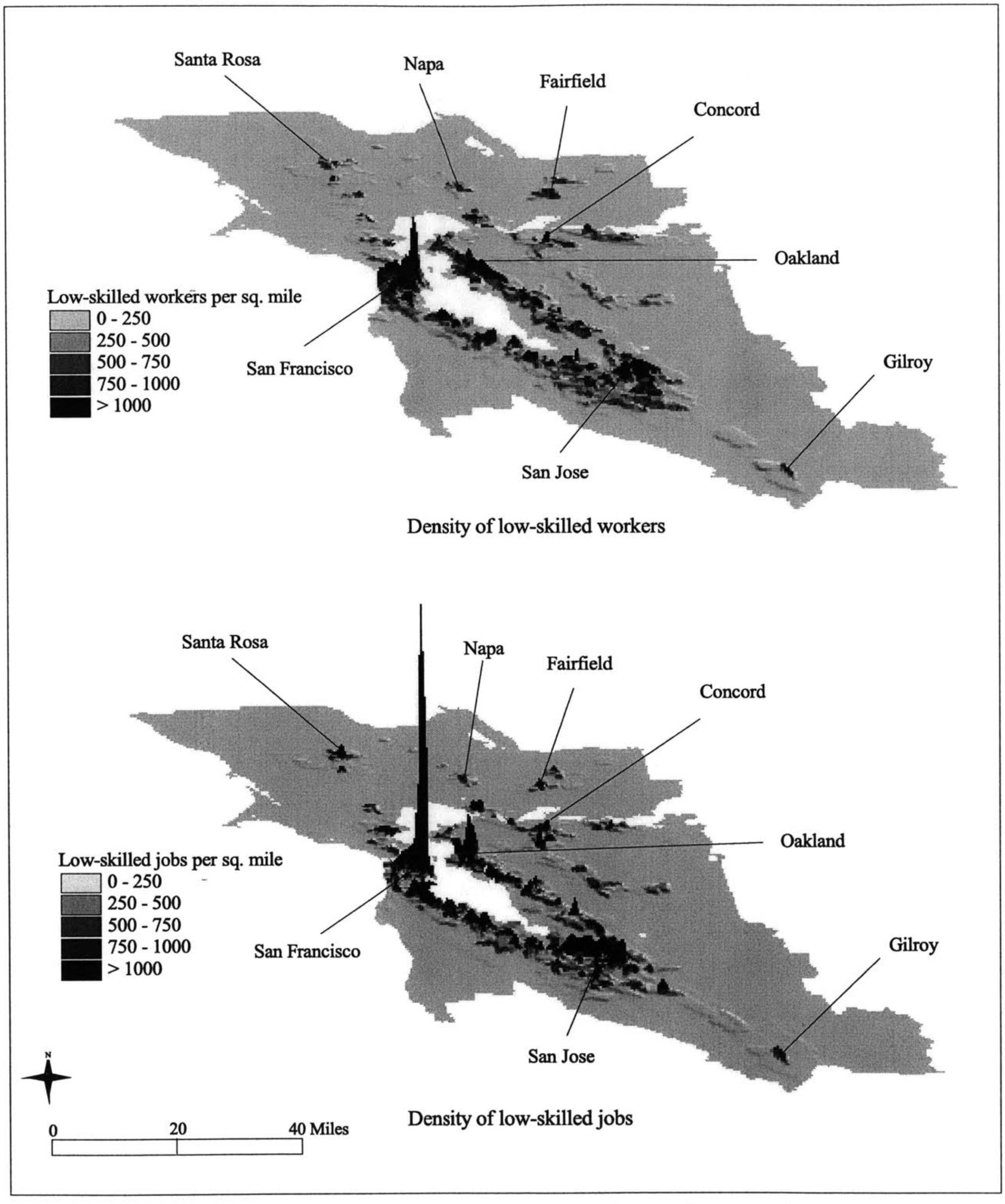

Figure 5.3.2a Geography of low-skilled workers and jobs in San Francisco Bay Area

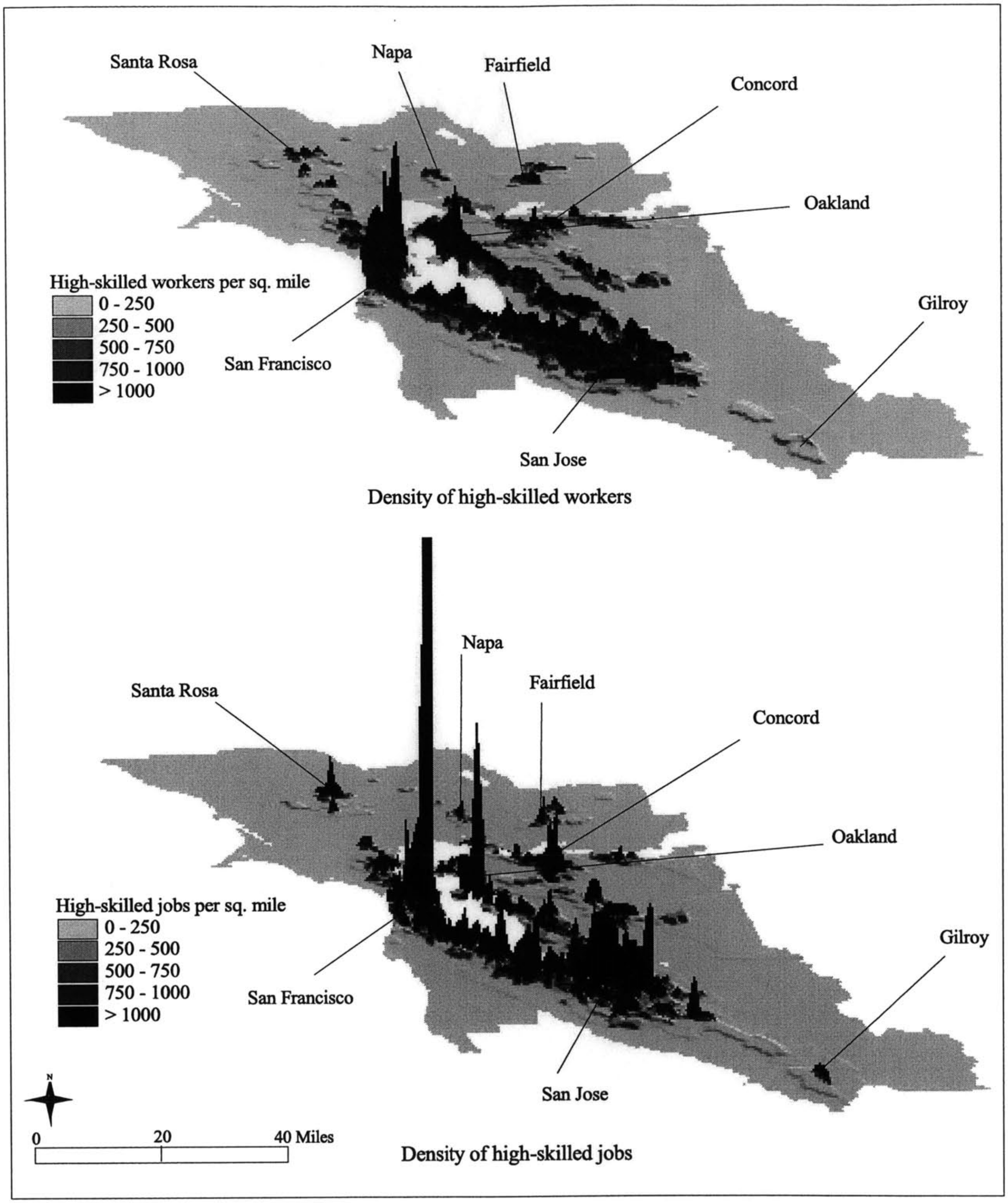

Figure 5.3.2b Geography of high-skilled workers and jobs in San Francisco Bay Area

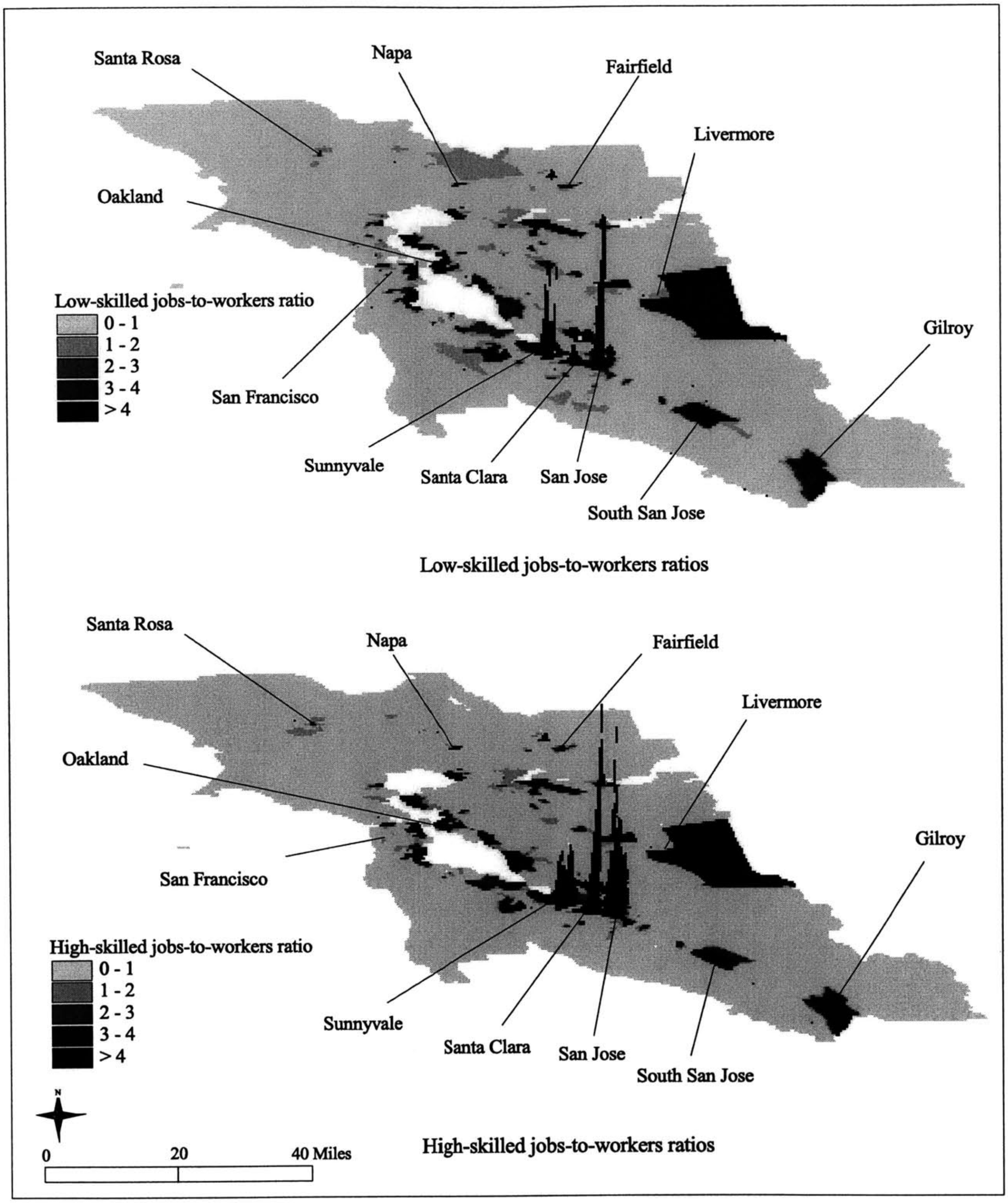

Figure 5.3.2c Jobs-to-workers ratio in San Francisco Bay Area

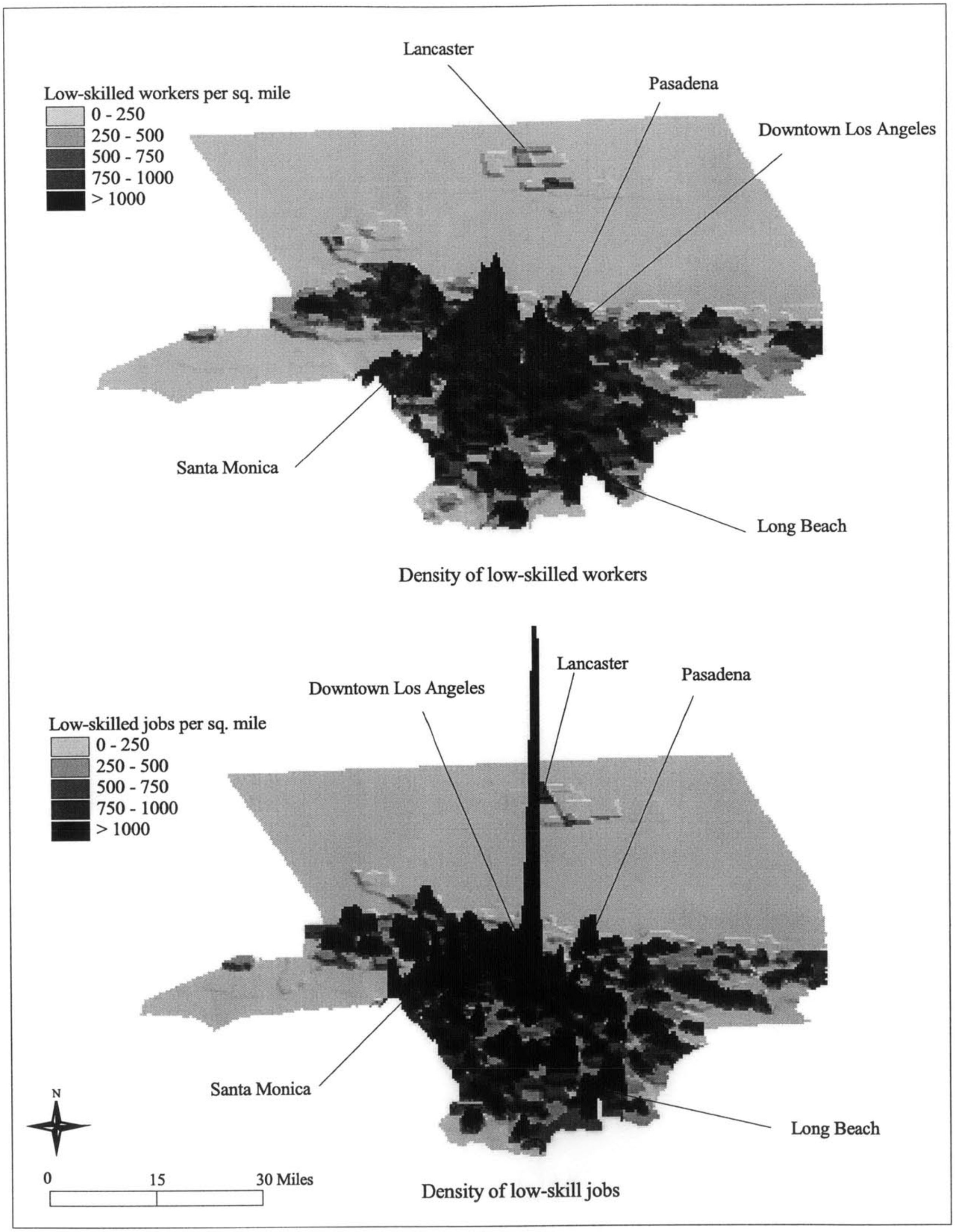

Figure 5.3.3a Geography of low-skilled workers and jobs in Los Angeles metropolitan area

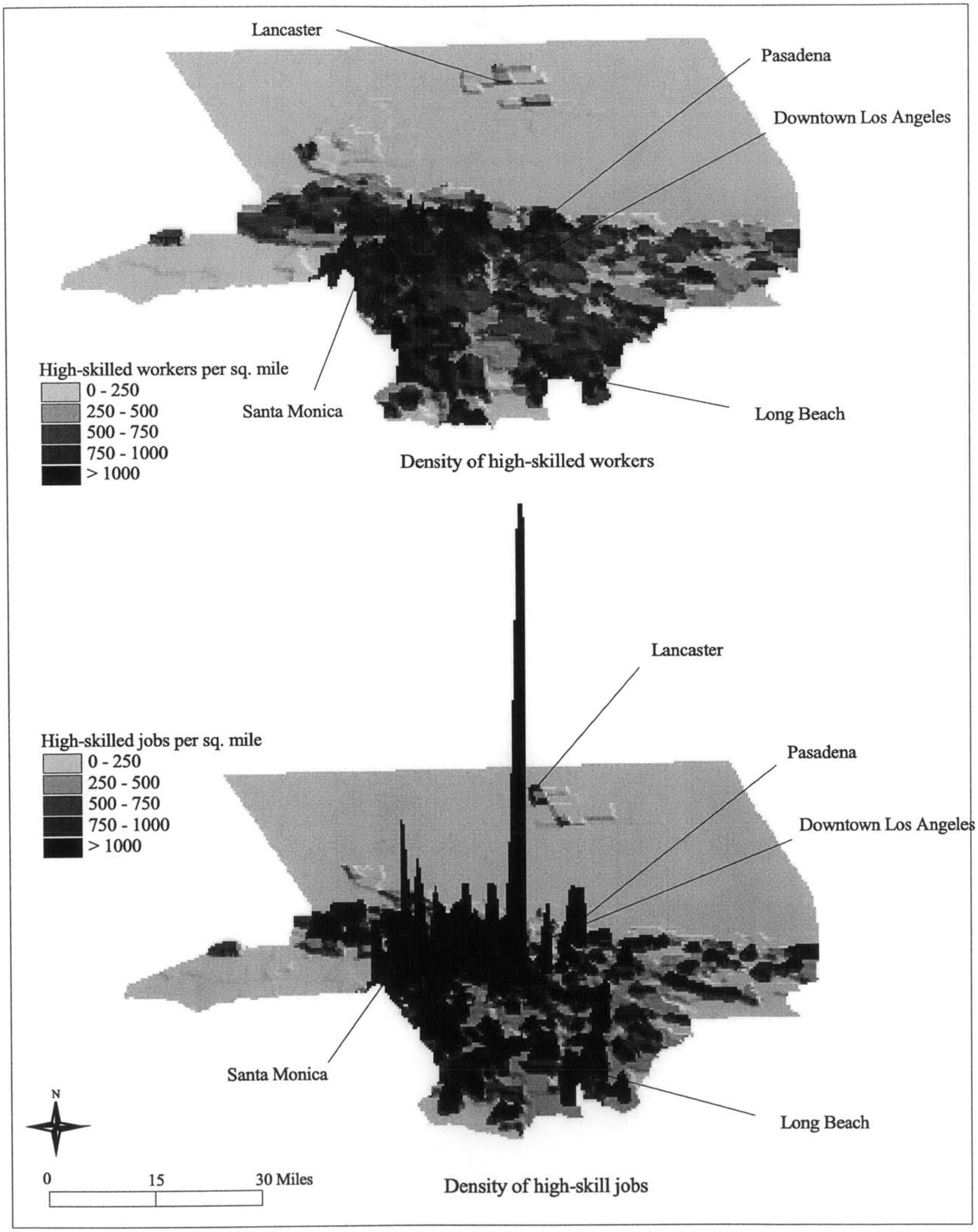

Figure 5.3.3b Geography of high-skilled workers and jobs in Los Angeles metropolitan area

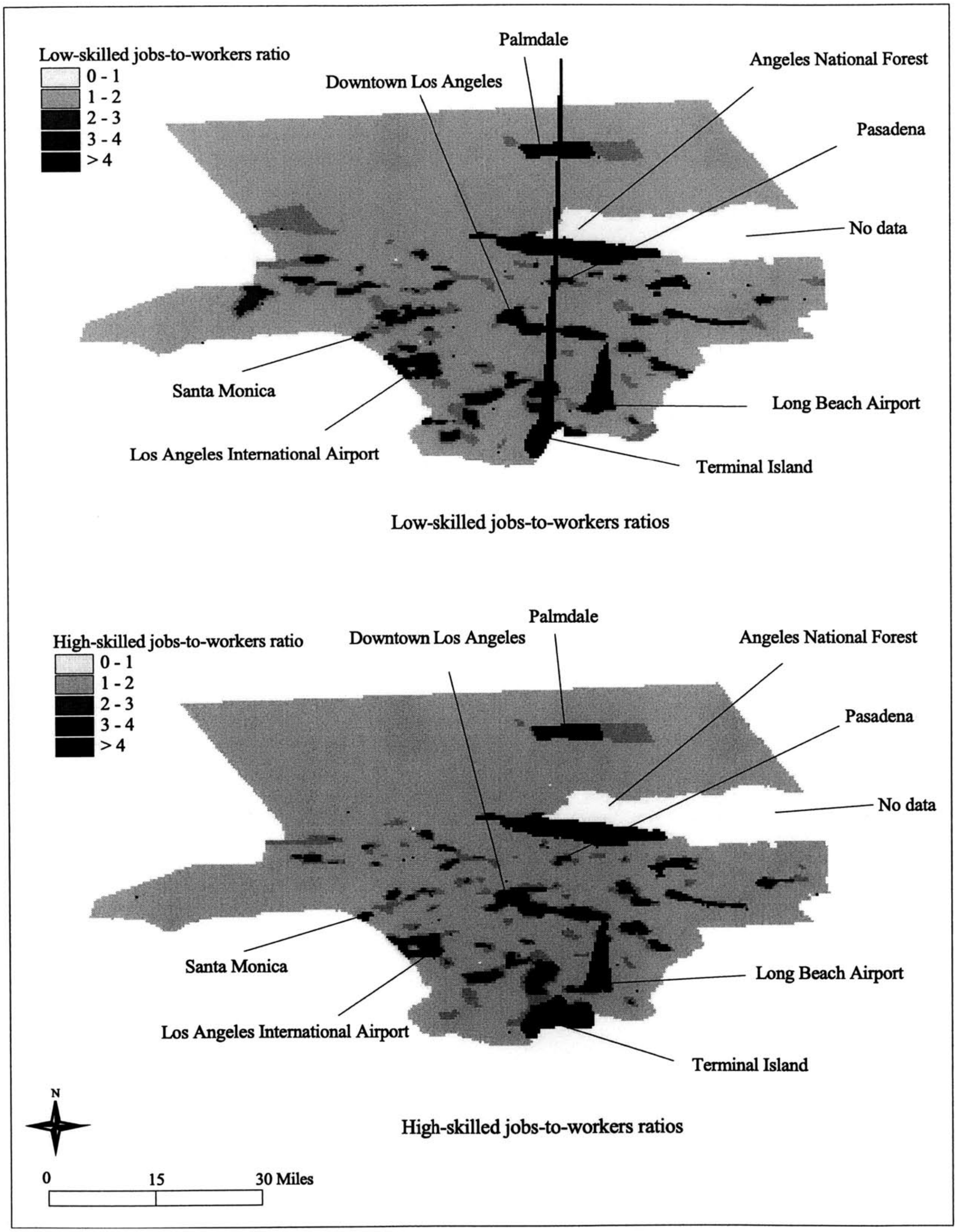

Figure 5.3.3c Jobs-to-workers ratio in Los Angeles metropolitan area

5.4 CHAPTER SUMMARY

The simple central city versus suburbs dichotomy showed that in all three metropolitan areas, workers were more suburbanized than jobs. While low-skilled workers were slightly more concentrated in the central cities than were high-skilled workers in Boston and Los Angeles (no difference for San Francisco), low-skilled jobs were more decentralized than were high-skilled jobs in the three areas. The jobs-to-workers ratios were therefore greater in the central cities than in the suburbs, and within the central cities, the ratios were lower for low-skilled workers than for high-skilled workers. The jobs-to-workers ratios in the suburbs were, on the other hand, higher for the low-skilled group than for the high-skilled group, but the difference was small with the exception of Boston.

What these results indicate is that in terms of job opportunities, the central-city areas provide more of a geographical advantage than do the suburban areas for both low-skilled and high-skilled workers. Still, compared to high-skilled workers, such a geographical advantage is much less for low-skilled workers.

More spatially disaggregated pictures of the distributions of workers and jobs were displayed in the maps in three dimensions. The 3D maps showed the great variations in the spatial distributions, which tables or 2D maps would not convey effectively. The maps revealed that despite the substantial suburbanization, areas around the CBDs still had high concentrations of workers and jobs, but jobs were much more concentrated than were workers. The 3D maps also indicated that the spatial patterns for the low-skilled and high-skilled groups were quite similar. These spatial patterns of workers and jobs, however, varied considerably across the three metropolitan areas.

Boston had a distinctive urban core with both workers and jobs being centered around the CBD, but jobs were far more concentrated around the CBD than were workers. While low-skilled workers were more centralized than high-skilled jobs, low-skilled jobs were more decentralized than high-skilled jobs. San Francisco was a more polycentric metropolitan area. While the city of San Francisco showed the highest concentrations of workers and jobs, workers and jobs were also clustered in areas surrounding the San Francisco Bay, and high levels of clusters were located in downtown Oakland and downtown San Jose.

Compared to the other two metropolitan areas, urban cores in Los Angeles were less conspicuous, and workers and jobs were widely distributed in the southern sections of Los Angeles County. Yet, areas around downtown Los Angeles have markedly high concentrations of jobs.

The ratios of jobs to workers were also presented in the 3D maps, but the maps indicated that using the simple jobs-to-workers ratio in an area of residence as a measurement of job accessibility could be misleading for a small geographic area. For example, Boston's CBD, downtown San Jose, and Los Angeles' Terminal Island and Long Beach Airport have exceedingly high jobs-to-workers ratios, but the ratios are likely to overestimate job accessibility since many workers who live nearby commute to fill those jobs. Conversely, the low jobs-to-workers ratios in the areas near the CBDs are likely to underestimate true job accessibility since workers in those areas actually have many jobs nearby.

Another example in which the jobs-to-workers ratio can be misleading is in an area with a small number of jobs but even a smaller number of workers. In such an area, the jobs-to-workers ratio is high, but the level of job opportunities is not as high. An example was the large areas at the south part of Angeles National Forest.

The job-access measures employed in this study mitigate the problems associated with the simple jobs-to-workers ratio, since the measures take into account workers and jobs not only within an area of residence but also in areas beyond that area of residence, depending on travel costs. In addition, the proposed measures capture the difference in travel modes. The next chapter formulates and computes the refined measures of job accessibility.

Chapter 6: Measuring Job Accessibility for Low-Skilled Workers

One of the essential components to explore the research questions asked in this dissertation is to construct a improved measurement of job accessibility that well represents the level of spatially accessible job opportunities with respect to residence. This chapter describes the formulation and computation of the improved job-access measures for low-skilled workers in three metropolitan areas: the Boston Primary Metropolitan Statistical Area (PMSA), nine-county San Francisco Bay Area, and Los Angeles PMSA (i.e., Los Angeles County).[6] Spatial variations in the computed measures are presented for two geographic levels: the traffic analysis zone (TAZ) and Public Use Microdata Area (PUMA).

6.1 FORMULATING JOB-ACCESS MEASURES FOR LOW-SKILLED WORKERS

As explained in Sections 2.2.3 and 2.2.4, a major reason for the conflicting results in spatial mismatch studies is the diversity in measurements of job accessibility. The most commonly used measurements to date are the following four: the jobs-per-area measurement, jobs-to-workers-per-area ratio, commuting time, and gravity-based measure. The detailed review of these measurements is presented in Section 2.2.4. This study uses the gravity-based measures that capture two factors: supply side (job seekers) and demand side (job openings) of the labor market and difference in travel modes. When these factors are taken into account, the gravity-based measures are quite an appealing measurement, since they can more accurately represent accessible job opportunities with respect to residence than the other three measurements listed above.

[6] The Boston PMSA has seven counties: Bristol, Essex, Middlesex, Norfolk, Plymouth, Suffolk, and Worcester Counties. The nine counties in the San Francisco Bay Area are Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties.

This research therefore uses Shen's (1998, 2001) formulas that incorporate the two factors to calculate job accessibility. The formulas are given by:

$$A_i^{auto} = \sum_j \frac{O_{j(t)} \times f(C_{ij}^{auto})}{\sum_k \{\alpha_k P_{k(t)} \times f(C_{kj}^{auto}) + (1-\alpha_k) P_{k(t)} \times f(C_{kj}^{pub})\}}, \tag{6.1}$$

$$A_i^{pub} = \sum_j \frac{O_{j(t)} \times f(C_{ij}^{pub})}{\sum_k \{\alpha_k P_{k(t)} \times f(C_{kj}^{auto}) + (1-\alpha_k) P_{k(t)} \times f(C_{kj}^{pub})\}}. \tag{6.2}$$

A_i^{auto} and A_i^{pub} are job-access measures for job seekers living in zone i who are, respectively, auto commuters and transit commuters. $O_{j(t)}$ represents the number of job opportunities in zone j at time t, and $P_{k(t)}$ indicates the number of job seekers living in zone k at time t. Impedance functions for commuters traveling between zone i and zone j are $f(C_{ij}^{auto})$ for auto users and $f(C_{ij}^{pub})$ for transit users. Likewise, $f(C_{kj}^{auto})$ and $f(C_{kj}^{pub})$ are impedance functions for auto commuters and transit commuters, respectively, traveling between zone k and zone j. The percentage of households with autos in zone k is expressed by α_k.. $i, j, k = 1, 2, \ldots, N$.

Equations 6.1 and 6.2 represent the refinement of the simple jobs-to-workers-per-area ratio. This simple ratio is less useful for the purpose of this study in that it ignores job opportunities beyond an area of residence and does not take travel modes into account. The equations presented above, on the other hand, incorporate not only opportunities within an area of residence but also opportunities in zones beyond that area, depending on travel costs and travel modes. The incorporation of travel modes in the job-access measures is particularly important in this research.

The year 1990 (t) is selected for this study because 1990 is the latest year for which all the necessary data are available. The geographic unit (zone) is the transportation analysis zone (TAZ), a typical geographic unit used in the field of transportation. Traffic analysis zones are designated by local transportation agencies and vary in size depending on density and homogeneity of land uses.

The simple travel time threshold function is used to estimate the impedance function ($f(C_{ij})$). When travel time between zone i and zone j is less than 30 minutes, I set the value of the impedance function equal to one.[7] The 1990 zone-to-zone commuting time matrices for auto users and transit users were provided by the Central Transportation Planning Staff (CTPS) for Boston, by the Metropolitan Transportation Commission (MTC) for San Francisco, and by the Southern California Association of Governments (SCAG) for Los Angeles.

To reflect the supply and demand of the labor market, the number of job seekers (P) and the number of job opportunities (O) represent the number of low-skilled unemployed workers who are looking for jobs and the number of job openings for these workers, respectively.

To calculate the number of job openings, I employ Shen's (2001) formulas for openings generated by both employment growth and employment levels (job turnover). The number of job openings in zone i at time t ($O_{i(t)}$) is given by

$$O_{i(t)} = O_{i(t)}^{growth} + O_{i(t)}^{turnover}, \qquad (6.3)$$

where

$$O_{i(t)}^{growth} = \frac{E_{i(t)} - E_{i(t')}}{(t - t') \times 12 months} \times v, \qquad (6.4)$$

$$O_{i(t)}^{turnover} = E_{i(t)} \times v \times z. \qquad (6.5)$$

$O_{i(t)}^{growth}$ is the number of job openings created by employment growth in zone i at time t, and $O_{i(t)}^{turnover}$ represents the number of job openings created by turnover in zone i at time t. The ending time (year) and the starting time (year) of the time period are given by t and t',

[7] The 30-minute threshold is also used by Ellwood (1986) and Shen (2001). In 1990, the average travel time in the largest 39 metropolitan areas is 25.2 minutes (Rossetti and Eversole, 1993). The results of Shen (1998, 2001) suggest that in the Boston metropolitan area, the access measures using the 30-minute threshold are close to the access measures using the exponential function, $f(C_{ij}) = exp(-\beta C_{ij})$, where the calibrated value of β is approximately 0.1

respectively. $E_{i(t)}$ is the employment level in zone i at the ending time, and $E_{i(t')}$ is the employment level in zone i at the starting time. The average vacancy duration is represented by v, and the monthly turnover rate is indicated by z.

This study selects 1980 for the starting year (t') and 1990 for the ending year (t). The 1980 employment data come from the 1980 Urban Transportation Planning Packages (UTPP), and the 1990 employment data come from the 1990 Census Transportation Planning Packages (CTPP). The UTPP and CTPP data include the number of workers by area of work, which are utilized as employment statistics.

I obtained the 1980 UTPP data for Boston and San Francisco, but the 1980 UTPP data for Los Angeles were not available. Therefore, while the job-access measures in Boston and San Francisco incorporate job openings created by employment growth as well as openings by job turnover (employment levels), the measures in Los Angeles reflect openings from only job turnover. This omission of employment growth, however, is not likely to alter the job-access measures significantly, since job openings by employment growth account for only a tiny proportion of total job openings, as indicated by Shen (2001).[8] Indeed, when I computed job-access measures in Boston and San Francisco using job openings created by only job turnover, the resulting job-access measures were almost the same as the measures calculated using openings created both by job turnover and by employment growth.

The average vacancy duration (v) and the monthly turnover rate (z) are set at 0.5 (month) and 0.03, respectively.[9] For the calculation of the employment level in zone i for low-skilled workers (E_i), I propose the following formula:

$$E_i = \sum_l \left(E_{il} \times p_l\right), \qquad (6.6)$$

[8] Shen (2001) finds that on a typical day in 1990 in the Boston metropolitan area, more than 95% of total job openings for less-educated workers are created from job turnover.

[9] According to Shen (2001), the average vacancy duration under normal macroeconomic conditions is approximately 15 days (0.5 month) and the average monthly turnover rate for quits and discharges is roughly three percent. Note that the turnover rate does not include layoffs as layoffs do not generate job openings.

where E_{il} is the number of workers in occupation l, working in zone i, and p_l indicates the proportion of low-skilled workers in occupation l. The 1990 CTPP data provide 14 occupational categories, but the 1980 UTPP data have 10 occupational categories. I therefore use 10 categories for Boston and San Francisco, for which both CTPP and UTPP data are obtainable, and use 14 categories for Los Angeles, for which only CTPP data are available.

To estimate the proportion of low-skilled workers in occupation l (p_l) in Equation 6.6, I use the five-percent Public Use Microdata Samples (PUMS) of the 1990 Census. I define low-skilled workers as workers without high school diplomas. Table 6.1.1 shows statistics in each area, excluding the armed forces.[10] Note that the proportion of low-skilled workers in each occupation (p_l) is assumed to be spatially homogeneous. If the actual proportion varies considerably within each metropolitan area, the estimated absolute values of low-skilled jobs in each zone may be distorted. However, the relative values, which have greater meaning than the absolute values for this study, would be less affected. Since the distortion is likely to be noticeable in urban cores with high concentrations of jobs, but not so noticeable in low-density suburban areas, the overall pictures of spatial distributions of employment opportunities would not change significantly.

Table 6.1.1 Proportion of low-skilled workers by occupation

Occupation	SOC code*	Percentage of low-skilled workers		
		BOS	SF	LA
Executive, administrative, managerial	000-042	3%	4%	8%
Professional specialty	043-202	1%	1%	3%
Technician and related support	203-242	4%	4%	7%
Sales	243-302	13%	12%	20%
Administrative support, including clerical	303-402	8%	8%	14%
Service	403-472	27%	31%	45%
Farming, forestry, fishing	473-502	22%	47%	62%
Precision production, craft, repair	503-702	19%	20%	39%
Operator, fabricator, laborer	703-902	31%	30%	57%

Note: The armed forces occupation is excluded in the calculation of job accessibility.
*SOC: Standard Occupational Classification.

[10] Even though Los Angeles uses the CTPP's occupational classification, the estimated proportions corresponding to the UTPP's classification are presented in Table 6.1.1 for the purpose of comparison.

For the calculation of the number of low-skilled job seekers in zone k (P_k), I propose the following formula:

$$P_k = U_k \times q_k, \qquad (6.7)$$

where U_k is the number of unemployed workers living in zone k, and q_k is the proportion of low-skilled workers living in zone k.

Data on the 1990 unemployed workers, workers by occupation, and auto ownership rate by zone of residence are obtained from CTPP.

The next two sections show the spatial variation in the computed job accessibility for two geographic units: the traffic analysis zone (TAZ) and Public Use Microdata Area (PUMA). Traffic analysis zones (TAZs) are widely used geographic areas in the field of transportation, as noted already, and PUMAs are geographic areas identified by PUMS.[11]

The TAZ-level measures are presented since the job-access measures are first computed for TAZs, and since measures at the level of TAZ can show detailed spatial variation in job accessibility. The job-access measures for PUMAs are also presented since the analyses in Chapter 7 that use the PUMS data require the PUMA-level measures. The conversion from TAZ to PUMA involves two steps: first, converting the job-access measures for TAZs to tract-level measures, and second, converting the tract-level measures to the PUMA-level measures.

When I present the results, the job-access measures in 10 out of 48 PUMAs in the San Francisco metropolitan area are excluded. The exclusion is because these 10 PUMAs have a significant number of TAZs with missing values in UTPP and CTPP; more than five percent of the population in each of these PUMAs is not represented in the calculation of job accessibility, and the resulting job-access measures may be significantly distorted. The 10 PUMAs cover the entire Napa and Sonoma Counties, a large part of Solano County, and small parts of Alameda,

[11] Each PUMA identified by the five percent sample of PUMS has at least 100,000 persons (U.S. Bureau of the Census 1993). In large metropolitan areas, PUMAs are usually larger than zip areas but smaller than counties.

Santa Clara, and San Mateo Counties. Two out of 58 PUMAs in the Los Angeles metropolitan area are also left out of the results owing to their considerably large size and geographically scattered locations. These two PUMAs are located in the northern part of Los Angeles County. The excluded PUMAs are identified in the maps in Section 6.3.

6.2 SPATIAL VARIATION IN JOB ACCESSIBILITY

Table 6.2.1 presents the low-skilled workers' average job-access measures by travel mode for TAZs, and Table 6.2.2 shows the average measures for more aggregated geographic areas, PUMAs. . Note that a job-access measure can be considered the number of spatially accessible job openings per job seeker in a given zone. Also note that the interpretation of the values is concerned more with the relative meaning than the absolute meaning. I define the central cities of the Boston, San Francisco, and Los Angeles metropolitan areas as the city of Boston, city of San Francisco, and city of Los Angeles, respectively

Table 6.2.1 Average job-access measures for low-skilled workers for TAZs

	Boston			San Francisco			Los Angeles		
	Entire area	Central city	Suburbs	Entire area	Central city	Suburbs	Entire area	Central city	Suburbs
Transit	0.03	0.08	0.02	0.02	0.08	0.01	0.02	0.03	0.02
Automobile	0.31	0.45	0.27	0.28	0.41	0.26	0.20	0.24	0.20
Transit/Auto	0.10	0.18	0.06	0.08	0.19	0.05	0.09	0.12	0.09

Note: I define central cities in the Boston, San Francisco, and Los Angeles as the city of Boston, city of San Francisco, and city of Los Angeles, respectively.

Table 6.2.2 Average job-access measures for low-skilled workers for PUMAs

	Boston			San Francisco			Los Angeles		
Travel mode	Entire area	Central city	Suburbs	Entire area	Central city	Suburbs	Entire area	Central city	Suburbs
Transit	0.03	0.06	0.02	0.02	0.07	0.01	0.02	0.03	0.01
Automobile	0.33	0.43	0.30	0.19	0.40	0.16	0.20	0.23	0.18
Transit/Auto	0.08	0.14	0.06	0.09	0.17	0.06	0.09	0.14	0.05

Note: I define central cities in the Boston, San Francisco, and Los Angeles as the city of Boston, city of San Francisco, and city of Los Angeles, respectively.

In all three metropolitan areas, a great discrepancy in job accessibility is found between auto commuters and transit commuters. Job accessibility for transit users is considerably low, and job accessibility for auto users is strikingly higher than that of transit users. In other words, spatial mismatch is much greater for transit users than for auto users. For example, in a typical TAZ in the city of Boston, while a typical low-skilled auto commuter has an access measure of 0.45 jobs per job seeker, a typical low-skilled transit user has an access measure of only 0.08 jobs per job seeker. In a typical TAZ in Boston's suburbs, a typical low-skilled auto user has an access measure of 0.27 jobs per job seeker, but a typical low-skilled transit user has an access measure of 0.02 jobs per job seeker. The great auto/transit discrepancy also applies to the San Francisco and Los Angeles cases. Low-skilled workers who depend on public transportation therefore face markedly lower levels of accessible job opportunities than those workers who have access to automobiles.

A large difference between the central cities and suburban areas is also discerned. Contrary to the perception of many spatial mismatch studies, job accessibility is consistently higher in central cities than in the suburbs, despite the substantial suburbanization of employment. In other words, spatial mismatch is greater in suburban areas than in central-city areas, which contradicts the dominant view among spatial mismatch researchers. This central-city/suburb disparity, however, is much smaller than the auto/transit disparity, suggesting that the mode of travel has greater importance in determining job accessibility than location. These findings suggest that spatial mismatch may pose a serious problem for autoless workers, particularly for those who live in suburban areas, although it may not be a problem for workers with autos.

Since the calculated average measures are not weighted by area, the statistics for TAZs somewhat differ from the statistics for PUMAs. This difference, however, is mostly minor. Only for auto commuters in San Francisco, do the measures show a noticeable discrepancy. This discrepancy is largely because of the 10 PUMAs that were excluded, as described earlier.

The direct comparison of the statistics across the three study areas needs caution, since the metropolitan areas and central cities vary considerably in size. The San Francisco and Los Angeles metropolitan areas are markedly larger (approximately 6,900 and 4,100 square miles of land area, respectively) than the Boston metropolitan area (1,800 square mile of land). The size of the central city also varies substantially. The city of Los Angeles is extremely large (470 square miles), while the cities of Boston and San Francisco are more compact (60 and 50 square miles, respectively). As a result, the proportion of the central-city in the Los Angeles metropolitan area is much higher (12%) than the proportions of the central-city areas in the Boston and San Francisco metropolitan areas (3% and 1%, respectively). The central cities are identified in the maps shown in the next chapter.

6.3 VISUALIZING JOB ACCESSIBILITY

The central city versus suburban dichotomy in the above two tables provides a rather aggregated picture of job accessibility. To show more detailed spatial variation in job accessibility, this section depicts the computed job-access measures for TAZs and PUMAs using Geographic Information Systems (GIS).

Figures 6.2.1, 6.2.2, and 6.3.3 show the job-access measures for transit commuters and for auto commuters by TAZ in Boston, San Francisco, and Los Angeles, respectively. For comparison, these maps use the same equal interval classification. In order to clarify the spatial variation, the maps that use the standard deviation classification are also presented in Figures 6.2.1b, 6.2.2b, and 6.2.3b.

The maps using the same equal interval classification (Figures 6.2.1, 6.2.2, and 6.2.3) reveal a striking difference in job accessibility between low-skilled auto commuters and transit commuters. In all three metropolitan areas, job accessibility is remarkably higher for auto commuters than for transit commuters.

The maps using the standard deviation classification (Figures 6.2.1b, 6.2.2b, and 6.2.3b) provide better pictures of the spatial variation in job accessibility. For simplicity, I define areas rich in job accessibility as zones with job-access measures above the mean, and define areas poor in job accessibility as zones with access measures below the mean. Some differences are found across the three metropolitan areas.

In the Boston metropolitan area, job accessibility is largely better in zones around the city of Boston than it is in suburban areas, particularly for transit commuters. For them, accessibility-rich areas are concentrated around the city of Boston, where public transportation systems are relatively well developed. Auto commuters' accessibility-rich areas, on the other hand, extend into the suburban areas. These results are for the most part consistent with the findings of Shen (1998, 2001).

The rich areas of job accessibility in the San Francisco Bay Area are more scattered. For transit commuters, areas around downtown San Francisco and downtown Oakland have notably high job accessibility, but accessibility-rich areas for transit commuters are also found in sparsely distributed zones surrounding the San Francisco Bay (these zones' accessibility is rather moderate, however). Auto commuters' accessibility-rich areas are also located around downtown San Francisco and downtown Oakland, but the accessibility-rich areas also include many zones near the San Francisco Bay.

In the Los Angeles metropolitan area, zones around downtown Los Angeles, Beverly Hills, and Santa Monica have relatively high job accessibility for both auto and transit commuters. For workers who commute by auto, however, accessibility-rich areas are far more widespread. Note that the large zone located at the southern part of Angeles National Forest has relatively high job accessibility for transit commuters; this sparsely-populated zone has a small number of job openings and even a smaller number of unemployed workers.

These findings suggest that persons who depend on public transportation, particularly those who live in the suburbs, face considerably low levels of spatially accessible job opportunities, and that for people who do not have access to autos, areas with relatively high levels of job opportunities are limited to small portions of the metropolitan areas.

The job-access measures for PUMAs are mapped in Figures 6.2.4 to 6.2.6. Although spatial resolution drops considerably for these geographic areas, the general findings discussed above apply. Note that job accessibility for transit in the TAZ located at the southern part of Angeles

National Forest becomes lower for the overlapping PUMA. This is because this PUMA is larger than the TAZ, adding some small but well-populated TAZs that have relatively low ratios of job openings to job seekers. The job-access measures for PUMAs are utilized in the next chapter, which uses the PUMS data to examine the importance of job accessibility for low-skilled workers without autos.

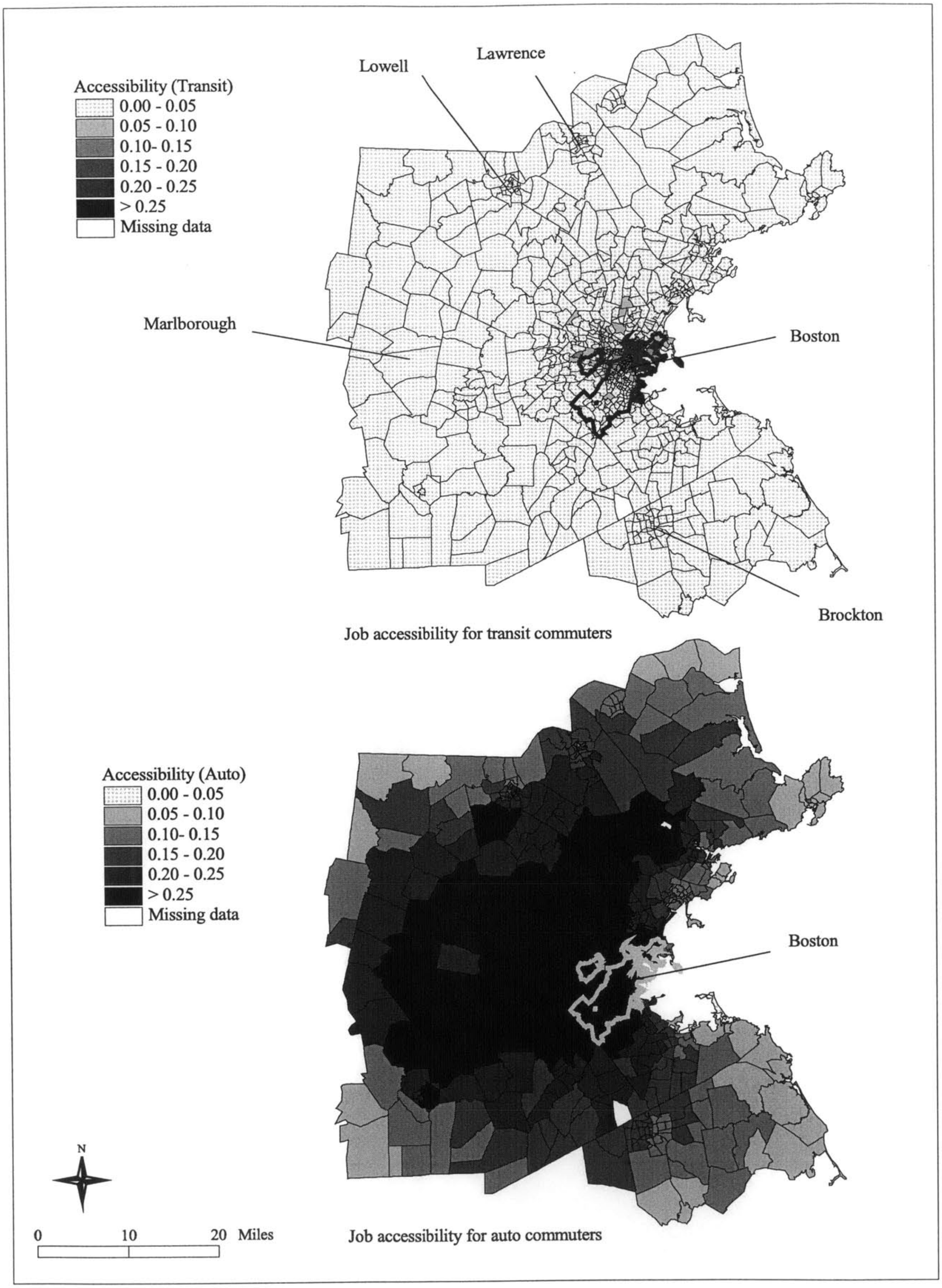

Figure 6.2.1 Job accessibility for low-skilled workers by TAZ in Boston metropolitan area

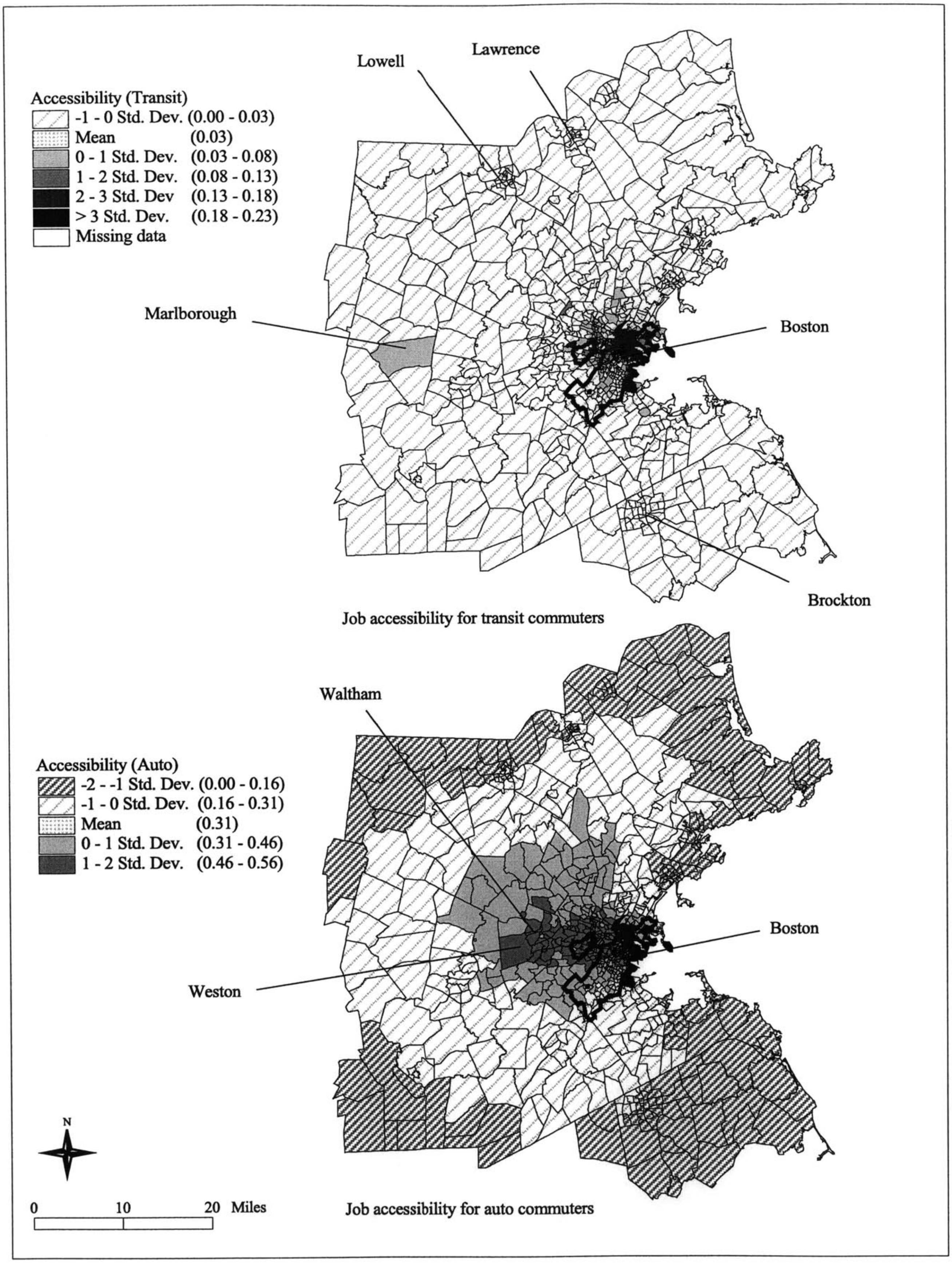

Figure 6.2.1b Job accessibility for low-skilled workers by TAZ in Boston metropolitan area (standard deviation classification)

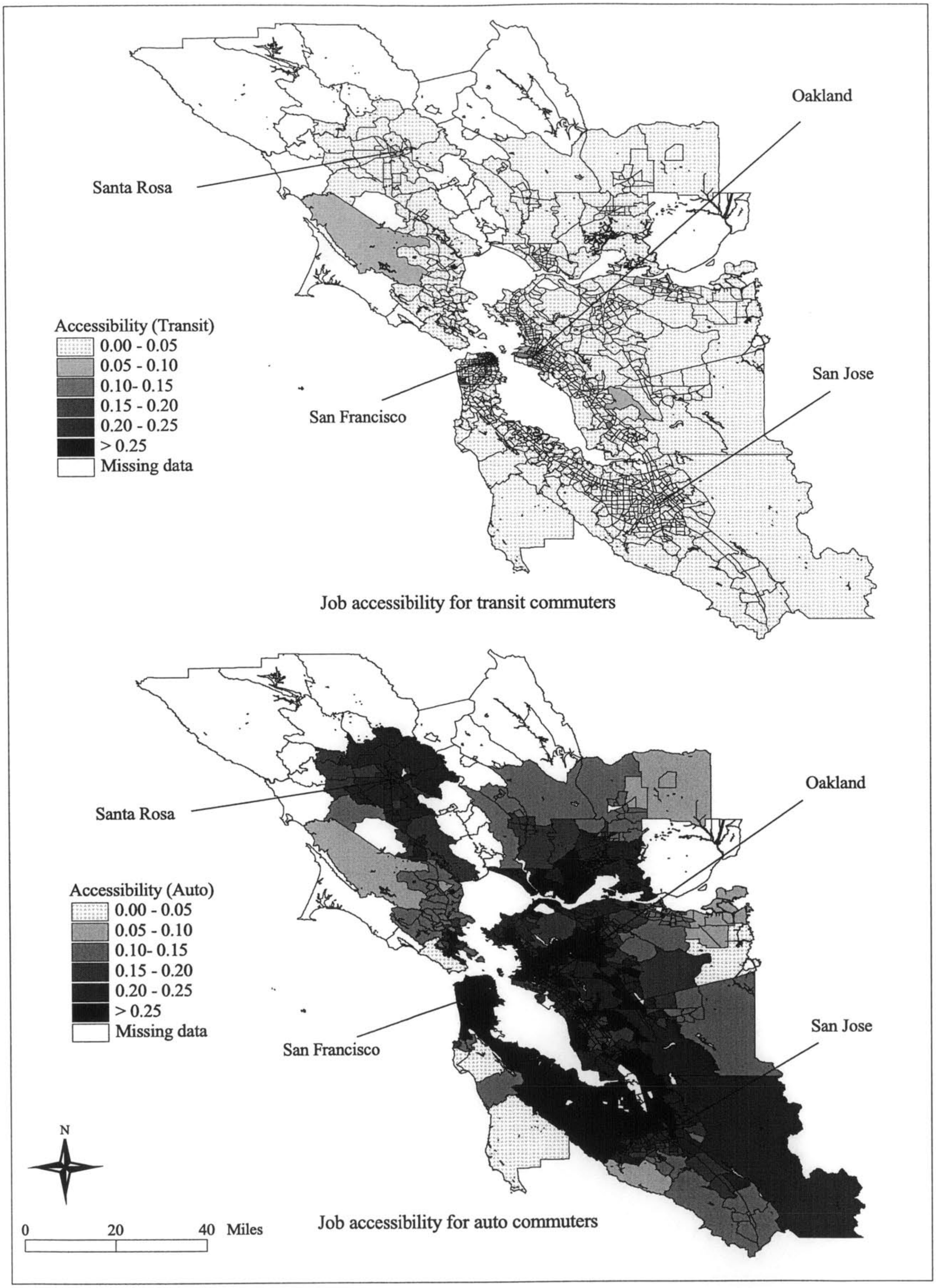

Figure 6.2.2 Job accessibility for low-skilled workers by TAZ in San Francisco Bay Area

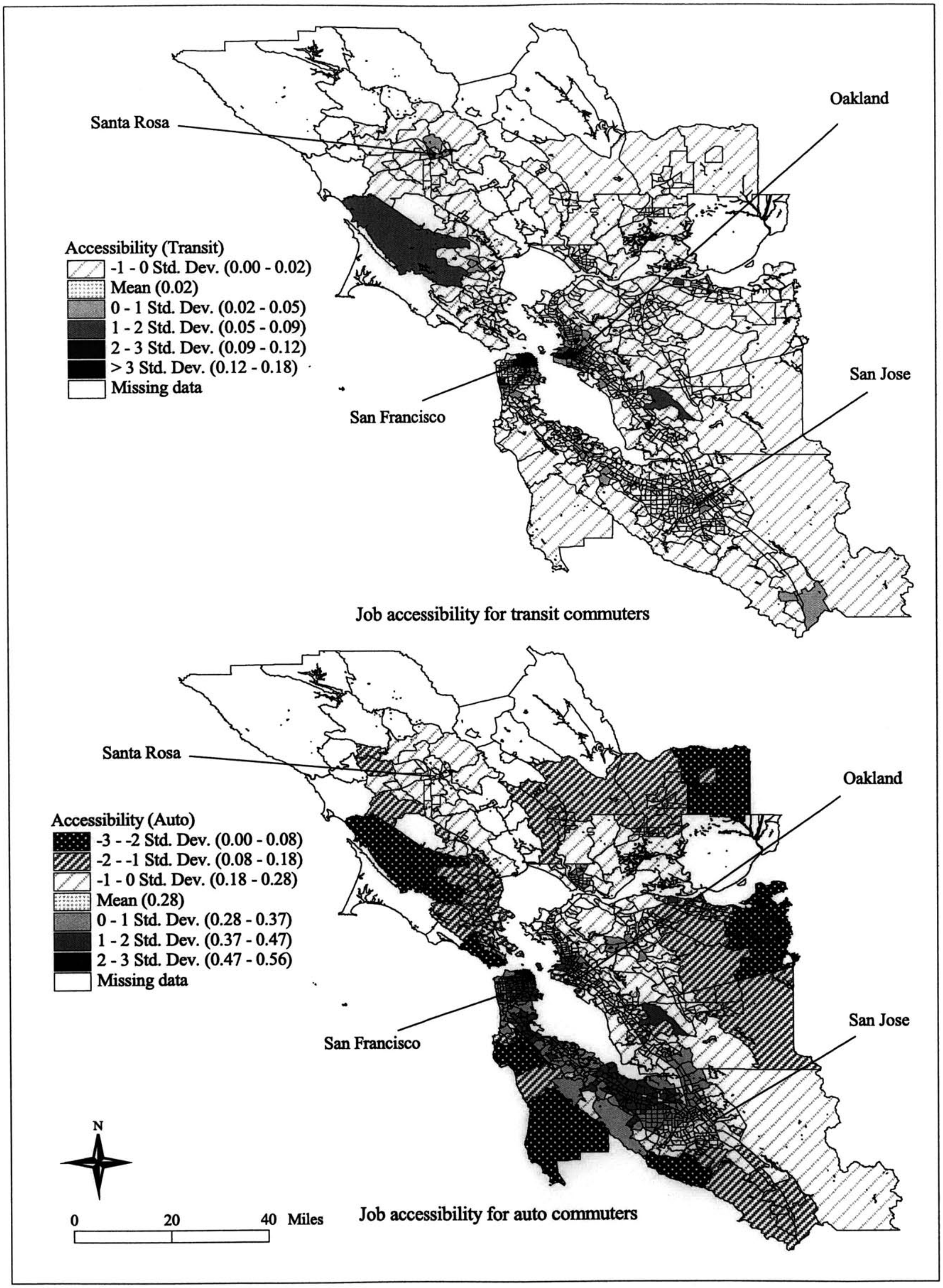

Figure 6.2.2b Job accessibility for low-skilled workers by TAZ in San Francisco Bay Area (standard deviation classification)

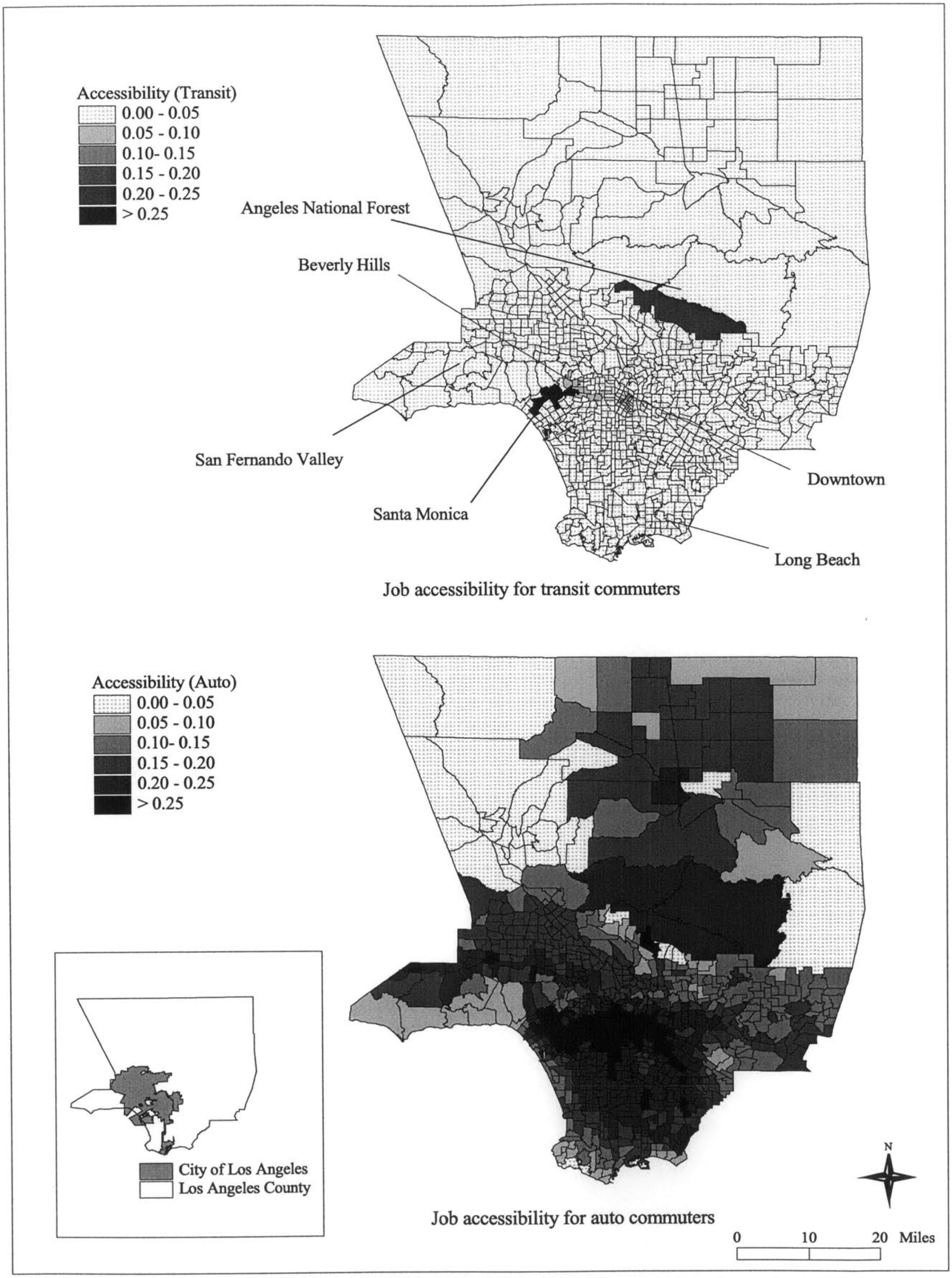

Figure 6.2.3 Job accessibility for low-skilled workers by TAZ in Los Angeles metropolitan area

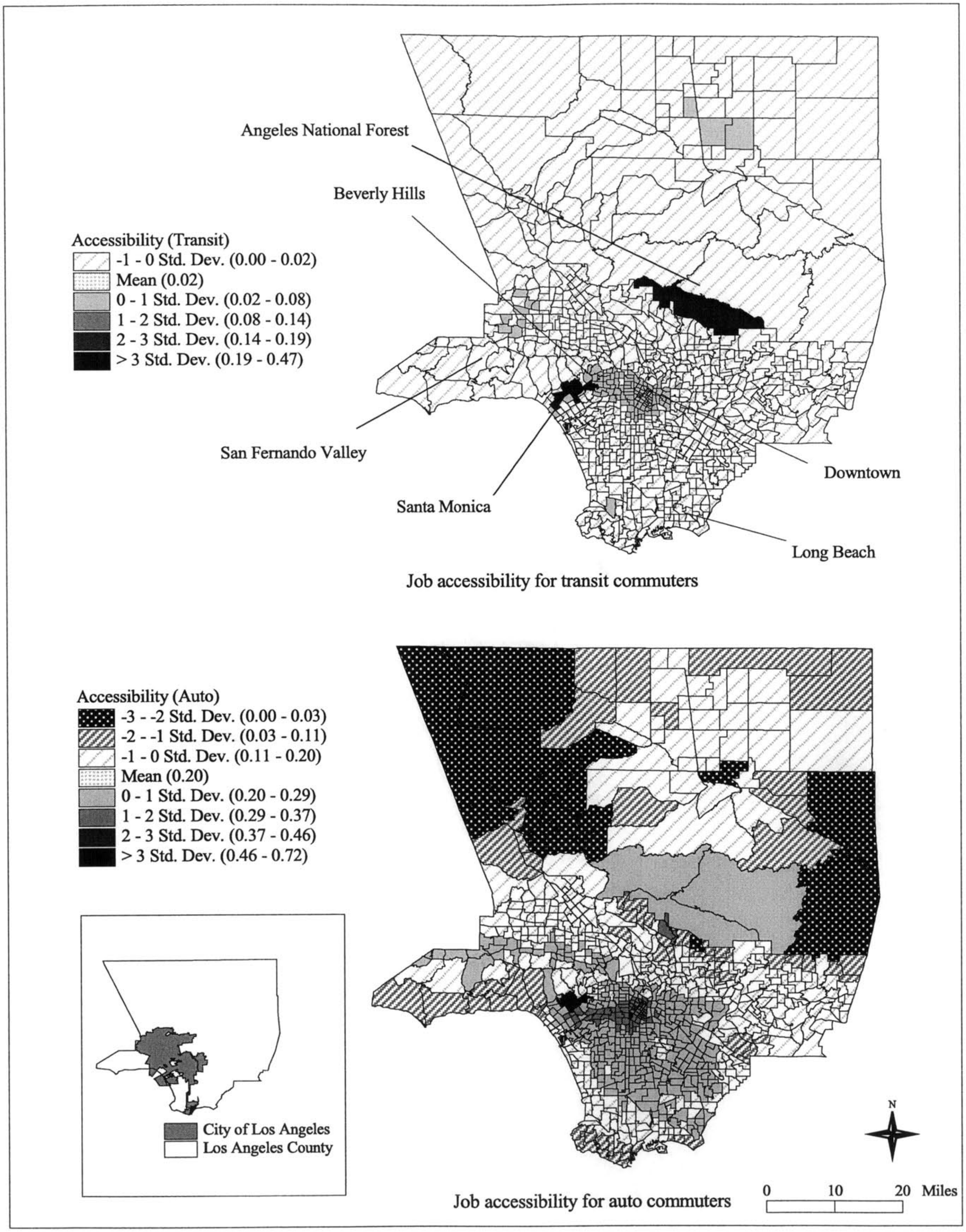

Figure 6.2.3b Job accessibility for low-skilled workers by TAZ in Los Angeles metropolitan area (standard deviation classification)

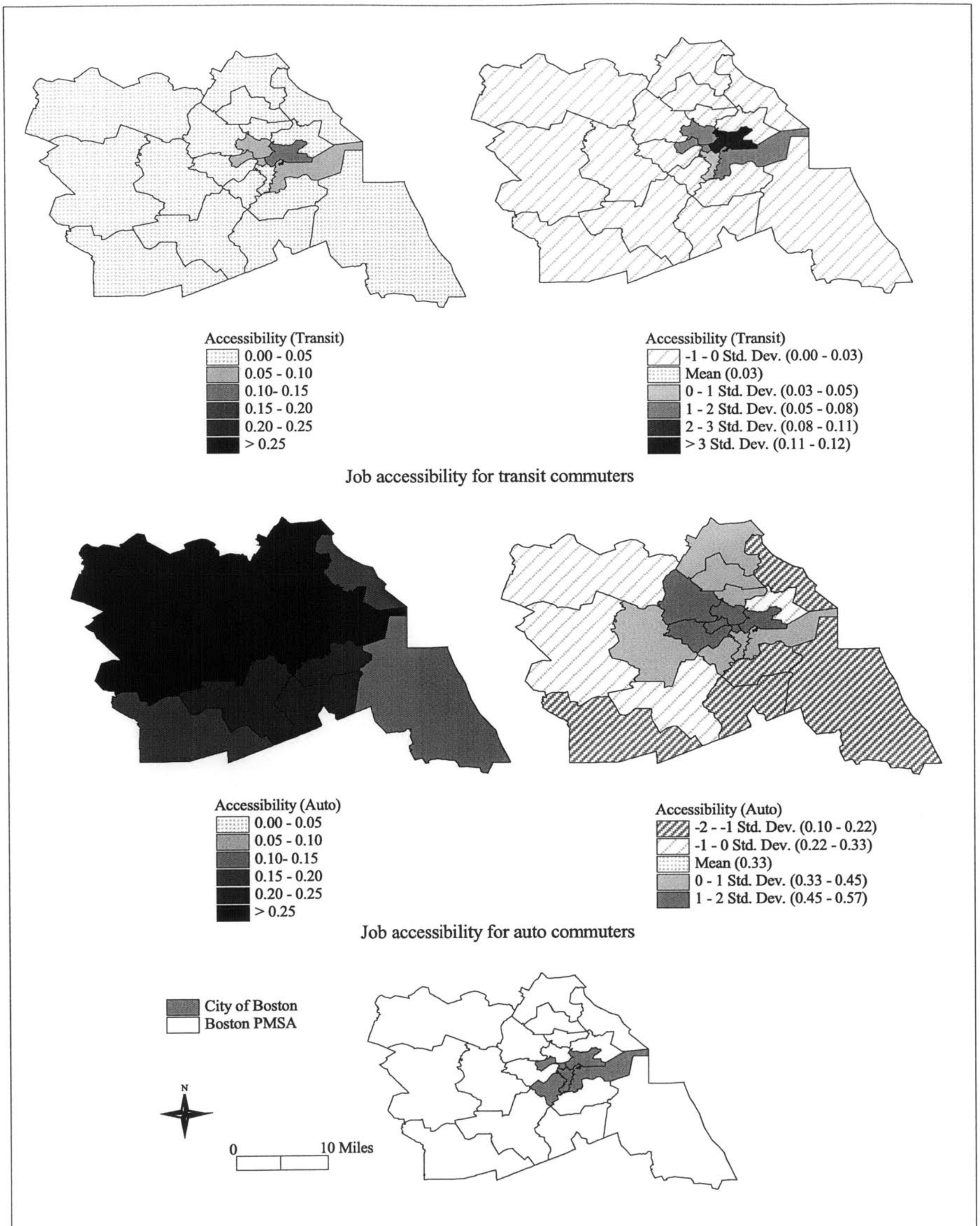

Figure 6.2.4. Job accessibility for low-skilled workers by PUMA in Boston metropolitan area

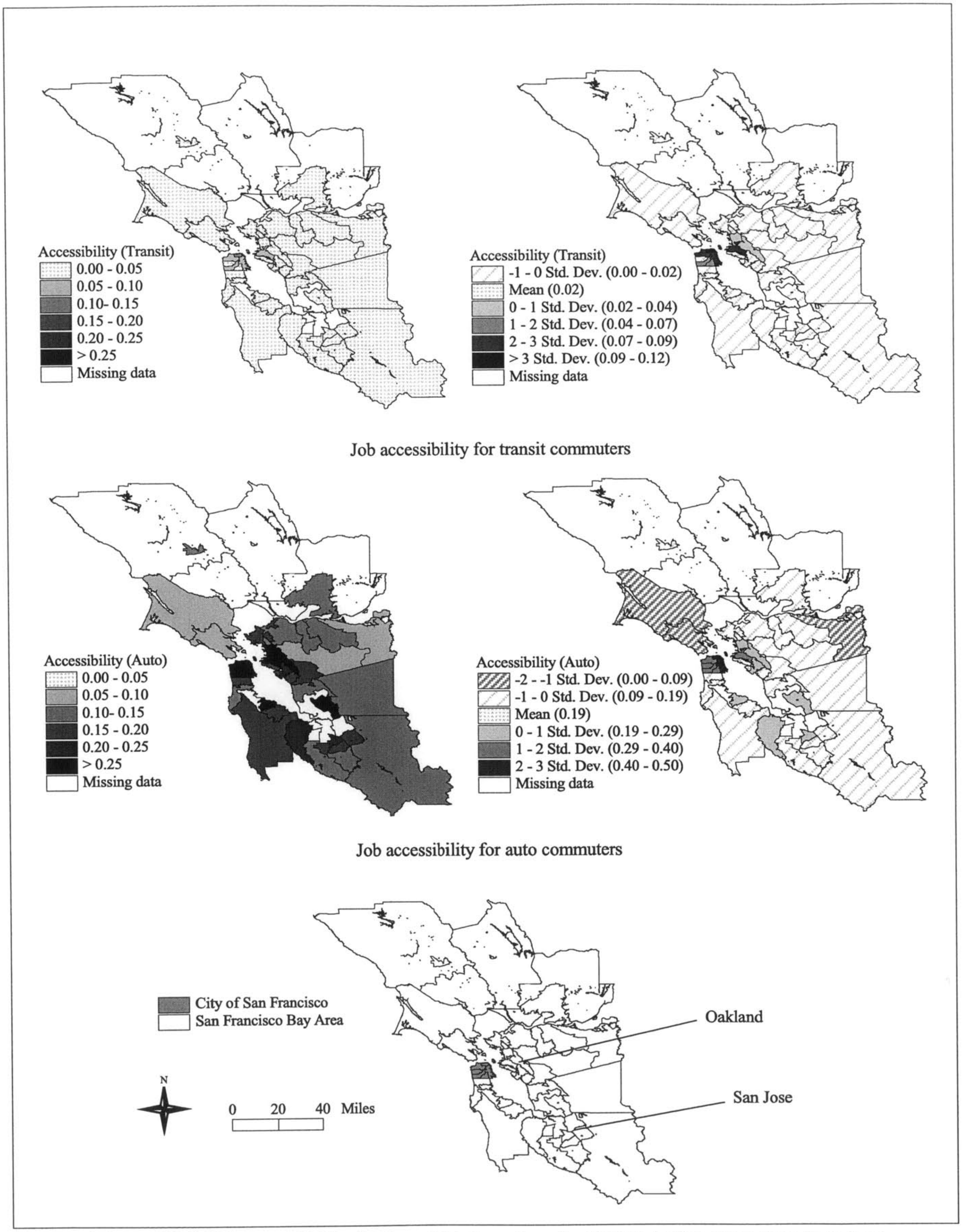

Figure 6.2.5. Job accessibility for low-skilled workers by PUMA in San Francisco Bay Area

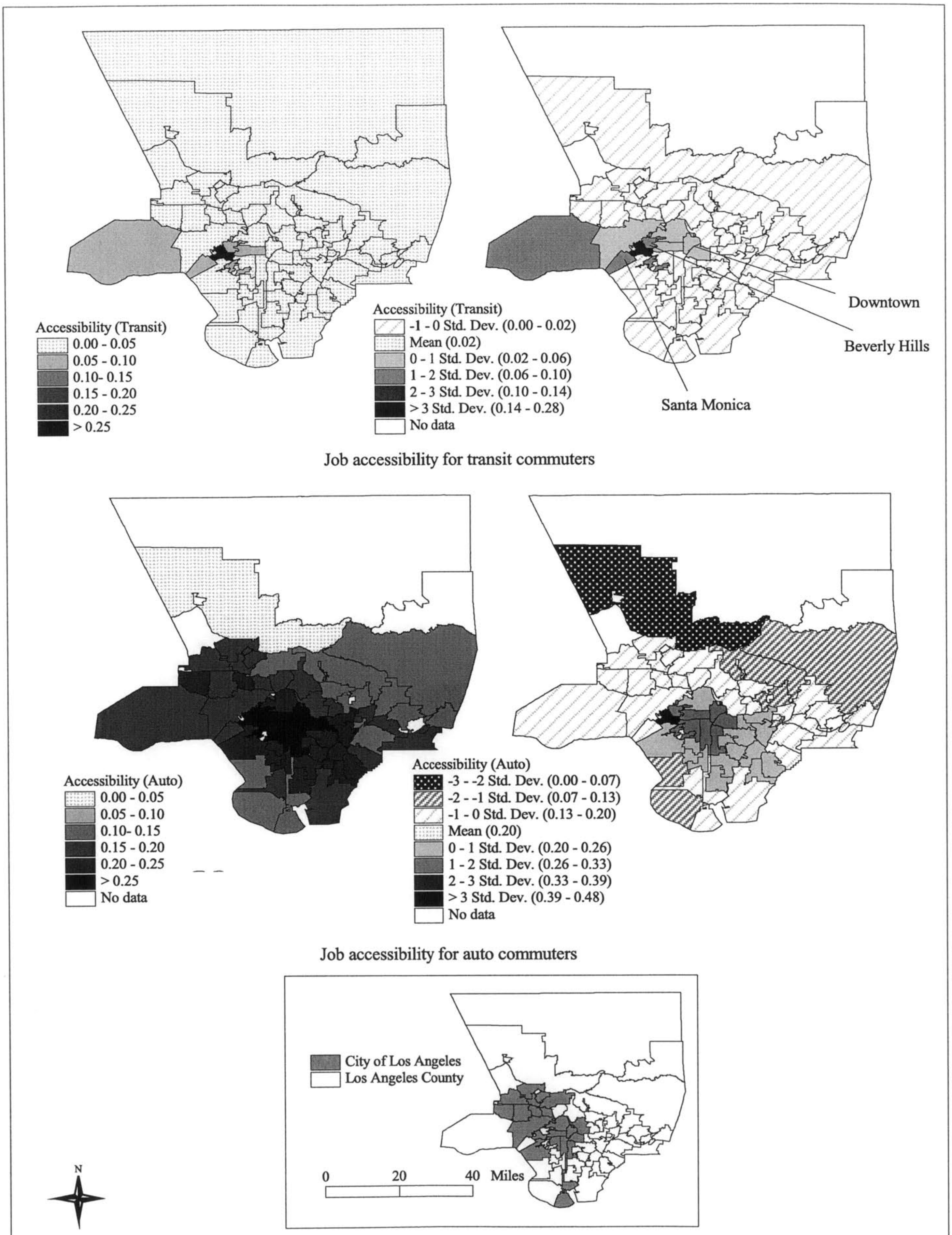

Figure 6.2.6 Job accessibility for low-skilled workers by PUMA in Los Angeles metropolitan area

Chapter 7: Job Access and Employment Outcomes for Low-Skilled Autoless Workers

As described in Chapters 1 and 2, an extensive body of the spatial mismatch literature has investigated the relationship between job accessibility and employment outcomes for disadvantaged workers. Most spatial mismatch studies, however, focus on inner-city minorities, and the access-employment relationship for all autoless workers in a metropolitan area as a whole has not been well explored. Given the auto-oriented, spatially dispersed nature of urban development in the U.S., levels of accessible job opportunities may be significantly more important in obtaining and keeping jobs for workers without autos than for workers with autos. This chapter attempts to provide new evidence on spatial mismatch by examining the effect of job accessibility on employment outcomes for low-skilled workers without autos. Specifically, I ask the following research questions:

(1) Does job accessibility for transit users significantly and positively affect employment outcomes for low-skilled workers who do not have automobiles?;
(2) Is the job-access effect for low-skilled workers greater for persons without autos than persons with autos?; and
(3) Does the job-access effect for low-skilled autoless workers vary across metropolitan areas with different urban spatial structures?

The three metropolitan areas studied are the Boston Primary Metropolitan Statistical Area, the nine-county San Francisco Bay Area, and Los Angeles County. The third question is examined since the metropolitan difference in the importance of job accessibility in employment outcomes has not been fully explored. Job accessibility may be more important in San Francisco and Los Angeles, highly auto-dependent areas, than in Boston, a more compact area with relatively well-developed public transit systems.

I use the job-access measures calculated in the previous chapter. These measures take into account travel modes, which is mostly ignored in the job-access measurements employed by the existing spatial mismatch studies. Since job accessibility differs greatly between transit and auto commuters, the differentiation of travel modes in the job-access measurement is critical to explore the access-employment relationships for autoless workers.

In order to shed light on the situations workers are most likely to experience, I analyze three employment outcomes: the probability of employment, the probability of working 30 or more hours per week, and earnings. The analytical methods employed in this chapter are multinomial logit (MNL) and the Heckman correction method. These methods are described in detail in Section 7.2.

This chapter is organized into four sections: Sections 7.1 and 7.2 explain the data and statistical models, respectively; Section 7.3 presents estimated results from the models; and Section 7.4 summarizes empirical findings.

7.1 DATA

This research selected the three metropolitan areas as the study areas: the Boston Primary Metropolitan Statistical Area (PMSA), nine-county San Francisco Bay Area, and Los Angeles PMSA (i.e., Los Angeles County).[12] The data set combines three data sources: individual low-skilled workers, job-access measures, and neighborhood characteristics.

The data on individual low-skilled workers come from the five-percent Public Use Microdata Samples (PUMS) of the 1990 Census, which provide five percent samples of housing units and the persons in them. The use of the publicly available census data enables the metropolitan comparison. The PUMS data have a unique geographic identification: the "Public Use Microdata Area (PUMA)."

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[12] The Boston PMSA has seven counties: Bristol, Essex, Middlesex, Norfolk, Plymouth, Suffolk, and Worcester Counties. The nine counties in the San Francisco Bay Area are Alameda, Contra Costa, Marin, Napa, San

There are five PUMAs in the city of Boston and 21 PUMAs in the Boston PMSA. These 21 PUMAs are completely within the Boston PMSA, and PUMAs that are partially but not completely within the Boston PMSA are not included. The nine-county San Francisco Bay Area has 48 PUMAs and the city of San Francisco includes six PUMAs. Ten out of 48 PUMAs are excluded in the analyses since the job-access measures for these 10 PUMAs may be significantly distorted, owing to missing data as explained in the previous chapter.[13] The excluded 10 PUMAs are entire Napa and Sonoma Counties, a large part of Solano County, and small parts of Alameda, Santa Clara, and San Mateo Counties. The Los Angeles PMSA contains 58 PUMAs and the city of Los Angeles has 21 PUMAs. Three PUMAs are excluded owing to their large size and geographically scattered locations. The excluded PUMAs are identified in Figure 7.1.1.

The job-access measures are from the gravity-based measures calculated in the previous chapter. The computed measures are quite appealing as a measurement of job accessibility, since they take into account the supply and demand sides of the labor market and differences in travel modes. An advantage of the gravity-based measures is that they capture opportunities not only within an area of residence but also in all accessible areas beyond that area of residence; these opportunities are attenuated with travel cost. The job-access measures, which are first computed for traffic analysis zones (TAZ), are converted to PUMA-level measures and then combined with PUMS.

I use the ratios of transit to auto job accessibility as job-access measures in the analyses. The ratios are used in order to capture the disparity in job accessibility between transit and autos, and to deal with the great difference in magnitude and variability between transit and auto job accessibility. The ratios in the three study areas are depicted in Figure 7.1.1. The high ratios of transit to auto job accessibility are found in areas where transit systems are relatively well developed. These areas are zones around the city of Boston for the Boston PMSA, zones around the city of San Francisco and downtown Oakland for the San Francisco Bay Area, and the west central zones, including Century City and Beverly Hills, for Los Angeles County.

Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties.

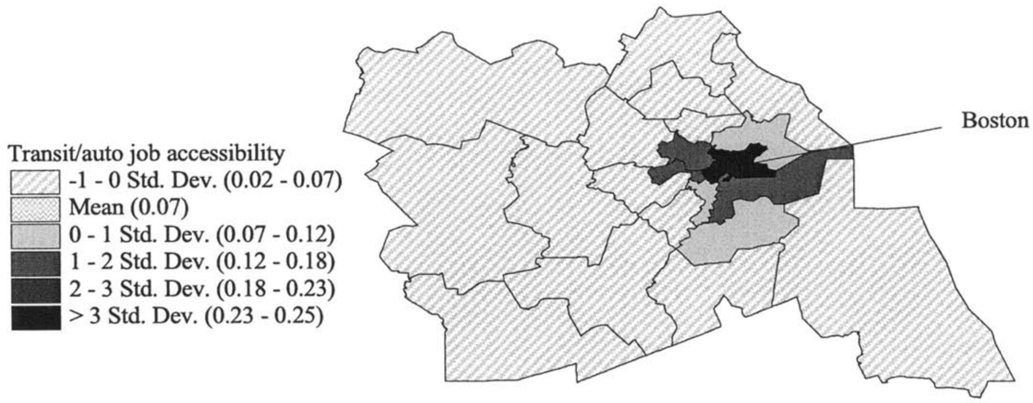
[13] Due to missing data in 1980 UTPP and 1990 CTPP, the five percent of population in each of these 10 PUMAs is

The use of the ratios instead of transit job-access measures may be questioned since areas with different sets of transit and auto job-access measures can generate similar ratios. For example, an area with relatively high auto and transit access measures of 0.450 and 0.150, respectively, and an area with relatively low auto and transit access measures of 0.045 and 0.015, respectively, yield the same ratio of 3.0. This potential problem, however, is not the case in this analysis, since the data indicate that there is a strong linear relationship between the ratios and transit job-access measures with the correlations between the two variables greater than 0.90.[14]

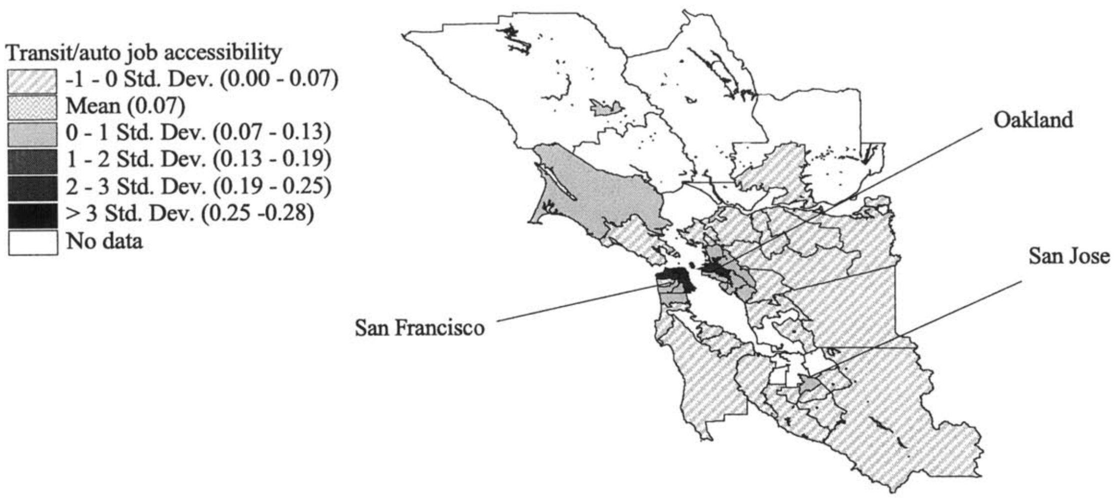
For the neighborhood data, I use tract-level data from the Summary Tape File 3A (STF3A) of the 1990 Census. Two approaches can be used to obtain neighborhood statistics by PUMA from the census data. One approach is to use PUMS to estimate neighborhood characteristics. Another approach is to combine STF3A with PUMS by linking census tracts to PUMAs. This study employs the latter approach because the STF3A data, which include 100 percent counts and unweighted sample counts for total persons and total housing units, provide more reliable neighborhood statistics.

not represented in the calculation of job accessibility.

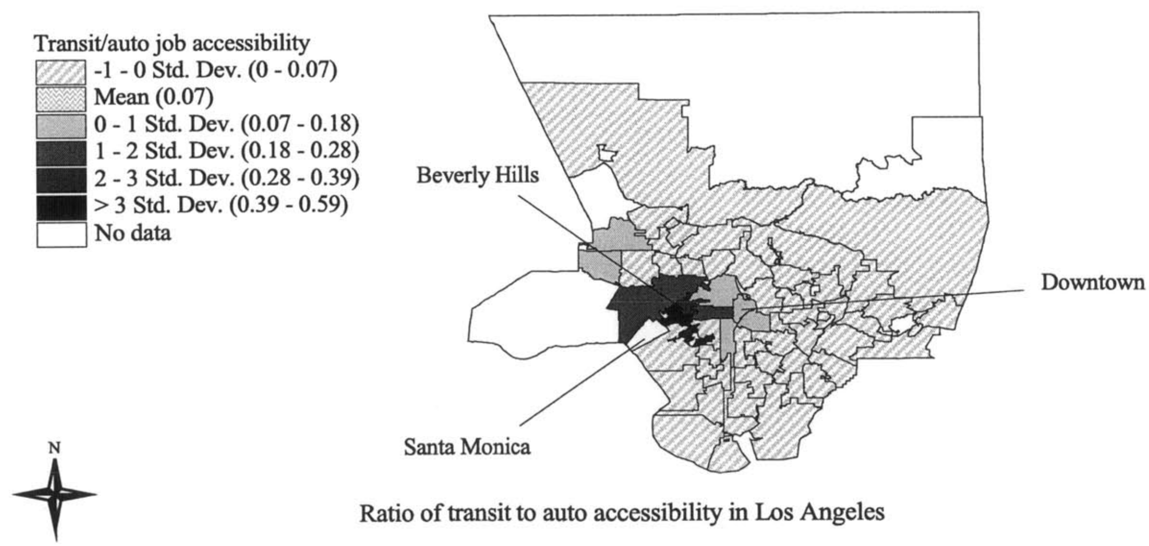
[14] The correlations between the ratios of transit to auto job-access measures and the transit job-access measures in Boston, San Francisco, and Los Angeles are 0.97, 0.97, and 0.91, respectively.



Ratio of transit to auto accessibility in Boston



Ratio of transit to auto accessibility in San Francisco



Ratio of transit to auto accessibility in Los Angeles

Figure 7.1.1 Ratios of transit to auto job accessibility by PUMA in three metropolitan areas.

7.2 MODELS

I use multinomial logit (MNL) and the Heckman correction method to estimate the job-access effect on employment outcomes of low-skilled workers without autos, and to examine the disparity in the effect between autoless workers and workers with autos.

The sample includes persons in the labor force without a high school diploma, aged 16-65. Note that sample stratification based on skills is unlikely to cause a sample selection problem because skills are likely to be exogenous to employment outcomes; that is, skills are likely to affect employment outcomes, but the reverse is unlikely. [15]

This study examines three typical employment outcomes: the employment probability, the probability of working 30 or more hours per week, and earnings. I employ MNL for the first two outcomes and use the Heckman correction method for the third outcome. The MNL and Heckman correction methods are used to deal with the potential selectivity problem. The statistical models are described in greater detail in Sections 7.2.1-7.2.5.

I also examine sensitivity to two alternative job-access measurements: the jobs-per-area measurement and the simple jobs-to-workers-per-area ratio. These are the first two measurements reviewed in Section 2.2, and they are not differentiated by travel mode. The objective of the sensitivity analyses is to investigate whether the estimated job-access effects using the alternative measurements provide different results. I also test sensitivity to different travel time thresholds of 15, 30, and 45 minutes. The results of the sensitivity analyses are reported in Section 7.3.4.

[15] The selection problem can be viewed as a problem of missing observations. In this case, to the extent that observations are missing because of conscious (self-selection) choices made by employment outcomes (e.g., the decision to work or to work 30 hours or longer per week), the estimated parameters will be biased.

7.2.1 Employment Model

I use multinomial logit (MNL) to examine the job-access effect on the first employment outcome, the employment probability. Multinomial logit works according to the random utility theory. For worker n faced with choice set C_n, suppose that the utility (U) of alternative i in choice set C_n is expressed as follows:

$$U_{in} = \beta' x_{in} + \varepsilon_{in}, \qquad (7.1)$$

where β' is a vector of coefficients; x_{in} is a vector describing the attributes of decision-maker n; and ε_{in} is a disturbance term.

If a worker chooses alternative i, then U_{in} is assumed to be the maximum among alternatives in choice set C_n. Hence, the probability that alternative i is chosen by worker n is

$$P_n(U_{in} \succ U_{jn}) \quad \text{for all } i, j \in C_n,\ i \neq j. \qquad (7.2)$$

Multinomial logit assumes that the disturbances ε_{in} are independently and identically distributed with Weibull distribution. The linear-in-parameters MNL is given by

$$P_n(i \mid C_n) = \frac{e^{\beta' x_{in}}}{\sum_{j \in C_n} e^{\beta' x_{jn}}}. \qquad (7.3)$$

$P_n(i / C_n)$ is the probability that a given individual n chooses alternative i within the choice set C_n; β' represents a vector of coefficients; and x_{in} and x_{jn} are vectors describing the attributes of decision-maker n.

Figure 7.2.1 illustrates the MNL structure with four auto-ownership and employment alternatives. The alternatives are listed as a variable, EMP4AUTO, in Table 7.2.1. Multinomial logit models that include all low-skilled workers are used, in order to avoid the selection problem. The selection problem arises if a model uses a sample that is stratified by a factor endogenous to the employment outcomes. For example, if a binary logit model of employment is used separately for those who own autos and for those who do not, such a model is likely to involve selectivity bias, since auto ownership and employment are likely to be endogenous.

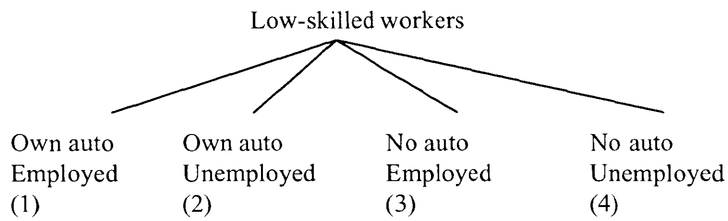


Figure 7.2.1 MNL structure for employment model.

Once the estimates are obtained, the conditional probability of employment given auto ownership can be calculated as follows:

$$P(Employed \mid Auto) = \frac{P(1)}{P(1) + P(2)}, \qquad (7.4)$$

$$P(Employed \mid NoAuto) = \frac{P(3)}{P(3) + P(4)}. \qquad (7.5)$$

7.2.2 Working-Hour Model

I also use MNL for examining the probability of working 30 or more hours per week. Figure 7.2.2 shows the MNL structure with six auto-ownership and working-hour alternatives. The six alternatives are represented by a variable, W30AUTO6, in Table 7.2.1.

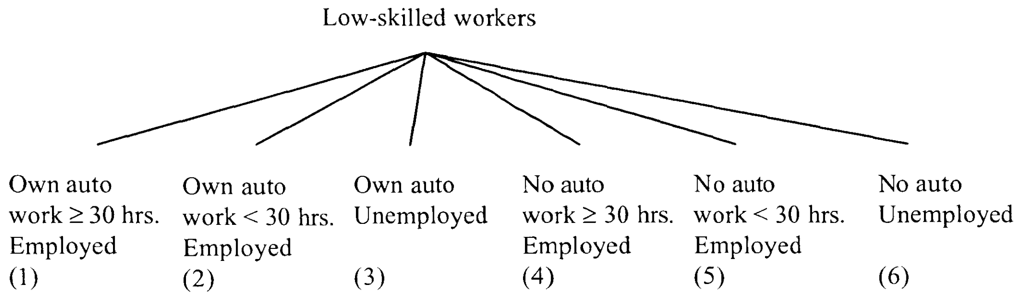


Figure 7.2.2 MNL structure for working-hour model.

Similar to the situation in the employment model presented earlier, MNL including all low-skilled workers is used to avoid the selectivity problem. For instance, if a model is used for a sample including only those who are employed (working hours are observed only for employed workers) and owning automobiles, the estimated parameters are likely to be biased since employment and auto ownership are likely to be endogenous to working hours. In other words, working hours are likely to affect a worker's decision about work and auto ownership.

The conditional probabilities of working 30 or more hours per week given auto ownership are calculated using the following formulas:

$$P(W \geq 30hrs. \mid Auto) = \frac{P(1)}{P(1)+P(2)+P(3)}, \qquad (7.6)$$

$$P(W \geq 30hrs. \mid NoAuto) = \frac{P(4)}{P(4)+P(5)+P(6)}. \qquad (7.7)$$

7.2.3 Earnings Model

The third outcome examined in this section is earnings, which are incorporated in the models as the natural logarithms of earnings .

To examine the job-access effect on earnings, I use two separate regression models: one for employed auto-owning workers and another for employed autoless workers. However, either one of the two models involves the selection problem because the sample includes only those individuals who have chosen to work and to own automobiles (or not to own automobiles). Note that earnings are observed only for those who are employed. I thus use the widely-used Heckman correction—often called the Heckit method—to deal with the selection problem (Heckman 1976, 1979). The Heckman correction can be applied as follows:

$$earnings_i^A = x_{1i}^A \beta_1^A + \varepsilon_{1i}^A, \qquad (7.8)$$

$$e_i^{*A} = x_{2i}^A \beta_2^A + \varepsilon_{2i}^A. \qquad (7.9)$$

A is auto ownership representing having an auto or not having an auto. $Earnings_i^A$ represents earnings for individual i if a person works, owns (or does not own) an auto, and does not have a high school diploma. e_i^{*A} indicates the latent variable that captures the propensity to work, own (or not own) an auto, and not to have a high school diploma. x_{1i}^A and x_{2i}^A are vectors of observed explanatory variables, and ε_{1i}^A and ε_{2i}^A are mean-zero stochastic error terms. Vectors of parameters are represented by β_1^A and β_2^A.

Define a dummy variable $e_i^A = 1$ if $e_i^{*A} >= 0$ and $e_i^A = 0$ otherwise. Earnings are observed only if $e_i^A = 1$, that is, if the individual works, owns (or does not own) an auto, and does not have a high school diploma. If ε_{1i}^A and ε_{2i}^A are correlated, the sample including only those low-skilled workers who work and have (or do not have) autos will generally produce inconsistent estimates in the earnings equations. Under the assumption that ε_{1i}^A and ε_{2i}^A are bivariate normal distributed, the regression equation that corrects the selection problem can be written as follows:

$$E(earnings_i^A \mid x_{1i}^A, e_i^A = 1) = x_{1i}^A \beta_1^A + \rho^A \sigma_1^A \lambda_i^A. \qquad (7.10)$$

where ρ^A is the correlation coefficient between ε_{1i}^A and ε_{2i}^A, and σ_1^A is the standard deviation of ε_{1i}^A. λ_i^A represents the inverse of Mill's ratio, which is given by

$$\lambda_i^A = \frac{\phi(x_{2i}^A \beta_2^A / \sigma_2^A)}{\Phi(x_{2i}^A \beta_2^A / \sigma_2^A)}, \qquad (7.11)$$

where ϕ and Φ are the density and distribution functions of the standard normal distribution and $\sigma_2{}^A$ is the standard deviation of $\varepsilon_{2i}{}^A$.

If $\rho^A = 0$, that is, if the estimated coefficient on the inverse Mill's ratio ($\lambda_i{}^A$) is zero, there is no selection bias. If the estimated coefficient on the inverse of Mill's ratio is significantly different from zero, the error term in the probit model is correlated with the error terms in the regression models, and the estimated parameters of the regression models without the correction will involve the selection bias.

7.2.4 MNL and IIA Property

An important property of MNL is the "Independence from Irrelevant Alternative (IIA)," which states that the ratio of the probabilities of choosing any two alternatives is independent of the properties of all other alternatives.

The IIA property can be described as follows:

$$\frac{P(i \mid \tilde{C}_n)}{P(j \mid \tilde{C}_n)} = \frac{P(i \mid C_n)}{P(j \mid C_n)} \quad i, j \in \tilde{C}_n \subseteq C_n, \qquad (7.12)$$

where i and j indicate alternatives, and $\tilde{C}_n$ and C_n indicate choice sets. $P(i \mid C_n)$ is the choice probability of i from C_n.

The IIA property is often a limitation for MNL models where the disturbances of some alternatives are highly correlated (i.e., where some alternatives are similar to each other). The well-known red bus/blue bus paradox depicts clearly this limitation. The popular tests of the validity of the IIA property include the Hausman-McFadden IIA test (Hausman and McFadden, 1984) and the McFadden IIA test (McFadden, 1987).

If the assumption of the IIA property is violated, more general models that can relax the IIA assumption are recommended. The most popular of the general models is nested logit (NL), introduced by Ben-Akiva (1973) and McFadden (1978). Nested logit is designed to capture some correlation within sets of mutually exclusive groups of alternatives. Since NL retains a quite tractable closed form solution, it is widely used, particularly in the area of travel demand modeling and marketing.

Therefore, for the employment and working-hour models, I used the Hausman-McFadden IIA test and the McFadden IIA test to test the null hypothesis that the IIA assumption was valid. With the exception of the employment model in Boston, the results rejected the null hypothesis. I thus estimated NL, but found that the NL models improved the MNL results only slightly; the adjusted ρ^2 increased by less than 1 percent. I therefore present the results of MNL, which is generally robust and serves the purpose at hand. The MNL and NL models were estimated using Alogit and HieLow.

7.2.5 Variable Descriptions

Table 7.2.1 reports the definition and descriptive statistics of variables included in the models. The three employment outcomes are represented by the dependent variables, EMP4AUTO, W30AUTO6, and LNEARN. The explanatory variables are the ratio of transit to auto job accessibility, personal and household characteristics, and neighborhood characteristics. Persons whose data are missing for any of the variables are excluded from the samples. The personal and household characteristics include dummy variables for age, gender, household structure, and race; these are considered as potential factors affecting employment outcomes. The two neighborhood variables capture minority and poverty levels.[16]

[16] I tested various specifications using available neighborhood characteristics such as the percentage of female-headed households with children under 5 years old. Neighborhood characteristics are, however, highly correlated with each other, suggesting the possible presence of multicollinearity. Indeed, the estimated coefficients and standard errors on the neighborhood variables were sensitive to model specifications, making interpretation quite

Table 7.2.1 Definitions and descriptive statistics of variables for low-skilled workers

Variable	Description	Boston		San Francisco		Los Angeles	
		Statistics					
Dependent variables		*Count*	*Percentage*	*Count*	*Percentage*	*Count*	*Percentage*
EMP4AUTO	1: Auto, employed	5,927	76%	12,926	80%	43,249	77%
	2: Auto, unemployed	741	9%	1,650	10%	6,038	11%
	3: No auto, employed	873	11%	1,338	8%	5,510	10%
	4: No auto, unemployed	270	3%	298	2%	1,247	2%
W30AUTO6	1: Auto, employed, worked >= 30 hrs. per	3,875	50%	10,439	64%	38,650	69%
	2: Auto, employed, worked <30 hrs. per	2,052	26%	2,487	15%	4,599	8%
	3: Auto, unemployed	741	9%	1,650	10%	6,038	11%
	4: No auto, employed, worked >=30 hrs. per week	636	8%	1,127	7%	5,019	9%
	5: No auto, employed, worked <30 hrs. per week	237	3%	211	1%	491	1%
	6: No auto, unemployed	270	3%	298	2%	1,247	2%
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
LNEARN	Natural logarithm of earnings	9.11	1.23	9.13	1.23	9.17	1.02
Explanatory variables: job access measures		*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
L30TD	Ratio of transit to auto job accessibility (30-min. threshold)	0.07	0.06	0.07	0.06	0.05	0.06
Explanatory variables: personal and household characteristics							
AGE16_25	1: 16-25 years old; 0: otherwise	0.35	0.48	0.33	0.47	0.31	0.46
AGE55_65	1: 55-65 years old; 0: otherwise	0.18	0.38	0.13	0.34	0.09	0.29
FEMALE	1: Female ; 0: otherwise	0.43	0.50	0.41	0.49	0.38	0.48
FEMHH	1: Female-headed household; 0: otherwise	0.22	0.42	0.22	0.42	0.19	0.39
NHBLACK	1: Non-Hispanic black; 0: otherwise	0.11	0.31	0.07	0.26	0.05	0.22
HISPA	1: Hispanic; 0: otherwise	0.07	0.26	0.09	0.29	0.18	0.38
ASIAPC	1: Non-Hispanic Asian or Pacific islander; 0: otherwise	0.05	0.22	0.18	0.38	0.05	0.23
OTHERR	1: Other minority race; 0: otherwise	0.03	0.17	0.16	0.37	0.34	0.48
Explanatory variables: neighborhood characteristics							
NHBL_PT	% Blacks	10	18	11	14	12	16
HISP_PT	% Hispanics	5	4	19	11	48	23
POVTY_PT	% Persons below poverty threshold	10	7	10	6	18	9
Number of observations		7,811		16,212		56,044	

Note: The sample includes persons in labor force, aged 16-65, without high school diplomas.

The statistics indicate that even for low-skilled workers, the great majority own automobiles. Workers who do not have autos account for only 14% in Boston, 10% in San Francisco, and

difficult. I therefore include the African-American proportion (NHBL_PT), Hispanic proportion (HISP_PT), and poverty level (POVTY_PT) as the neighborhood variables. Overall the estimated coefficients on the individual and household variables, except for the racial dummies, were relatively insensitive to model specifications.

12% in Los Angeles. Indeed, persons without cars are becoming increasingly scarce. Even so, however, this disadvantaged population should not be ignored.

Interestingly, although the proportion of employed workers varies only slightly across the three metropolitan areas, a sizable difference is found in working hours between Boston and the other two metropolitan areas. The percentage of persons who work 30 or more hours per week is markedly lower in Boston (58%) than in San Francisco (71%) and Los Angeles (78%); conversely, the percentage of persons who work fewer than 30 hours is higher in Boston (29%) than in San Francisco (17%) and Los Angeles (9%).[17] The variation in earnings is small across the three areas.

Among the explanatory variables, noticeable differences are found in racial composition. Los Angeles is the most hetero-racial area, having a remarkably high proportion of minority workers (62%). In Boston, on the other hand, only 26% of low-skilled workers are minority members. San Francisco stands around the middle, with 50% nonwhite workers. The share of each minority group also varies substantially across the three metropolitan areas. In Boston, African-American persons consist of the highest proportion among the minority groups, accounting for 11% of total low-skilled workers. The proportions of other minority races are small: 7% for Hispanics, 5% for Asians, and 3% for other-race persons (minorities other than African-Americans, Hispanics, and Asians). In San Francisco, on the other hand, while 7% and 9% of total low-skilled workers are African-American and Hispanic persons, respectively, much higher, 18% and 16%, are Asian and other-race persons, respectively. In Los Angeles, other-race workers consist of a considerably high proportion, 34%, and Hispanic workers has also a high proportion, 18%. The proportions of African-American and Asian workers are relatively low, 5% each.

7.3 RESULTS

The following Sections 7.3.1, 7.3.2, and 7.3.3 report the estimation results for the employment

[17] That the percentage of workers who work fewer than 30 hours per week in San Francisco is 17% (vs. 16%) is due to rounding.

probability, the probability of working 30 or more hours per week, and earnings, respectively. The results of the sensitivity analyses for the alternative job-access measurements are presented in Section 7.3.4.

7.3.1 Employment

Table 7.3.1 shows the estimation results of the MNL models where the dependent variable is EMP4AUTO (four auto-ownership and employment alternatives) and the base case is alternative 4 (no auto, unemployed). The variable, EMP4AUTO, is described in Figure 7.2.1 and Table 7.2.1. To clarify variables' effects for autoless and auto-owning workers, I offer Table 7.3.1b that simulates to what extent the conditional probabilities of employment given auto ownership vary by changing variables. The probabilities are calculated for an average person in each sample. Note that the significance level for auto-owning workers comes from the significance of alternative 1 (auto, employed) relative to alternative 2 (auto, unemployed).[18]

Job-access characteristics

The job-access variable, the ratio of transit to auto job accessibility, is represented by L30TD. The L30TD coefficient for alternative 3 is positive and significant in San Francisco and Los Angeles, but it is negative and insignificant in Boston. In all three study areas, the L30TD coefficient for alternative 1 is higher than that for alternative 2. These coefficients reflect the fact that job accessibility of transit relative to autos has a positive effect on the conditional probability of employment given auto ownership, with the exception of Boston's autoless workers.

[18] An easy method to obtain this relative significance for auto-owning workers is to estimate a model where the base case is alternative 2 (auto, unemployed). The estimated coefficients from this model are not presented, but whether the base case is alternative 2 or 4, the magnitude of the effects is the same. When interpreting the coefficients of MNL, all that matters is the *difference* between their values.

Table 7.3.1 Estimation results for multinomial logit models for employment for low-skilled workers

	Boston			San Francisco			Los Angeles		
	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
(Appearing for numbered choice)									
constant [1]	5.764	***	25.06	5.808	***	27.06	5.338	***	47.49
constant [2]	3.470	***	14.14	2.974	***	13.20	2.700	***	22.57
constant [3]	1.602	***	6.45	1.675	***	7.19	1.694	***	13.90
age16_ 25 [1]	-0.337	**	-2.40	-0.321	**	-2.49	-0.627	***	-10.24
age16_ 25 [2]	0.142		0.90	0.384	***	2.81	0.102		1.55
age16_ 25 [3]	-0.470	***	-3.07	-0.329	**	-2.33	-0.452	***	-6.80
age55_65 [1]	1.153	***	3.85	0.783	***	3.26	0.326	**	2.55
age55_65 [2]	0.631	*	1.95	0.463	*	1.81	0.080		0.58
age55_65 [3]	1.411	***	4.62	0.889	***	3.58	0.294	**	2.15
female [1]	0.330	**	2.39	-0.034		-0.27	-0.121	**	-1.97
female [2]	-0.085		-0.55	-0.002		-0.02	0.079		1.19
female [3]	0.293	**	1.98	-0.104		-0.77	-0.239	***	-3.59
femhh [1]	-1.932	***	-13.44	-1.336	***	-10.34	-1.296	***	-20.68
femhh [2]	-1.694	***	-10.21	-0.950	***	-6.82	-1.111	***	-16.01
femhh [3]	-0.546	***	-3.56	-0.273	*	-1.95	-0.252	***	-3.73
nhblack [1]	-0.788	***	-3.70	-1.524	***	-8.16	-1.025	***	-9.29
nhblack [2]	-0.600	**	-2.37	-0.841	***	-4.17	-0.335	***	-2.81
nhblack [3]	-0.466	**	-2.03	-1.117	***	-5.32	-0.772	***	-6.18
hispa [1]	-1.074	***	-5.00	-0.616	***	-2.86	-0.183	**	-2.13
hispa [2]	-0.833	***	-3.32	-0.583	**	-2.51	-0.176	*	-1.89
hispa [3]	-0.228		-1.01	-0.092		-0.40	0.246	***	2.67
asiapc [1]	-0.708	**	-2.36	-0.361	*	-1.83	0.215		1.30
asiapc [2]	-0.989	***	-2.74	-0.230		-1.10	0.174		1.00
asiapc [3]	-0.066		-0.21	0.026		0.12	0.154		0.87
otherr [1]	-1.782	***	-6.91	-0.339	*	-1.66	-0.102		-1.31
otherr [2]	-1.574	***	-4.74	-0.242		-1.13	-0.135		-1.63
otherr [3]	-0.784	***	-2.87	-0.035		-0.16	0.232	***	2.77
l30td [1]	-5.402	***	-3.98	-9.308	***	-5.16	-0.911	*	-1.75
l30td [2]	-6.109	***	-3.74	-12.034	***	-6.18	-1.673	***	-2.87
l30td [3]	-0.118		-0.08	4.444	**	2.29	1.906	***	3.52
nhbl_pt [1]	0.010		1.54	0.002		0.22	0.025	***	8.83
nhbl_pt [2]	0.010		1.29	-0.001		-0.16	0.025	***	8.15
nhbl_pt [3]	-0.007		-1.03	-0.013		-1.36	0.000		-0.08
hisp_pt [1]	-0.069	*	-1.92	-0.003		-0.29	0.017	***	7.39
hisp_pt [2]	-0.075	*	-1.86	-0.007		-0.60	0.019	***	7.62
hisp_pt [3]	0.015		0.38	0.006		0.51	0.001		0.38
povty_pt [1]	-0.072	***	-3.05	-0.027		-0.85	-0.106	***	-17.44
povty_pt [2]	-0.045		-1.60	0.032		0.96	-0.093	***	-14.17
povty_pt [3]	0.000		0.01	-0.015		-0.45	-0.005		-0.73
Number of observations	7,811			16,212			56,044		
Log likelihood when parameters set to zero	-10,828			-22,475			-77,693		
Log-likelihood at convergence	-5,378			-10,006			-39,481		
ρ^2	0.50			0.56			0.49		
Adjusted ρ^2	0.50			0.55			0.49		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table 7.3.1b Effects of changes in variables on employment probabilities by auto ownership for low-skilled workers

	Changes in P(Employed | auto ownership)					
	Boston		San Francisco		Los Angeles	
Variable	Auto	No auto	Auto	No auto	Auto	No auto
AGE16_25	-0.05 ***	-0.07 ***	-0.07 ***	-0.05 **	-0.08 ***	-0.07 ***
AGE55_65	0.04 ***	0.15 ***	0.03 ***	0.10 ***	0.02 ***	0.04 **
FEMALE	0.04 ***	0.04 **	0.00	-0.01	-0.02 ***	-0.03 ***
FEMHH	-0.02 **	-0.08 ***	-0.04 ***	-0.04 *	-0.02 ***	-0.04 ***
NHBLACK	-0.02	-0.07 **	-0.08 ***	-0.21 ***	-0.09 ***	-0.13 ***
HISPA	-0.02	-0.03	0.00	-0.01	0.00	0.03 ***
ASIAPC	0.02	-0.01	-0.01	0.00	0.00	0.02
OTHERR	-0.02	-0.14 ***	-0.01	0.00	0.00	0.03 ***
L30TD	0.01	0.00	0.03 ***	0.08 **	0.01 **	0.03 ***
NHBL_PT	0.00	-0.04	0.01	-0.05	0.00	0.00
HISP_PT	0.01	0.02	0.01	0.02	-0.01 *	0.01
POVTY_PT	-0.04	0.00	-0.07 ***	-0.03	-0.02 ***	-0.01

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.
Significance levels for auto-owning workers are from estimates of models where the base case is alternative 2 (auto, unemployed).
Continuous variables were changed one standard deviation on either side of the mean vector of variables.

Figures 7.3.1a, 7.3.1b, and 7.3.1c show the simulations of changes in the conditional probabilities of employment given auto ownership as a function of job accessibility in Boston, San Francisco, and Los Angeles, respectively. The probabilities are calculated for an average person in each sample. Unexpectedly, the job-access effect in Boston is slightly greater for auto-owning workers than for autoless workers. The job-access effects for both types of workers are, however, not significant and small, as the gentle slopes suggest. In San Francisco and Los Angeles, on the other hand, improving job accessibility of transit relative to autos significantly increases the employment probability of autoless workers, and this effect is greater than that of workers with autos.

The differences in the job-access effects between autoless and auto-owning workers are quantified in Table 7.3.1b. If an average low-skilled worker does not have an auto, increasing job accessibility of transit relative to autos by one standard deviation on either side of the mean raises his/her employment probability by 0.08 in San Francisco and by 0.03 in Los Angeles. If this average person has an auto, the change in his/her employment probability is smaller: 0.03 in San Francisco and 0.01 in Los Angeles. In Boston, the simulated job-access effect for an average autoless worker is practically zero, and the effect is insignificant for both autoless and auto-owning workers.

Take two well-known areas in the San Francisco Bay Area: downtown San Jose and downtown San Francisco. An area around downtown San Jose has a moderate level of job accessibility of transit at 0.017 (the ratio of transit to auto accessibility also is moderate, 0.076), and downtown San Francisco has a high level of job accessibility for transit users at 0.091 (the ratio of transit to auto accessibility also is high, 0.209). If an average low-skilled person did not have an auto and lived in the San Jose area, his/her probability of employment would be 0.84. If the same autoless person lived in downtown San Francisco, the probability would be 0.90, or a 0.06 increase. (For simplicity, neighborhood characteristics are held constant at the average.) If an average low-skilled person had an auto, on the other hand, his/her employment probability would be 0.90 if the person lived in the San Jose area and would be 0.93 if the person lived in downtown San Francisco, or a 0.03 increase. Therefore, the benefit of living in downtown San Francisco in terms of employment is greater for a person without an auto than a person with an auto.

A similar scenario can be presented for Los Angeles. Suppose that an average low-skilled worker lives in East Los Angeles, where job accessibility for transit users is comparatively low at 0.011 (the ratio of transit to auto accessibility also is low, 0.042). If this person did not have an auto, his/her employment probability would be 0.83. If this autoless person lived in the Rimpau neighborhood, which is located between Beverly Hills and downtown Los Angeles and has a relatively high level of job accessibility for transit users at 0.051 (the ratio of transit to auto accessibility also is high, 0.193), his/her probability of employment would be 0.86, or a 0.03 increase. (Again, neighborhood characteristics are held constant at the average.) If an average low-skilled person had an auto, on the other hand, his/her employment probability would be 0.88 in East Los Angeles but 0.89 in the Rimpau neighborhood, or a 0.01 increase. An autoless low-skilled person can therefore enjoy a higher likelihood of employment in the Rimpau area than in East Los Angeles. For a low-skilled person with an auto, on the other hand, the employment benefit of being in the Rimpau neighborhood is not so great.

At first glance, the 0.06 and 0.03 increases for the autoless workers in San Francisco and Los

Angeles, respectively, appear small. However, given the fact that the unemployment rate for low-skilled workers in the sample is 0.12 for San Francisco and 0.13 for Los Angeles, these 0.06 and 0.03 increases in the employment probability (i.e., decreases in the unemployment rates) are actually considerable gains.

When the job-access effect for autoless workers is compared across the three study areas, magnitude is largest in San Francisco, but significance is greatest in Los Angeles. Both magnitude and significance are smallest in Boston. The disparity in the job-access effect between autoless and auto-owning workers is widest in San Francisco and smallest in Boston.

One may question the positive effect of job accessibility of transit relative to autos for workers with autos. This positive effect is probably related to the fact that not all auto-owning workers have full access to autos. For workers who cannot always use cars, higher job accessibility for transit users would be helpful in accessing employment opportunities.

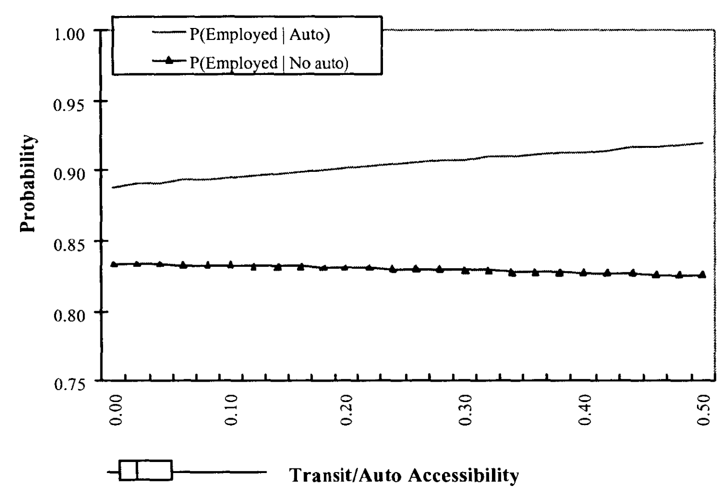


Figure 7.3.1a Effect of job access on conditional probability of employment given auto ownership for low-skilled workers in Boston.

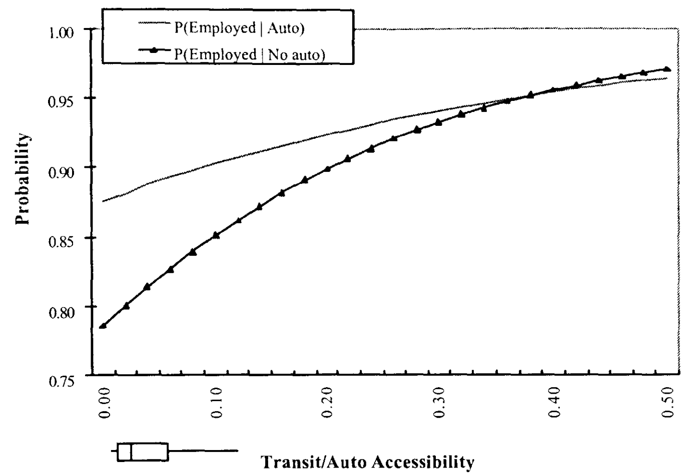


Figure 7.3.1b Effect of job access on conditional probability of employment given auto ownership for low-skilled workers in San Francisco.

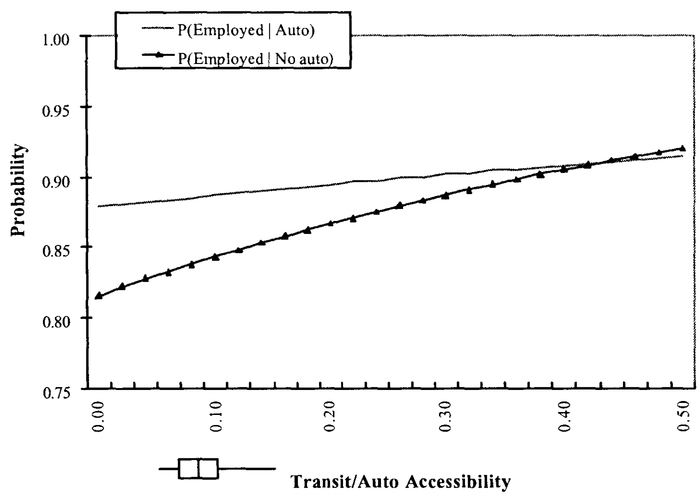


Figure 7.3.1c Effect of job access on conditional probability of employment given auto ownership for low-skilled workers in Los Angeles.

Personal and household characteristics

Personal and household characteristics also influence employment. The results of the two age variables, AGE16_25 and AGE55_65, are consistent across the three areas. For both autoless and auto-owning workers, young low-skilled workers aged 16-25 are significantly less likely to be employed than to be unemployed, whereas older workers 55 to 65 years old are significantly more likely to be working.

For both autoless and auto-owning workers, the employment probability is significantly decreased for persons in female-headed households (FEMHH) in all three areas. The results of gender (FEMALE), however, are inconsistent. In Los Angeles, controlling for auto ownership, female workers are significantly less likely to be employed; however in Boston, low-skilled women are significantly more likely to be employed. In San Francisco, gender does not matter in employment.

Among the racial variables, only the African-American race (NHBLACK) shows a relatively consistent result. Being African-American decreases the employment probability for both autoless and auto-owning workers, and this effect is mostly significant. The African-American race has a particularly strong impact for workers without autos in San Francisco and Los Angeles.

Interestingly, only for autoless workers in Los Angeles, are Hispanic or other-race workers successful in employment. Hispanic or other-race workers without autos in Los Angeles are significantly more likely to be employed than to be unemployed, while in the other two areas, these minority workers are overall less likely to be employed (but only the other-race variable for autoless workers in Boston is significant). The result may be related to the fact that Los Angeles has markedly high proportions of Hispanic and other-race workers (see Table 7.2.1), and that racial barriers for these workers may be less significant in this multiethnic area than in most other areas.

Neighborhood characteristics

Few neighborhood variables significantly affect employment, and these are the proportion of Hispanic residents (HISP_PT) in Los Angeles and the poverty level (POVTY_PT) in San Francisco and Los Angeles, all for auto-owning workers. In Los Angeles, a higher percentage of Hispanic residents significantly decreases the employment probability for workers with autos. The employment probability is also significantly reduced for auto-owning workers in areas with greater poverty in San Francisco and Los Angeles.

It is interesting to find that job accessibility plays a more important role in determining employment than do the neighborhood characteristics for autoless workers in San Francisco and Los Angeles. For workers with autos in these two areas, on the other hand, job accessibility is less significant than is the neighborhood's poverty level (POVTY_PT).

7.3.2 Working Hours

Table 7.3.2 presents the estimated results from the MNL models where the dependent variable is W30AUTO6 (six auto-ownership and working-hour alternatives) and the base case is alternative 6 (no auto, unemployed). The W30AUTO6 variable is shown in Figure 7.2.2 and Table 7.2.1. Based on the estimates, I simulate changes in the probabilities of working 30 or more hours per week by changing variables. The calculation is made for an average person in each sample, and the simulated results are reported in Table 7.3.2b. Note that the significance of each variable's effect for workers with autos is from the significance of alternative 1 (auto, worked ≥ 30 hours per week) relative to alternative 3 (auto, unemployed).[19]

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[19] The significance level for workers with an auto can be obtained from a model where the base case is alternative 3 (auto, unemployed).

Table 7.3.2 Estimation results for multinomial logit models for working hours for low-skilled workers

	Boston		San Francisco		Los Angeles	
	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic
(Appearing for numbered choice)						
constant [1]	5.545 ***	24.05	5.629 ***	26.30	5.219 ***	46.44
constant [2]	3.635 ***	15.28	3.449 ***	15.47	2.778 ***	22.88
constant [3]	3.408 ***	13.95	2.978 ***	13.30	2.699 ***	22.61
constant [4]	1.403 ***	5.47	1.567 ***	6.66	1.608 ***	13.09
constant [5]	-0.189	-0.61	-0.725 **	-2.19	-0.945 ***	-4.66
age16_25 [1]	-1.261 ***	-8.62	-0.775 ***	-5.96	-0.796 ***	-12.93
age16_25 [2]	1.420 ***	9.32	1.410 ***	10.25	0.597 ***	8.71
age16_25 [3]	0.245	1.54	0.388 ***	2.83	0.104	1.59
age16_25 [4]	-0.778 ***	-4.67	-0.485 ***	-3.34	-0.493 ***	-7.32
age16_25 [5]	0.312	1.59	0.434 **	2.13	-0.154	-1.33
age55_65 [1]	1.158 ***	3.86	0.755 ***	3.15	0.296 **	2.30
age55_65 [2]	1.387 ***	4.47	1.219 ***	4.85	0.751 ***	5.45
age55_65 [3]	0.656 **	2.03	0.460 *	1.80	0.080	0.58
age55_65 [4]	1.420 ***	4.59	0.798 ***	3.18	0.243 *	1.76
age55_65 [5]	1.457 ***	4.20	1.414 ***	4.72	0.709 ***	3.66
female [1]	-0.039	-0.28	-0.221 *	-1.75	-0.235 ***	-3.82
female [2]	1.058 ***	7.19	0.647 ***	4.91	0.685 ***	10.06
female [3]	0.003	0.02	0.027	0.20	0.085	1.28
female [4]	0.080	0.51	-0.246 *	-1.78	-0.311 ***	-4.61
female [5]	0.694 ***	3.65	0.497 ***	2.58	0.323 ***	2.86
femhh [1]	-1.816 ***	-12.39	-1.296 ***	-9.97	-1.287 ***	-20.48
femhh [2]	-2.074 ***	-13.39	-1.428 ***	-10.30	-1.309 ***	-18.01
femhh [3]	-1.727 ***	-10.37	-0.956 ***	-6.86	-1.111 ***	-16.02
femhh [4]	-0.586 ***	-3.64	-0.304 **	-2.13	-0.274 ***	-4.00
femhh [5]	-0.406 **	-2.10	-0.076	-0.39	-0.038	-0.33
nhblack [1]	-0.724 ***	-3.33	-1.500 ***	-7.96	-1.058 ***	-9.52
nhblack [2]	-0.844 ***	-3.53	-1.576 ***	-7.65	-0.804 ***	-6.22
nhblack [3]	-0.595 **	-2.35	-0.840 ***	-4.17	-0.335 ***	-2.80
nhblack [4]	-0.390	-1.62	-1.104 ***	-5.11	-0.843 ***	-6.60
nhblack [5]	-0.615 **	-2.05	-1.169 ***	-3.62	-0.216	-0.98
hispa [1]	-0.891 ***	-4.08	-0.549 **	-2.54	-0.137	-1.59
hispa [2]	-1.466 ***	-5.97	-0.773 ***	-3.39	-0.475 ***	-4.89
hispa [3]	-0.843 ***	-3.36	-0.587 **	-2.53	-0.177 *	-1.90
hispa [4]	-0.187	-0.79	-0.108	-0.46	0.254 ***	2.74
hispa [5]	-0.264	-0.93	0.074	0.24	0.214	1.38
asiapc [1]	-0.555 *	-1.84	-0.281	-1.42	0.176	1.06
asiapc [2]	-1.173 ***	-3.54	-0.608 ***	-2.94	0.454 ***	2.63
asiapc [3]	-1.010 ***	-2.80	-0.240	-1.15	0.176	1.01
asiapc [4]	0.035	0.11	-0.013	-0.06	0.034	0.19
asiapc [5]	-0.322	-0.81	0.294	1.05	0.873 ***	3.65
otherr [1]	-1.697 ***	-6.36	-0.211	-1.04	-0.048	-0.62
otherr [2]	-1.944 ***	-6.31	-0.873 ***	-4.05	-0.510 ***	-5.95
otherr [3]	-1.584 ***	-4.77	-0.253	-1.18	-0.137 *	-1.66
otherr [4]	-0.899 ***	-3.03	0.008	0.04	0.243 ***	2.87
otherr [5]	-0.522	-1.52	-0.208	-0.63	0.169	1.16
l30td [1]	-5.013 ***	-3.63	-9.165 ***	-5.07	-0.917 *	-1.75
l30td [2]	-6.465 ***	-4.25	-9.282 ***	-4.86	-0.899	-1.60
l30td [3]	-6.176 ***	-3.77	-12.002 ***	-6.17	-1.667 ***	-2.85
l30td [4]	0.277	0.19	5.023 **	2.54	2.075 ***	3.80
l30td [5]	-1.116	-0.64	1.732	0.66	0.402	0.48
nhbl_pt [1]	0.009	1.38	0.003	0.29	0.026 ***	9.19
nhbl_pt [2]	0.010	1.32	0.002	0.24	0.017 ***	5.46
nhbl_pt [3]	0.010	1.29	-0.002	-0.16	0.025 ***	8.15
nhbl_pt [4]	-0.007	-0.90	-0.013	-1.29	0.002	0.51
nhbl_pt [5]	-0.010	-1.14	-0.014	-0.97	-0.017 ***	-3.13
hisp_pt [1]	-0.055	-1.52	0.002	0.17	0.018 ***	7.89
hisp_pt [2]	-0.089 **	-2.31	-0.021 *	-1.91	0.009 ***	3.64
hisp_pt [3]	-0.074 **	-1.85	-0.007	-0.64	0.019 ***	7.61
hisp_pt [4]	0.027	0.68	0.011	0.95	0.002	0.92
hisp_pt [5]	-0.008	-0.17	-0.019	-1.13	-0.011 **	-2.42
povty_pt [1]	-0.071 ***	-2.93	-0.026	-0.84	-0.106 ***	-17.37
povty_pt [2]	-0.075 ***	-2.86	-0.037	-1.12	-0.108 ***	-15.62
povty_pt [3]	-0.045	-1.61	0.031	0.94	-0.093 ***	-14.16
povty_pt [4]	-0.007	-0.28	-0.023	-0.65	-0.007	-1.12
povty_pt [5]	0.019	0.64	0.020	0.42	0.021 *	1.83
Number of observations	7,811		16,212		56,044	
Log likelihood when parameters set to zero	-13,995		-29,048		-100,420	
Log-likelihood at convergence	-8,585		-15,613		-54,186	
ρ^2	0.39		0.46		0.46	
Adjusted ρ^2	0.38		0.46		0.46	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table 7.3.2b Effects of changes in variables on probabilities of working 30 or more hours per week by auto ownership for low-skilled workers

	Changes in P(Worked >=30 hrs. | auto ownership)					
	Boston		San Francisco		Los Angeles	
Variable	Auto	No auto	Auto	No auto	Auto	No auto
AGE16_25	-0.52 ***	-0.23 ***	-0.35 ***	-0.14 ***	-0.19 ***	-0.08 ***
AGE55_65	0.00 ***	0.10 ***	-0.03 ***	0.01 ***	-0.01 ***	0.00 *
FEMALE	-0.18	-0.08	-0.11 ***	-0.09 *	-0.09 ***	-0.07 ***
FEMHH	0.03	-0.09 ***	-0.02 ***	-0.06 **	-0.02 ***	-0.05 ***
NHBLACK	0.01	-0.02	-0.07 ***	-0.18 ***	-0.10 ***	-0.17 ***
HISPA	0.07	-0.01	0.02	-0.03	0.02	0.03 ***
ASIAPC	0.12 **	0.05	0.02	-0.03	-0.02	-0.05
OTHERR	0.03	-0.16 ***	0.06	0.02	0.03 ***	0.03 ***
L30TD	0.04	0.02	0.03 ***	0.11 **	0.01 **	0.04 ***
NHBL_PT	0.00	-0.01	0.01	-0.04	0.02	0.04
HISP_PT	0.06	0.07	0.07 **	0.09	0.02	0.04
POVTY_PT	-0.02	-0.06	-0.05 ***	-0.07	-0.02 ***	-0.04

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.
Significance levels for auto-owning workers are from estimates of models where the base case is alternative 3 (auto, unemployed).
Significance levels for autoless workers are from estimates of models where the base case is alternative 6 (no auto, unemployed).
Continuous variables were changed one standard deviation on either side of the mean vector of variables.

Job-access characteristics

The job-access effects on the conditional probabilities of the three employment alternatives—working 30 or more hours per week, working fewer than 30 hours, and being unemployed—are depicted in Figures 7.3.2a to 7.3.2f. These figures show changes in the conditional probabilities of the three employment alternatives given auto ownership as a function of job accessibility. The probabilities are calculated for an average person in each sample.

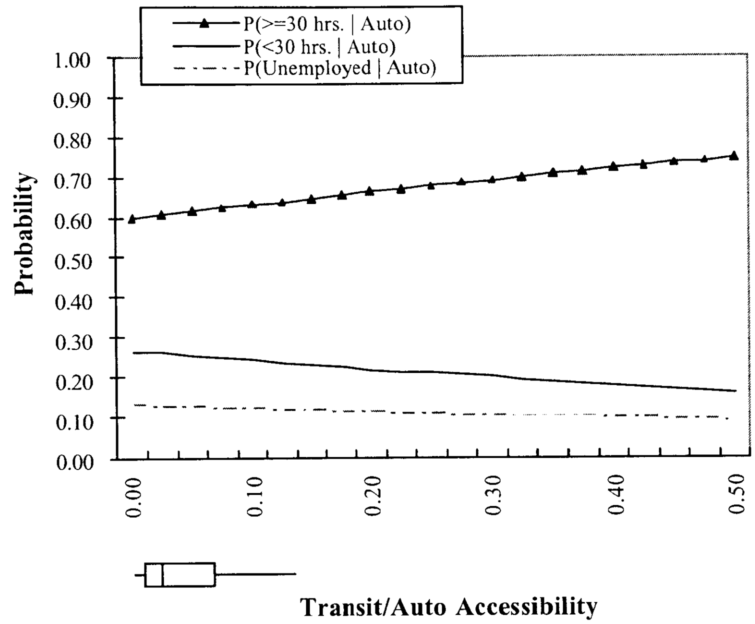

Figure 7.3.2a Effect of job access on probability of working 30 or more hours per week conditional on having an auto for low-skilled workers in Boston.

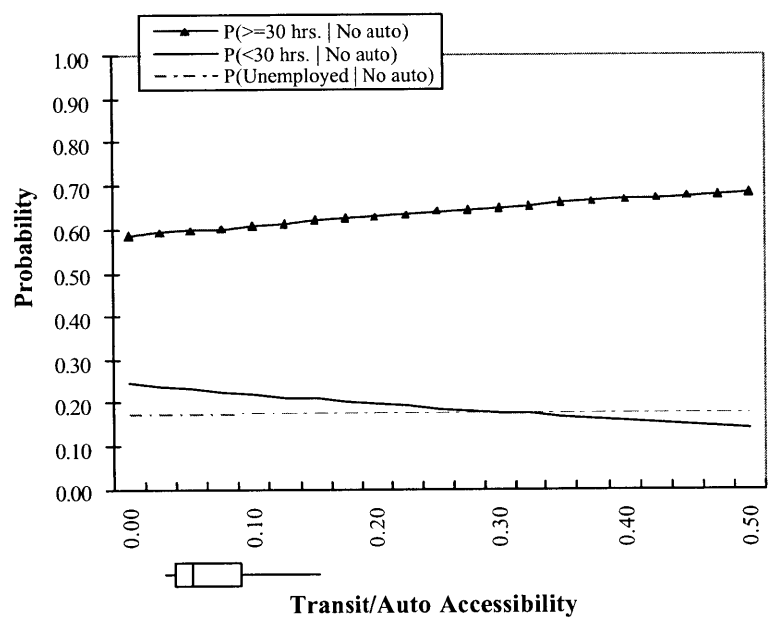

Figure 7.3.2b Effect of job access on probability of working 30 or more hours per week conditional on not having an auto for low-skilled workers in Boston.

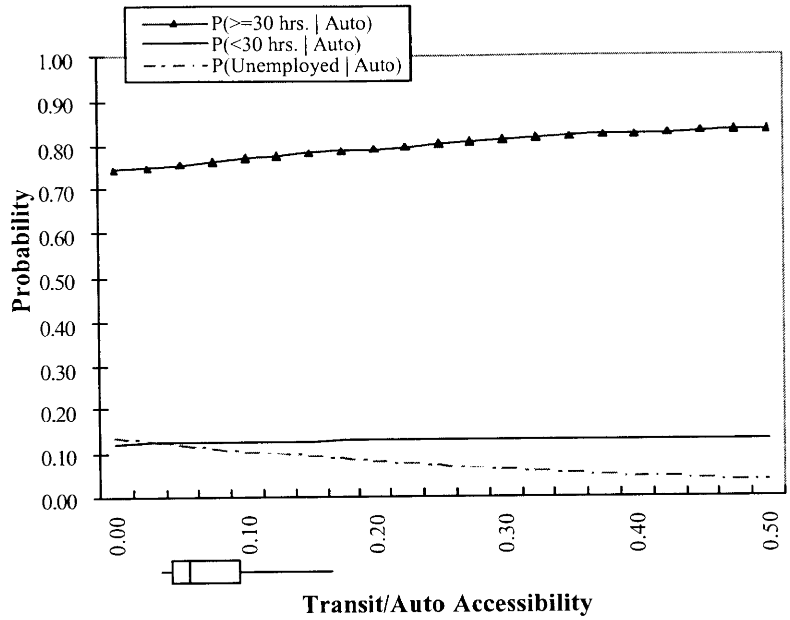

Figure 7.3.2c Effect of job access on probability of working 30 or more hours per week conditional on having an auto for low-skilled workers in San Francisco.

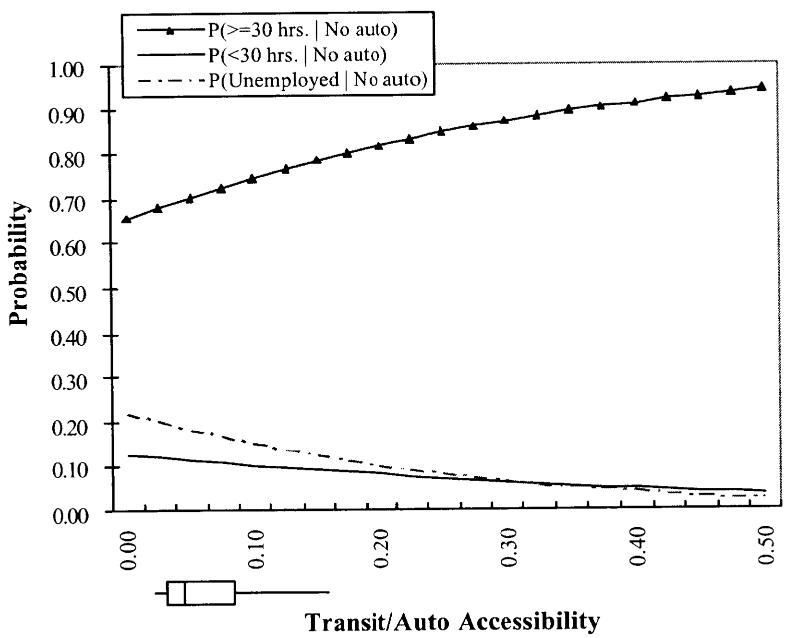

Figure 7.3.2d Effect of job access on probability of working 30 or more hours per week conditional on not having an auto for low-skilled workers in San Francisco.

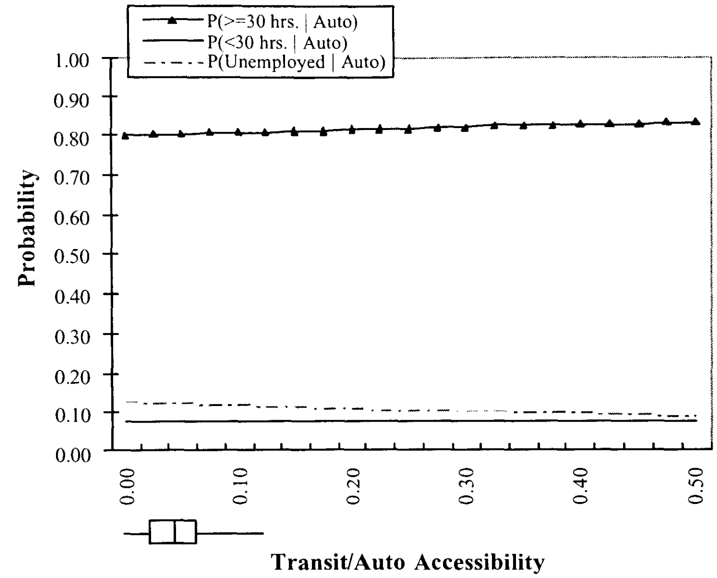

Figure 7.3.2e Effect of job access on probability of working 30 or more hours per week conditional on having an auto for low-skilled workers in Los Angeles.

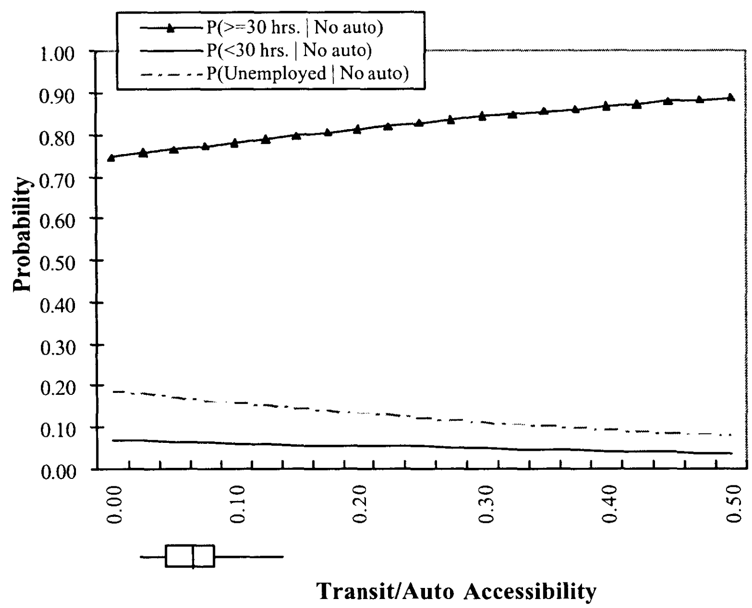

Figure 7.3.2f Effect of job access on probability of working 30 or more hours per week conditional on not having an auto for low-skilled workers in Los Angeles.

In San Francisco and Los Angeles, improving job accessibility of transit relative to autos (L30TD) significantly increases the likelihood that a person works 30 or more hours per week for both autoless and auto-owning workers, but this effect is greater for autoless workers than for workers with autos. The job-access effects are quantified in Table 7.3.2b. If an average low-skilled worker has an auto, improving job accessibility of transit relative to autos by one standard deviation on either side of the mean increases his/her probability of working 30 or more hours per week by 0.11 in San Francisco and by 0.04 in Los Angeles. If an average person has an auto, the increased value is smaller: 0.03 in San Francisco and 0.01 in Los Angeles.

An example of a hypothetical situation follows. Suppose that an average low-skilled person lives in a San Jose neighborhood that has a moderate level of job accessibility of transit at 0.017 (the ratio of transit to auto accessibility also is moderate, 0.076). If this person did not have an auto, his/her probability of working 30 or more hours per week would be 0.73. If the same autoless person lived in downtown San Francisco, which has a high level of job accessibility for transit users at 0.091 (the ratio of transit to auto accessibility also is high, 0.209), the probability would be 0.82, or a 0.09 increase. (For simplicity, neighborhood characteristics are held constant at the average.) If an average low-skilled person had an auto, on the other hand, his/her probability of working 30 or more hours per week would be 0.76 in the San Jose neighborhood and 0.79 in downtown San Francisco, or a 0.03 difference. Thus, for a low-skilled worker without an auto, downtown San Francisco has a locational advantage in getting a full-time job, but for a low-skilled worker owning an auto, it is not as advantageous.

Likewise, suppose that an average low-skilled worker resides in East Los Angeles with a comparatively low level of job accessibility of transit at 0.011 (the ratio of transit to auto accessibility also is low, 0.042). If this person did not own an auto, his/her likelihood of working 30 or more hours per week would be 0.76. If the same autoless person lived in the Rimpau area, which has a relatively high level of job accessibility for transit users at 0.051 (the ratio of transit to auto accessibility also is high, 0.193), his/her probability of working at least 30 or more hours per week would be 0.81, or a 0.05 increase. If an average low-skilled person owned an auto, his/her likelihood of working 30 or more hours per week would be 0.81 in East

Los Angeles and 0.82 in the Rimpau neighborhood, or only an 0.01 difference. Again, in terms of the likelihood of obtaining a full-time job, living in the Rimpau neighborhood is beneficial for a low-skilled worker without an auto, but does not make much difference for a worker with an auto.

Given the fact that the proportion of workers who work fewer than 30 hours per week is 0.29 for San Francisco and 0.22 for Los Angeles, these 0.09 and 0.05 increases in the probability of working 30 or more hours per week for San Francisco and Los Angeles, respectively, would indicate significant gains.

The results for Boston are somewhat different. In Boston, higher job accessibility of transit relative to auto accessibility raises the probability of working 30 or more hours per week for auto-owning as well as autoless workers. However, the job-access effect is not significant for either type of worker. Unlike the case of the other two areas, the magnitude of the job-access effect for autoless workers is smaller than that for auto-owning workers, but this difference is minor.

The comparison of the job-access effects indicates that the magnitude of the job-access effects is largest in San Francisco, but significance is greatest in Los Angeles. The disparity in the job-access effect between autoless and auto-owning workers is the greatest in San Francisco. These results are consistent with those for the employment models presented earlier.

Personal and household characteristics

Personal and household characteristics also have an impact on hours worked. As one would expect, young workers are less likely to work full-time. In all three areas, the probability of working 30 or more hours per week is significantly reduced for workers between 16 and 25 years old (AGE16_25), with or without autos. The magnitude of the reduction is quite large, particularly in Boston. The reduced probability for an average low-skilled worker in Boston is 0.52 with an auto and 0.23 without an auto. A large number of Boston's young workers may be part-time students who cannot fully participate in the labor force. The AGE55_65 coefficients indicate that controlling for auto ownership, workers between 55 and 65 years old are more likely to work than to be unemployed, but employed persons are more likely to work fewer than 30 hours per week than to work 30 or more hours per week.

Female workers, all else being equal, tend to work part-time. Controlling for auto ownership, the probability of working at least 30 hours per week is reduced for female workers. Being in a female-headed household has also a significant and negative effect on the probability of working 30 or more hours per week, but only for auto-owning workers in Boston, is the effect positive but insignificant.

The results of minority races vary across the study areas, but the African-American race has a relatively consistent result. The conditional probability of working 30 hours or more per week given auto ownership is significantly lowered for African-American workers in San Francisco and Los Angeles. The African-American race does not matter significantly in Boston, however.

Hispanic and other-race workers in Los Angeles do well in working hours. For these minority workers, the probability of working at least 30 hours per week is increased for both autoless and auto-owning workers. In Boston, being an Asian worker with an auto significantly increases the probability of working 30 or more hours per week, but being an other-race worker without an auto significantly decreases this probability. In San Francisco, none of the Hispanic, Asian, or other-race variables has a significant effect. The variation in the racial effects is probably attributable to the metropolitan difference in racial composition, as discussed in Section 7.4.

Neighborhood characteristics

Among the neighborhood variables, only the Hispanic proportion (HISP_PT) for auto-owning workers in San Francisco and the poverty level (POVTY_PT) for workers with autos in San Francisco and Los Angeles significantly affect the probability of working full-time. The probability of working 30 or more hours per week for auto-owning workers in San Francisco is significantly and positively associated with a higher percentage of Hispanic residents. A higher percentage of poor residents significantly decreases the likelihood that a person with an auto works 30 or more hours per week in San Francisco and Los Angeles.

Although most neighborhood effects are insignificant, in many cases an increase in the Hispanic or African-American proportion raises the conditional probability of working at least 30 hours per week given auto ownership. Previous research might indicate the reverse to be true. This result, however, may be because of the inclusion of the poverty level (POVTY_PT), which is highly correlated with the proportion of African-American residents (NHBL_PT) and the proportion of Hispanic residents (HISP_PT).[20] Indeed, the effects of the poverty-level on the probability of working 30 or more hours per week are negative for both autoless and auto-owning workers.

As in the employent models, for autoless workers in San Francisco and Los Angeles, the job-access effects are more significant than are the neighborhood effects, whereas for auto-owning workers in these two areas, the neighborhood's poverty level has more significant effects than does job accessibility.

7.3.3 Earnings

The job-access effects on earnings are estimated using the Heckit method, and the estimation results are presented in Table 7.3.3.[21] The upper half of the table shows the estimates for the sample of low-skilled workers who are employed and with autos, and the lower half of the table reports the estimates for the sample of low-skilled workers who are employed and without autos. The RAMDA1 and RAMDA2 variables indicate the inverse of Mill's ratios for the auto-owning worker group and for the autoless worker group, respectively.

[20] The correlation between the poverty level and the African-American proportion in Boston, San Francisco, and Los Angeles is 0.81, 0.77, and 0.46, respectively. The correlation between the poverty level and the Hispanic proportion in Boston, San Francisco, and Los Angeles is 0.90, 0.35, and 0.59, respectively.

[21] The participation equation uses the set of the independent variables in the earnings equation and the following additional neighborhood variables: the proportion of Asian persons, the proportion of low-skilled persons, and the proportion of female-headed households with children under 5 years of age.

Table 7.3.3 Estimation results for regression models for earnings for low-skilled workers

(Auto)	Boston			San Francisco			Los Angeles		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	10.396	***	47.55	9.820	***	33.89	9.252	***	47.59
age16_25	-1.682	***	-29.51	-1.333	***	-21.33	-0.750	***	-43.99
age55_65	-0.079		-1.36	0.138	**	2.52	0.225	***	9.64
female	-0.517	***	-20.64	-0.494	***	-23.09	-0.446	***	-34.25
femhh	0.124	***	3.32	-0.054	*	-1.94	-0.085	***	-4.63
nhblack	-0.100	*	-1.63	-0.006		-0.12	-0.053		-1.28
hispa	-0.209	***	-2.66	-0.111	*	-1.75	-0.057		-1.17
asiapc	-0.225	***	-3.39	-0.078	**	-2.42	-0.198	***	-7.51
otherr	-0.226	**	-2.30	0.042		0.50	0.067		1.31
l30td	0.126		0.39	0.207		0.67	-0.338	***	-3.61
nhbl_pt	-0.004	**	-2.39	0.003		1.58	0.003	***	3.91
hisp_pt	0.004		0.56	0.006	***	2.58	0.004	***	4.15
povty_pt	0.008		1.40	-0.014	***	-2.98	-0.010	***	-9.74
ramda1	-0.266	**	-2.49	0.001		0.01	0.289	***	2.80
Number of observations	5,599			12,016			39,689		
R^2	0.45			0.32			0.19		
Adjusted R^2	0.45			0.31			0.19		

(No Auto)	Boston			San Francisco			Los Angeles		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	9.675	***	11.02	8.842	***	8.18	8.356	***	23.85
age16_25	-0.732	***	-8.52	-0.731	***	-7.80	-0.370	***	-12.73
age55_65	0.037		0.25	0.091		0.74	0.180	***	3.82
female	-0.410	***	-5.52	-0.277	***	-3.82	-0.312	***	-10.00
femhh	0.034		0.31	-0.070		-0.68	0.075	*	1.66
nhblack	-0.062		-0.44	-0.037		-0.28	0.082		1.33
hispa	-0.134		-0.58	-0.094		-0.48	0.048		0.75
asiapc	-0.477	**	-2.57	-0.219		-1.28	-0.250	***	-3.81
otherr	-0.266		-1.15	0.090		0.44	0.089		1.59
l30td	1.059		1.37	1.357		0.91	0.513	**	2.26
nhbl_pt	0.006	*	1.79	0.004		0.84	0.003	**	2.40
hisp_pt	0.005		0.28	0.008		1.41	0.002	**	2.47
povty_pt	-0.012		-1.13	-0.016		-1.15	-0.001		-0.24
ramda2	-0.036		-0.14	0.169		0.56	0.284	***	2.60
Number of observations	780			1,200			4,808		
R^2	0.16			0.12			0.08		
Adjusted R^2	0.15			0.11			0.08		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Job-access characteristics

The estimated coefficients of the job-access variable (L30TD) for autoless workers are all positive, indicating that if a person does not have an auto, higher job accessibility of transit relative to autos increases his/her earnings. This job-access effect, however, is significant in Los Angeles only. In all study areas, the estimated job-access effects are greater for autoless workers than for workers with autos.

As in the employment and working-hour models, the magnitude of the job-access effect for autoless workers is greatest in San Francisco, but the significance is strongest in Los Angeles. The disparity in the job-access effect between autoless and auto-owning workers is the widest in San Francisco. These results are consistent with the results for the employment and working-hour models.

Personal and household characteristics

All AGE16_25 coefficients are negative and significant at the 0.01 level, reflecting that earnings are significantly decreased for low-skilled workers aged 16-25, with or without autos, and the magnitude of this effect is relatively large. This result is not surprising, given that earnings generally increase with age, and that real earnings for low-skilled young workers, particularly among men, have been declining over the past two decades, as the literature suggests. Overall, workers 55 to 65 years old (AGE55_65) are more likely to have higher earnings, but the magnitude and significance of the AGE55_65 effect are much smaller than those of the AGE16_25 effect.

For both the worker groups, earnings are consistently and significantly lowered for female workers, as the significant and negative coefficients of FEMALE indicate. The estimated effects of the female-headed household (FEMHH) are inconsistent, but the effects are mostly small. Only for auto-owning workers in Boston, is the effect sizable and, interestingly, positive. This positive effect may be related to the previously presented evidence that for auto-owning workers in Boston, the probability of working 30 or more hours per week is increased for persons in female-headed households. In San Francisco and Los Angeles, this probability is decreased for the equivalent workers.

Most coefficients for the racial variables are negative, but their significance varies across the three metropolitan areas. In Boston, all four racial variables are significant for the auto-owning group, reflecting that being a minority worker significantly reduces earnings for low-skilled workers with autos. For autoless workers, only the Asian race is significant, indicating that earnings are significantly lowered for Asian workers without autos. In San Francisco and Los

Angeles, on the other hand, few racial variables are significant. In San Francisco, being a Hispanic or Asian worker significantly decreases earnings for workers with autos. In Los Angeles, earnings are significantly lowered for Asian workers, regardless of auto ownership.

Neighborhood characteristics

With the exception of workers with autos in Boston, the directions of the neighborhood effects are the same. A higher percentage of African-American residents (NHBL_PT) or Hispanic residents (HISP_PT) positively affects earnings, but the neighborhood's poverty level (POVTY_PT) negatively influences earnings. Only for workers with autos in Boston, are the effects different; a higher percentage of African-American residents decreases earnings, but the neighborhood's poverty level increases earnings (this effect is not significant, however).

The positive effects of some of the neighborhood variables might contradict the previous research. These positive effects may be owing to the high correlation between the poverty level and the percentage of African-American residents and between the poverty level and the percentage of Hispanic residents, as discussed earlier. Indeed, there is no case where all of the three neighborhood variables positively affect earnings.

7.3.4 Sensitivity to Alternative Job-Access Measurements

For each of the employment, working-hour, and earnings models, I tested sensitivity to the first two alternative job-access measurements reviewed in Section 2.2.2: the jobs-per-area measurement and the simple jobs-to-workers-per-area ratio. Note that these alternative measurements are not differentiated by travel mode. The third alternative measurement, commuting time, is not tested since commuting time is not available for unemployed workers. I also tested sensitivity to the alternative measures that use different travel time thresholds of 15, 30 and 45 minutes. The definitions and descriptive statistics of the alternative job-access measurements are shown in Table 7.3.4, and the estimated results are reported in Appendix A.

Table 7.3.4 Definitions and descriptive statistics of alternative job-access measurements for low-skilled workers

Variable	Description	Boston		San Francisco		Los Angeles	
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
L15TD	Ratio of transit to auto job accessibility (15-min. threshold)	0.06	0.07	0.02	0.02	0.04	0.05
L30TD	Ratio of transit to auto job accessibility (30-min. threshold)	0.07	0.06	0.07	0.06	0.05	0.06
L45TD	Ratio of transit to auto job accessibility (45-min. threshold)	0.12	0.08	0.13	0.09	0.08	0.05
LNJPAL	Natural logarithm of jobs per square miles for low-skilled workers	5.33	1.06	4.89	1.25	6.75	0.83
JWRATIOL	Jobs-to-workers ratio for low-skilled workers	1.04	0.45	0.98	0.68	1.02	0.79

Note: The statistics are for persons in labor force, aged 16-65, without high school diplomas.

The results are summarized as follows. When the jobs-per-area measurement (LNJPAL) was used, the job-access effect on the employment probability and the probability of working 30 or more hours per week for autoless workers became more significant in San Francisco but less significant in Los Angeles. The effects in Boston, on the other hand, remained small and insignificant. The significance of the job-access effects on earnings was lessened in all three areas. When the jobs-to-workers-per-area ratio (JWRATIOL) was used, the estimated job-access effect for autoless workers tended to become smaller.

When the different travel time thresholds were used, overall the estimated job-access effects on the employment probability and the probability of working 30 or more hours per week for autoless workers became greater for the 30- or 45-minute thresholds than for the 15-minute threshold. The job-access effects on earnings of low-skilled autoless workers were greatest for the 30-minute threshold than for the 15- or 45-minute thresholds. One may question the use of the 30-minute threshold in my analyses. According to 1990 PUMS, the average commuting times of low-skilled workers without autos in Boston, San Francisco and Los Angeles are 28, 29, and 25 minutes, respectively. The use of the 30-minute threshold in my models should be therefore reasonable.

7.4 CHAPTER SUMMARY

The empirical results suggest that overall job accessibility for transit users is one of the important factors affecting employment outcomes of low-skilled workers without autos in San Francisco and Los Angeles, but it does not make much difference in Boston.

In San Francisco and Los Angeles, improving job accessibility of transit (relative to autos) significantly increased the employment probability and the probability of working full-time (30 or more hours per week) for both autoless and auto-owning workers. Earnings were also raised by higher job accessibility of transit relative to autos, but this effect was significant in Los Angeles only. In Boston, none of the job-access effects was significant.

Is the job-access effect greater for autoless workers than auto-owning workers? In San Francisco and Los Angeles, the job-access effects were indeed consistently greater for workers without autos than for workers with autos. In Boston, on the other hand, although the same held true for the effect on earnings, the job-access effects on the employment probability and the probability of working 30 or more hours per week were greater for auto-owning workers than for autoless workers. This difference, however, was minor and the job-access effects were all insignificant.

The variation in the estimated job-access effects across the study areas is probably related to metropolitan differences. An example is a difference in auto dependency; auto dependency is much higher in San Francisco and Los Angeles than in Boston. As shown in Section 4.3, the proportions of low-skilled workers who are auto commuters in the San Francisco and Los Angeles metropolitan areas are markedly high, 77% and 76%, respectively, but in the Boston metropolitan area, only 69% use autos for commuting. Conversely, the proportion of low-skilled transit commuters is higher in Boston (18%) than in Los Angeles and San Francisco (14% and 12%, respectively).

The higher auto dependency reflects the sprawling and auto-oriented nature of urban development. A question raised in this study is whether the job-access effect for autoless workers varies across metropolitan areas with different urban spatial structures. More specifically, is the job-access effect for low-skilled workers without autos greater in San Francisco and Los Angeles, highly auto-dependent areas, than in Boston, a relatively compact area where public transit systems are comparatively well developed? The answer is yes.

The simulations showed that for low-skilled workers without autos, job accessibility of transit relative to autos played a more important role in the employment outcomes in San Francisco and Los Angeles than it did in Boston. In Boston, none of the job-access effects was significant, as noted already. The job-access effects in San Francisco and Los Angeles were mostly significant, and for each of the three outcomes the magnitude of the job-access effect was greatest in San Francisco, but the significance was strongest in Los Angeles.

Additionally, the auto/no-auto disparities in the job-access effects on the employment probability and the probability of working 30 or more hours per week were greater in San Francisco and Los Angeles than in Boston. As for the job-access effects on earnings, Boston's disparity was slightly wider than Los Angeles', but the job-access effects in Boston were not significant, while the effects in Los Angeles were significant. For all three employment outcomes, the auto/no-auto gaps in the job-access effects were largest in San Francisco.

Hence, it seems fair to conclude that in highly auto-oriented metropolitan areas like San Francisco and Los Angeles, improving job accessibility for transit users is helpful in enhancing autoless workers' employment success, but in a less auto-dependent area like Boston, it is not as beneficial.

Other variables that are associated with human capital and neighborhood characteristics also significantly influenced the employment outcomes of low-skilled workers, and the relative significance of the job-access effect for autoless workers was examined. In Boston, the job-access effects were not significant, and the variables that had significant impacts on employment and working hours for autoless workers were the younger age, older ages, female-headed household, and other race (minorities other than African-Americans, Hispanics, and Asians). The variables that had significant effects on earnings were the younger age, gender, Asian race, and the percentage of African-American residents.

For autoless workers in San Francisco, the job-access effects on the employment and working hours were significant at the 0.05 significance level, but the following variables had more significant effects: the younger age, older age, female-headed household, and African-American race. Job accessibility of transit relative to autos was not an important factor in earnings, as noted earlier, but the important factors were the younger age and gender.

In Los Angeles, although the estimated job-access effects for low-skilled autoless workers were all significant, a number of other variables showed greater significance. In the employment and work-hour models, these variables were the younger age, gender, female-headed household, and African-American race. In the earnings model, the more significant variables were the younger age, older age, gender, and Asian race. The significance of job accessibility and the two neighborhood variables—the African-American proportion and Hispanic proportion—were similar.

The only variable that significantly and consistently affected the employment outcomes across the three metropolitan areas was the younger age; all three outcomes—the employment probability, probability of working at least 30 or more hours per week, and earnings—were significantly lowered for young low-skilled workers aged 16-25. The younger age was especially a strong impediment to achieving higher earnings. This result is not surprising, given that generally earnings is positively associated with age, and that less-educated young workers, particularly men, have experienced declining employment and real earnings over the past few decades, as the literature suggests (e.g., Freeman and Holzer, 1986; Levy and Murnane, 1992; Peterson and Vroman,. 1992; Wilson, 1996).

Among the other variables, the older age, female-headed household, and African-American race exhibited largely consistent impacts on employment and working hours. Controlling for auto ownership, workers aged 55-65 were more likely to be employed than to be unemployed, but among the employed, these older workers were less likely to work full-time (30 or more hours per week) than to work part-time (fewer than 30 hours per week). Being in a female-headed household overall decreased the employment probability and the probability of working

30 or more hours per week.

The likelihood of employment and the likelihood of working 30 or more hours per week were mostly lowered for African-American workers. The results of the other racial variables—the Hispanic race, Asian race, and other race—were rather mixed. Interestingly, only in Los Angeles, were Hispanic or other-race workers relatively successful in the employment outcomes.

The mixed results of the racial variables, with the exception of the African-American race, are probably related to the metropolitan differences in racial composition. Los Angeles is well known for its racial heterogeneity. Indeed, as Table 7.1.1 indicates, the great majority (63%) of low-skilled workers are minority members in Los Angeles, whereas only 26% belong to minority groups in Boston. The proportion in San Francisco stands around the middle, 50%. The proportions of Hispanic and other-race workers in Los Angeles are particularly high, 18% and 34%, respectively, and racial barriers to employment for these workers may be less significant in this multiethnic area than in most other metropolitan areas.

It is interesting to find that for low-skilled autoless workers in San Francisco and Los Angeles, job accessibility played a more important role in determining employment and working hours than did the neighborhood characteristics, while for auto-owning workers the neighborhoods' poverty level was a more important determinant than was job accessibility. In the earnings models, job accessibility was significant only in Los Angeles, where job accessibility and the neighborhood's proportion of African-Americans and proportion of Hispanics had similar significance for autoless workers. For workers with autos in Los Angeles, all the three neighborhood variables—the African-American proportion, Hispanic proportion, and poverty level—had greater significance than did job accessibility. These results confirm the greater relative significance of job accessibility for workers without autos than for workers with autos.

There are some limitations to this study. The estimated job-access effect may be biased, because residential choice and employment outcomes are likely to be jointly endogenous; that is, an improvement in the employment outcomes may enable workers to change their residential location. In order to avoid the endogeneity problem, many spatial mismatch studies focus on youths living at home because youths' residential locations are likely to be predetermined by their parents (e.g., Ihlanfeldt and Sjoquist, 1991; Raphael, 1998). The inclusion of only low-skilled workers, however, is likely to reduce the bias. Compared to their counterparts, low-skilled workers would be more restricted in choosing residential location because of their fewer resources to finance transaction costs associated with moving.

Also to be considered is the size of the geographic unit that had to be used in the analyses. Due to the large size of PUMAs (geographic areas of PUMS), the estimated job-access and neighborhood variables might not capture the full effects of the neighborhood characteristics. Unfortunately, person-level data for small geographic units are not publicly available and are usually protected under strict confidentiality agreement. The use of the publicly available PUMS, however, makes the metropolitan comparisons feasible. Additionally, the analytical framework developed in this research can be applied for further (extended) studies. For example, similar research using Census 2000 data that are being gradually released would be interesting to look at.

The next chapter focuses on another disadvantaged group in today's urban labor market, welfare recipients. I obtained permission to use confidential survey data on individual adults on welfare in Los Angeles to examine the effect of job accessibility on employment outcomes for welfare recipients who do not have access to cars. The survey data provide residential location information at the census-tract level. Since census tracts are reasonably small geographic areas for defining neighborhoods, the results may be useful in identifying possible bias in the job-access and neighborhood effects estimated in this chapter.

Chapter 8: Job Access and Employment Outcomes for Autoless Welfare Recipients in Los Angeles

This chapter employs the travel-mode sensitive methodology developed in the previous chapter to examine the importance of job accessibility in employment outcomes for autoless adults receiving welfare.

Welfare recipients are among the most disadvantaged groups in today's urban labor market. The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) enacted in 1996 replaced the Aid to Families with Dependent Children (AFDC) program with the Temporary Aid to Needy Families (TANF), requiring most welfare recipients to work as a condition of receiving public assistance. This dramatic change in welfare policy put welfare recipients under strong pressure to make the transition from welfare to work. Finding and keeping a job, however, is a severe challenge for people trying to achieve this transition. Most welfare recipients are single mothers who, besides working, have to perform diverse tasks including child and medical care, housework, and shopping. All these obligations have to be handled by the sole adult in the household. Furthermore, multiple barriers are common among welfare recipients and many of them are not qualified for a decent job. Using data from the 1997 National Survey of America's Families (NSAF), Zedlewski (1999) shows that more than 40% of welfare recipients have two or more significant employment barriers, and that the most prevalent barriers are poor mental or general health, the lack of work experience, and low educational attainment. Danziger et al. (2000), using the survey of single welfare mothers with children in a Michigan city, show that 64% have at least two potential barriers to work, and more than 27% report four or more. They find that those with more barriers are less likely to be working.

The lack of reliable transportation is also frequently cited as a major barrier to employment.

Despite the fact that households without autos are becoming increasingly scarce, many low-income people still do not have private vehicles, severely limiting their mobility. Even for those who have autos, many welfare recipients have old and unreliable vehicles (Ong et al. 2001). The limited spatial mobility especially hurts single adults on welfare who have to make multiple trips a day, traveling to and from childcare facilities, schools, workplaces, supermarkets, and so on. Recent studies find that auto ownership significantly increases employment (Ong, 1996; Raphael and Rice, 2000; Sanchez, 1999), and that job accessibility is considerably greater for auto commuters than for transit commuters (Shen, 1998, 2001; Taylor and Ong, 1995). Very few empirical studies, however, focus on welfare recipients without autos to examine the job-access effect on employment outcomes, and almost no study quantifies the disparity in the job-access effect between those who own autos and those who do not.

Therefore, using recent survey data on welfare recipients in Los Angeles, this chapter attempts to answer the following research questions:

(1) Does improving job accessibility for transit users significantly enhance employment outcomes for welfare recipients who do not have automobiles?
(2) Is the job-access effect on employment outcomes greater for welfare recipients without autos than for welfare recipients with autos?

The remainder of this chapter proceeds as follows. Section 8.1 explains data used in this chapter, and Section 8.2 computes and visualizes the job-access measures for welfare recipients. Section 8.3 describes models that examine the research questions presented above. Sections 8.4 and 8.5 show estimation results and sensitivity analyses, respectively. The results are summarized in Section 8.6.

8.1 DATA

The data set combines three different data: individual adults on welfare, neighborhood characteristics, and job-access measures. Each of these three data comes from a different source.

The data on individual adults on welfare are from the survey of CalWORKs Transportation Needs and Assessment (CTNA) conducted between late November 1999 and February 2000. The survey was designed by the Ralph & Goldy Lewis Center for Regional Policy Studies at UCLA and implemented by the Survey Research Center at the California State University, Fullerton. The sample includes over 1,500 TANF recipients who participated in the Greater Avenues for Independence (GAIN) welfare-to-work program in late 1999. The data made available for my research exclude personal identifiers and home addresses to protect confidentiality, but residential locations are provided for census tracts and for traffic analysis zones (TAZs). Figure 8.1.1 maps the location and density of CTNA respondents. As the map indicates, residential areas of CTNA respondents are widely spread out, but high concentrations are found mostly in south-central sections of Los Angeles County.

For the neighborhood characteristics, I use the PL94-171 data (the Census 2000 Demonstration Disc), which were released preliminary to the complete Summary Tape File 3A (STF3A) in 2000. The PL94-171 data provide population by race, but such statistics as persons below the poverty threshold are not yet available.

The job-access measures are calculated based on the gravity-based model and are computed separately for transit users and for auto users. The formulation and resulting measures are described in the next section. The neighborhood data and job-access measures are combined with the individual welfare recipient data.

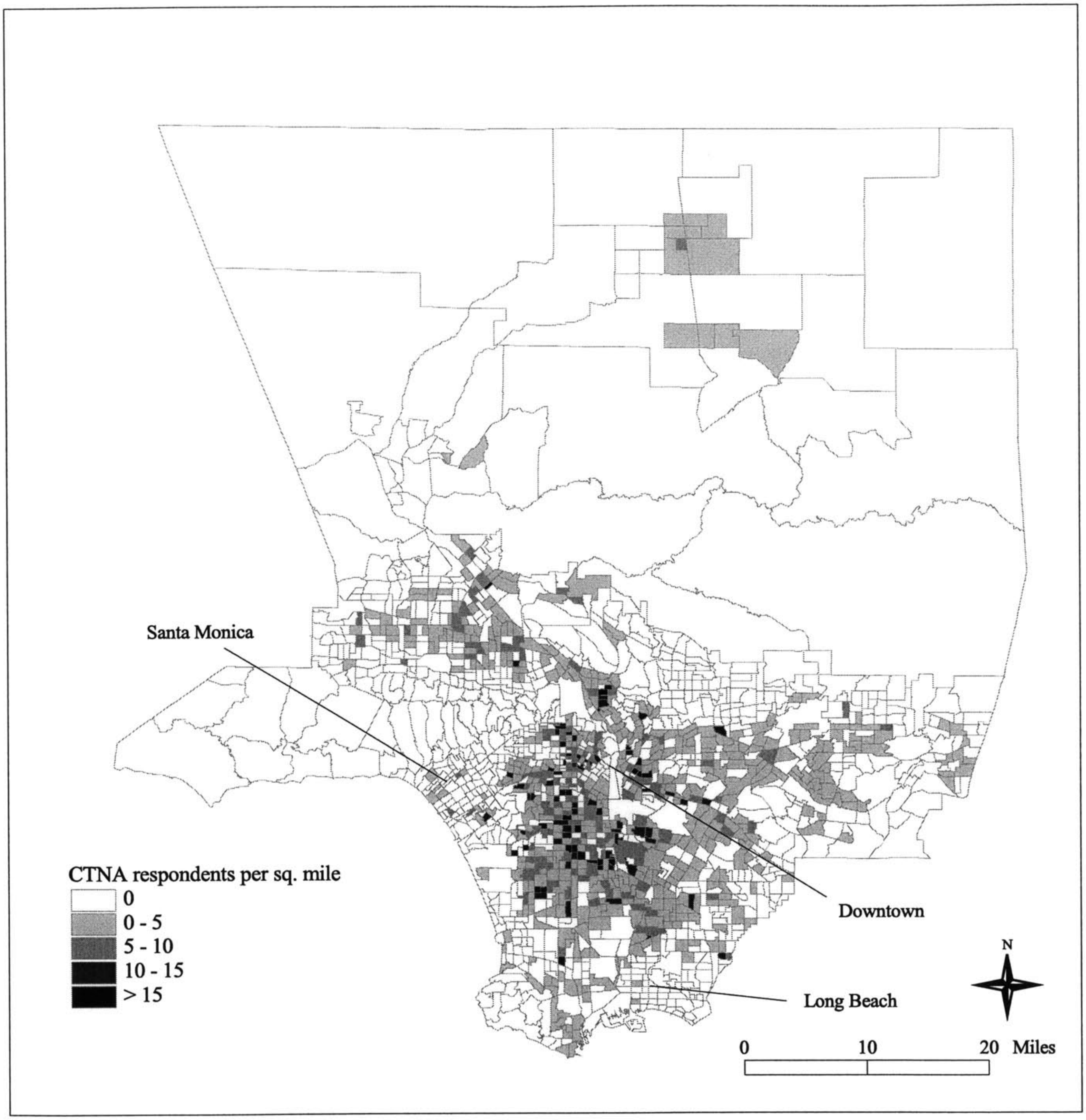

Figure 8.1.1 Distribution of CTNA respondents by census tract in Los Angeles

Table 8.1.1 lists the definition and descriptive statistics of variables. Observations with missing values in any of the listed variables are excluded. The statistics are shown for total welfare recipients and for welfare recipients with autos and without autos.

Table 8.1.1 Definitions and descriptive statistics of variables for welfare recipients in Los Angeles

		Statistics					
Variable	Description	Total		With auto		Without auto	
Dependent variables		*Count*	*Percentage*	*Count*	*Percentage*	*Count*	*Percentage*
EMP4A	1: Auto, employed	496	33%	496	57%	-	-
	2: Auto, unemployed	378	25%	378	43%	-	-
	3: No auto, employed	276	18%	-	-	276	43%
	4: No auto, unemployed	368	24%	-	-	368	57%
EAR45A6	1: Auto, employed, earned >= $4,500 per year	284	19%	284	32%	-	-
	2: Auto, employed, earned < $4,500 per year	209	14%	209	24%	-	-
	3: Auto, unemployed	381	25%	381	44%	-	-
	4: No auto, employed, earned >= $4,500 per year	170	11%	-	-	170	26%
	5: No auto, employed, earned < $4,500 per year	162	11%	-	-	162	25%
	6: No auto, unemployed	312	21%	-	-	312	48%
Explanatory variable: job access measures		*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
OFHS30TD	Ratio of transit to auto job accessibility (30-min. threshold)	0.58	0.43	0.60	0.46	0.55	0.38
Explanatory variables: personal and household characteristics							
AGE18_25	1: 18-25 years old; 0: otherwise	0.22	0.42	0.19	0.39	0.26	0.44
AGE45_	1: >=45 years old; 0: otherwise	0.12	0.33	0.13	0.33	0.11	0.31
BLACK	1: Non-Hispanic black; 0: otherwise	0.28	0.45	0.21	0.41	0.37	0.48
HISPA	1: Hispanic; 0: otherwise	0.51	0.50	0.51	0.50	0.51	0.50
OTHERR	1: Other minority race; 0: otherwise	0.00	0.05	0.00	0.05	0.00	0.06
NOHI	1: Less than high school degree; 0: otherwise	0.41	0.49	0.39	0.49	0.45	0.50
SIGLP	1: Single-parent household; 0: otherwise	0.77	0.42	0.66	0.47	0.91	0.29
KIDU6	1: With child under 6 yrs. old; 0 otherwise	0.35	0.48	0.33	0.47	0.38	0.48
Explanatory variables: neighborhood characteristics							
PCTBL	% Blacks	16	20	14	18	18	22
PCTHISP	% Hispanics	57	25	56	26	59	25
Number of observations		1,518		874		644	

Note: Observations that have null values in the list variables are excluded.

Even for welfare recipients the majority own autos, accounting for 58% of welfare recipients in the sample. This auto ownership rate may be surprisingly high, but recent studies find similar rates. For example, according to the Flint Mass Transit Authority (NTA), more than half of Michigan's Work First participants, the welfare population, have access to autos. Green et al. (2000) also report that about half of welfare recipients in Alameda County in California have automobiles available for use. Using the 1990 PUMS data, I find that of poor female heads in the labor force, with a child under 6 years old (as proxy for the welfare population), 69% have autos in Los Angeles County. Even in Boston, a more compact area, 54% of this population own private vehicles. Still, auto-ownership rates of welfare recipients are considerably lower than those of other general populations. According to 1990 PUMS, for example, in Los Angeles County 94% of total workers and 88% of low-skilled workers (workers without high school diplomas) own autos.

It should be noted, however, that having an auto does not necessarily mean that a welfare recipient has dependable mobility. Due to their limited financial budget, many low-income people have autos that are old and undependable. Indeed, 69% of autos owned by CTNA respondents are 10 years old or older and at high risk of maintenance and mechanical problems.

As expected, economic status of welfare recipients is especially low. Of welfare recipients in the sample, barely half are working and only 30% earn at least $4,500 or more per year (the median annual earnings among those who have earnings). The economic profiles for autoless welfare recipients are even lower. While the proportion of employed persons is 57% for auto-owning welfare recipients, the proportion is much lower, 43%, for autoless recipients. While 32% of auto-owning welfare recipients earn $4,500 or more per year, only 26% of autoless welfare recipients achieve this earnings.

The job-access variable (OFHS30TD) represents the ratio of transit to auto job accessibility. The ratio is used in order to capture the disparity between transit and auto access measures, and to deal with the large difference in the values and variability between these two measures.[22] The mean ratio of transit to auto job accessibility is 0.58, indicating lower job accessibility for transit commuters than for auto commuters. Interestingly, auto-owning welfare recipients have the higher mean ratio (0.60) than do autoless welfare recipients (0.55). This is not because job accessibility for transit users is higher for auto-owning recipients, but because auto job accessibility for recipients with autos is relatively small, making the ratio slightly higher for auto-owning recipients. In fact, both transit and auto job-access measures are lower for auto-

[22] One may question the use of the ratios since areas with different sets of transit and auto job-access measures can yield similar ratios. There is, however, a moderately strong linear relationship between the ratios and transit job-

owning welfare recipients than for autoless recipients, suggesting that recipients owning autos are more likely to live in dispersed areas distant from employment cores.

Of welfare recipients in the sample, 22% range from 18 to 25 years old and 12% are 45 years old or older (mean, minimum, and maximum ages are 34, 18, and 60, respectively).[23] Autoless welfare recipients are younger than are recipients with autos. While the proportions of persons aged 45 years old or older for autoless and auto-owning recipients are roughly the same (11% and 13%, respectively), the proportion of persons aged 18-25 is much higher for autoless recipients (26%) than for auto-owning recipients (19%).

The great majority (79%) of welfare recipients in the sample are nonwhite, and Hispanic recipients comprise the largest proportion (51%). Although the proportion of Hispanic recipients does not vary by auto ownership, the proportion of African-American persons is higher for autoless welfare recipients (37%) than for auto-owning recipients (21%).

A considerable number of welfare recipients, particularly autoless persons, are low-skilled and single parents. Of welfare recipients in the sample, 41% do not have high school diplomas and 77% are single parents. These proportions become even higher for autoless recipients (45% and 91%, respectively). The proportion of persons with a child under 6 years old is 35%, and this proportion is slightly higher for autoless recipients (38%) than for recipients with autos (33%).

Many welfare recipients live in Hispanic neighborhoods. The average percentage of Hispanic residents is strikingly high, 57%, which is probably related to the fact that the high proportion (51%) of persons in the sample are Hispanic.

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access measures with the correlation coefficient of 0.48.

[23] The 45-60 range is used since only 19 observations (1% of the sample) fall into the 55-65 age range, which was used for the analysis for low-skilled workers in the previous chapter.

8.2 MEASURING JOB ACCESSIBILITY FOR WELFARE RECIPIENTS IN LOS ANGELES

8.2.1 Formulation of Job-Access Measures

The calculation of job accessibility for welfare recipients uses the following formulas:

$$A_i^{auto} = \sum_j (O_{j(t)} \times f(C_{ij}^{auto})), \tag{8.1}$$

$$A_i^{pub} = \sum_j (O_{j(t)} \times f(C_{ij}^{pub})). \tag{8.2}$$

A_i^{auto} and A_i^{pub} represent job-access measures for welfare recipients living in zone i who are, respectively, auto commuters and transit commuters. The number of job opportunities in zone j at time t is represented by $O_{j(t)}$. $f(C_{ij}^{auto})$ and $f(C_{ij}^{pub})$ are impedance functions for commuters traveling between zone i and zone j for auto users and for transit users, respectively. $i, j= 1, 2,\ldots, N$.

Unlike the computed job-access measures for general low-skilled workers, these measures do not take into account job seekers (i.e., the supply side of the labor market). Unfortunately, at this time data on low-skilled job seekers, which can be matched with low-skilled jobs (i.e., the demand side of the labor market), are not available for recent years. These measures, however, are useful in capturing spatially accessible employment levels with respect to residence, and the measures incorporate travel modes.

The geographic unit (zone) in Equations 8.1 and 8.2 is the transportation analysis zone (TAZ). The simple travel time threshold function is used to estimate the impedance function ($f(C_{ij})$). When travel time between zone i and zone j is less than 30 minutes, I set the value of the impedance function equal to one.[24] The 2000 zone-to-zone commuting time matrices for auto

[24] According to the 1990 Public Use Microdata Samples (PUMS), the average commuting time of poor female householders with a child less than 6 years old in Los Angeles County is 23 minutes for auto users and 44 minutes for transit users.

users and for transit users were provided by the Southern California Association of Governments (SCAG).

For the calculation of the number of job opportunities (O_i) for welfare recipients, I propose the following formula:

$$O_{i(t)} = \sum_{l} (E_{il} \times p_l), \qquad (8.3)$$

where E_{il} is the number of jobs per square mile in occupation l in zone i, and p_l indicates the proportion of low-skilled female workers in occupation l. This formula is based on the assumption that the proportion of low-skilled female workers in each occupation is spatially homogeneous. If the proportion varies considerably within the metropolitan area, the calculated absolute values could be distorted. However, the relative values, which have greater meaning than the absolute values for this analysis, would be less affected.

Employment data on the number of jobs by occupation (E_{il}) come from 1998 American Business Information (ABI) data by census block group. To estimate the proportion of low-skilled female workers in occupation l (p_l), I use the Current Population Survey (CPS) for 1998 (Table 8.2.1). I define low-skilled female workers as women in the labor force with high school degrees or less education. The block-group-level employment data computed from Equation 8.3 are aggregated to the TAZ level, in order to match the commuting time matrices.

Table 8.2.1 Proportion of low-skilled female workers by occupation in Los Angeles County

ABI Variable	ABI Label	CPS SOC code	Percentage of female workers with <= high school diplomas
O98EXEC	Executive and Managerial	003 - 042	9%
O98PROF	Professional	043 - 202	4%
O98TECH	Technical	203 - 242	16%
O98SALES	Sales	243 - 302	21%
O98CLER	Clerical	303 - 402	25%
O98PRHHD	Private Household	403 - 412	81%
O98PROT	Protective Services	413 - 432	8%
O98SERV	Services	433 - 472	36%
O98PRIM	Agriculture, Forestry, and Fishing	473 - 502	8%
O98PROD	Production and Related	503 - 702	5%
O98OPER	Operators	703 - 863	32%
O98MALA	Materials Handlers and Laborers	864 - 889	11%

Note: SOC: Standard Occupational Classification. Statistics took account of weighting.
The variable O98MASA combines O98MATER (materials handlers) and O98LABOR (laborers) since SOC for these two occupations are not clearly defined.

Figure 8.2.1 maps the geography of jobs that are suitable for low-skilled women (O_i) in Los Angeles. High concentrations of these jobs are found around such areas as downtown Los Angeles, Beverly Hills, Santa Monica, Pasadena, Glendale, and Long Beach.

The job-access measures for TAZ are converted to the tract-level measures to be combined with the survey data on individual welfare recipients.

8.2.2 Job-Access Measures for Welfare Recipients in Los Angeles

Figure 8.2.2 illustrates the spatial variation in the computed job-access measures for transit and auto users in Los Angeles. The two maps use the same equal interval classification to clarify the difference. As expected, job accessibility for automobiles is greater than that for transit. For both types of commuters, relatively high-accessibility areas are spread around the south central sections of Los Angeles County, but accessibility-rich areas for auto users are relatively concentrated in the southwestern sections of the county.

Table 8.2.2 reports the descriptive statistics of the job-access measures for total tracts with CTNA respondents and for tracts that have high concentrations of CTNA respondents (more than 15 persons per square mile) in Los Angeles. The former tracts include all the shaded areas in Figure 8.1.1, and the latter tracts are the areas with the darkest color in this figure. Table 8.2.3 lists the job-access measures for tracts with high densities of welfare recipients.

Table 8.2.2 Descriptive statistics of job-access measures for welfare recipients in Los Angeles

	Mean	Std.. Dev.	Min	Max
Total tracts with CTNA respondents				
Transit	622	373	0	1,210
Automobile	1,096	581	8	1,938
Transit / auto	0.61	0.46	0.00	4.48
*Tracts with high concentrations of CTNA respondents**				
Transit	876	280	178	1,210
Automobile	1,561	315	436	1,900
Transit / auto	0.56	0.15	0.25	0.88

Note: *Tracts that have more than 15 CTNA respondents per square mile.

Table 8.2.3 Job-access measures of tracts having high concentrations of welfare recipients in Los Angeles*

Obs.	Tract ID	City	Transit job accessibility	Auto job accessibility	Transit / auto job accessibility
1	06037104701	Los Angeles city	178	436	0.41
2	06037190400	Los Angeles city	975	1501	0.65
3	06037190500	Los Angeles city	1003	1557	0.64
4	06037203100	Los Angeles city	1043	1661	0.63
5	06037203700	Los Angeles city	1059	1631	0.65
6	06037203800	Los Angeles city	1059	1631	0.65
7	06037208700	Los Angeles city	1070	1835	0.58
8	06037208901	Los Angeles city	1062	1854	0.57
9	06037209101	Los Angeles city	1168	1897	0.62
10	06037209402	Los Angeles city	1183	1879	0.63
11	06037211900	Los Angeles city	1179	1752	0.67
12	06037212400	Los Angeles city	1158	1795	0.65
13	06037212900	Los Angeles city	1139	1701	0.67
14	06037221301	Los Angeles city	1151	1803	0.64
15	06037222500	Los Angeles city	1076	1826	0.59
16	06037222600	Los Angeles city	1079	1900	0.57
17	06037228700	Los Angeles city	862	1800	0.48
18	06037232600	Los Angeles city	852	1823	0.47
19	06037234900	Los Angeles city	681	1716	0.40
20	06037237600	Los Angeles city	1007	1780	0.57
21	06037240300	Los Angeles city	803	1624	0.49
22	06037240800	Los Angeles city	519	1420	0.37
23	06037242000	Los Angeles city	550	1374	0.40
24	06037242100	Los Angeles city	739	1432	0.52
25	06037242600	Los Angeles city	550	1374	0.40
26	06037243000	Los Angeles city	767	1364	0.56
27	06037269600	Los Angeles city	1168	1757	0.67
28	06037302001	Glendale city	1058	1205	0.88
29	06037302200	Glendale city	1062	1238	0.86
30	06037530900	East Los Angeles	833	1509	0.55
31	06037533600	Bell city	1210	1412	0.86
	06037533600	Cudahy city	1210	1412	0.86
32	06037571600	Long Beach city	392	638	0.61
33	06037600100	Westmont	876	1587	0.55
34	06037601212	Inglewood city	400	1625	0.25
35	06037601303	Inglewood city	522	1604	0.33
36	06037602502	Hawthorne city	495	1405	0.35
37	06037602503	Hawthorne city	495	1405	0.35

Note: *Tracts with more than 15 CTNA respondents per square mile. A tract (06037533600) is divided into two cities.

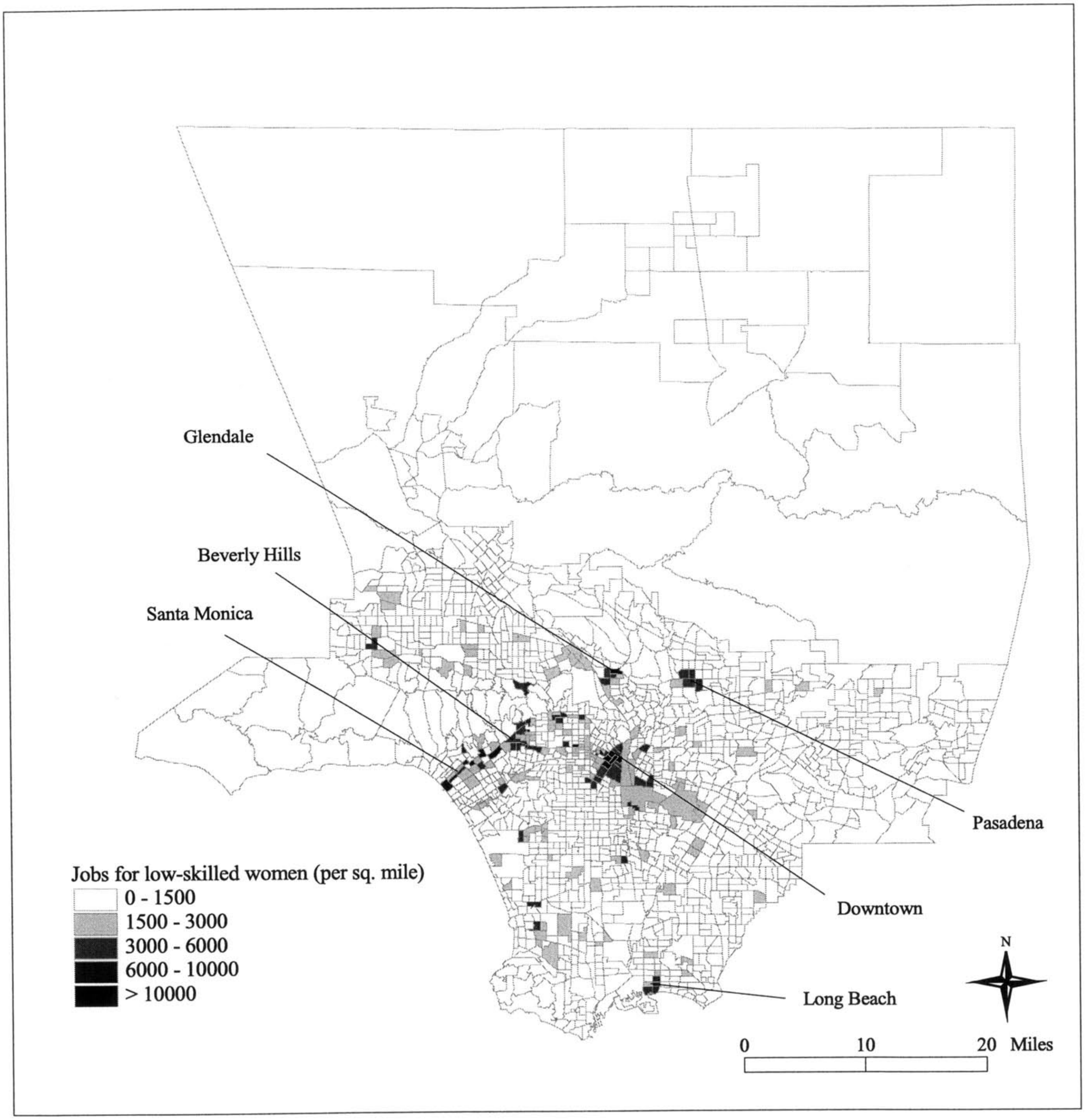

Figure 8.2.1 Geography of jobs suitable for low-skilled women by census tract in Los Angeles

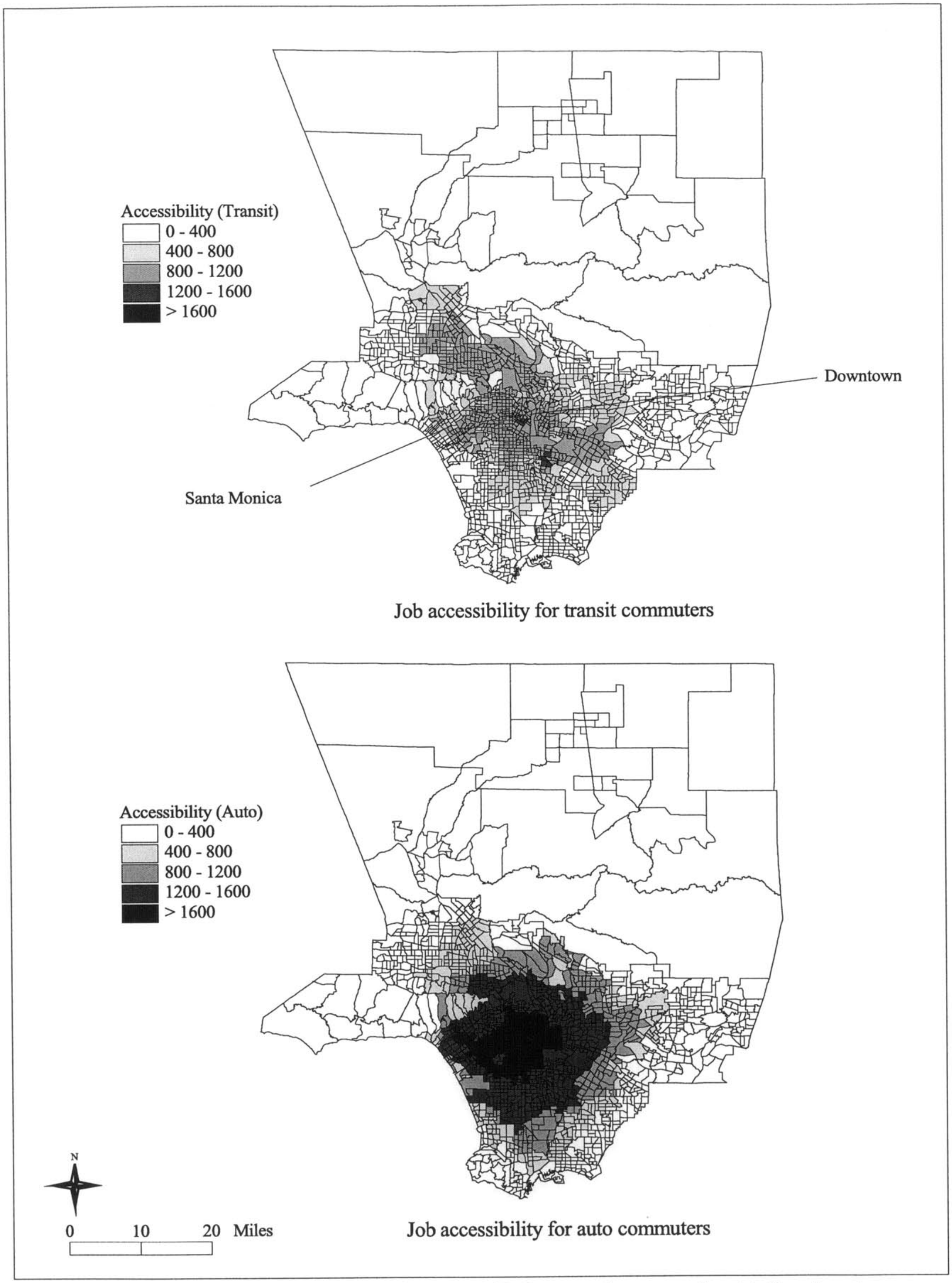

Figure 8.2.2 Job accessibility for low-skilled women by census tract in Los Angeles

8.3 MODELS

Is job accessibility for transit users an important determinant of employment outcomes for autoless welfare recipients? Using multinomial logit (MNL), this chapter examines whether job accessibility for transit users (relative to auto users) has a significant positive effect on employment outcomes for autoless welfare recipients, and whether this effect is greater for autoless welfare recipients than for welfare recipients having autos.

I examine two employment outcomes: the probability of employment and the probability of earning $4,500 or more per year (the median earnings of welfare recipients who have earned income). Since data on reliable working hours are not available, I do not investigate the probability of working 30 or more hours per week, which was investigated for general low-skilled workers in the previous chapter.

Multinomial logit is used to avoid the selection problem due to potential endogeneity between auto ownership and employment outcomes.[25] Figure 8.3.1 illustrates the MNL structure for the model of employment probability with four employment and auto-ownership alternatives. The alternatives are listed as a variable, EMP4A, in Table 8.1.1.

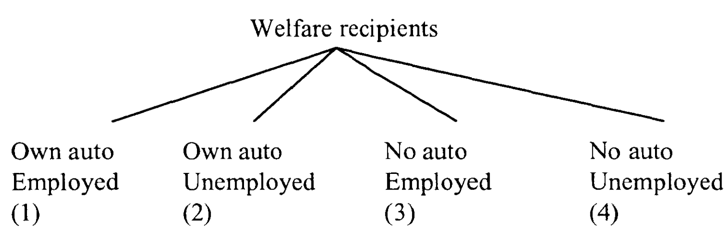

Figure 8.3.1 MNL structure for employment model.

The MNL structure for the model of the probability of earning $4,500 per year is shown in Figure 8.3.2. This structure has six alternatives, which are represented by a variable,

[25] Since higher employment outcomes are likely to encourage auto ownership, auto ownership is likely to be endogenous to employment outcomes. Therefore, if a model is estimated only for those who own autos or for those who do not have autos, estimated parameters are likely to involve selectivity bias.

EAR45A6, in Table 8.1.1.

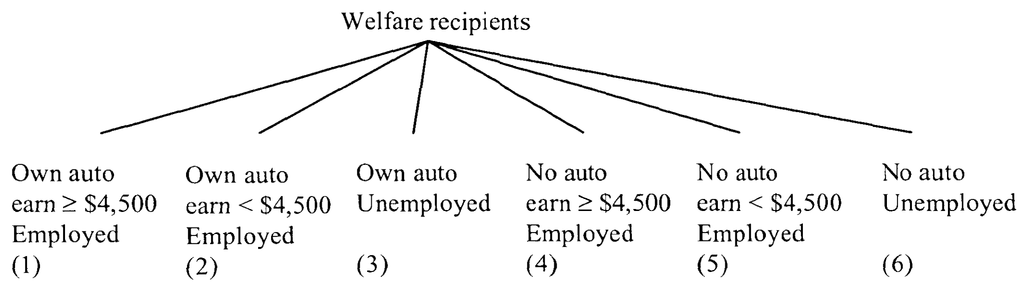

Figure 8.3.2 MNL structure for earnings model.

An important property of MNL is the "Independence from Irrelevant Alternative (IIA)," which states that the ratio of the probabilities of choosing any two alternatives is independent of the properties of all other alternatives. The IIA property is often a limitation for MNL models where the disturbances of some alternatives are highly correlated (i.e., where some alternatives are similar to each other). For each of the employment and earnings models, I therefore used the Hausman-McFadden IIA test (Hausman and McFadden 1984) and the McFadden IIA test (McFadden 1987) to test the null hypothesis that the IIA assumption was valid. Since there was no subset of alternatives that was rejected by both the IIA tests, I assume that the MNL model structure is valid.

In order to test the sensitivity of the estimates, I examine three models: first, Model 1, a model that includes only personal and household characteristics; second, Model 2, a model that adds job-access measures; and third, Model 3, which adds neighborhood characteristics to the previous models' characteristics.

8.4 RESULTS

8.4.1 Employment Probability

Table 8.4.1 presents the estimation results of the three MNL models where the dependent variable is EMP4A (which is described in Table 8.1.1) and the base case is alternative 4 (no auto, unemployed). Overall, the personal and household characteristics are not highly sensitive to the inclusion of the job-access and neighborhood variables. The job-access variable also is not particularly sensitive to the introduction of the neighborhood characteristics. The results I interpret are those from Model 3, which includes all the variables.

To clarify each variable's effect, I simulate to what extent the conditional probability of employment given auto ownership varies by changing each explanatory variable (Table 8.4.1b). The simulation is calculated for an average person in the sample.[26]

As listed in Table 8.1.1, the job-access variable (OFHS30TD) represents the ratio of transit to auto job accessibility. The job-access coefficient for alternative 1 is higher than that for alternative 2, and the coefficient for alternative 3 is greater than zero (i.e., the coefficient for alternative 4). These relative differences reflect the fact that improved job accessibility of transit (relative to autos) increases the conditional probability of employment given auto ownership. Note that when interpreting coefficients of MNL, all that matters is *differences* between their values.

[26] The significance of the effect of each variable for those who own autos is the significance of alternative 1 (auto, employed) relative to alternative 2 (auto, unemployed). An easy way to obtain the significance of the variables' effects for the auto-owning group is to estimate the model where the base case is alternative 2 (auto, unemployed) instead of alternative 4 (no auto, unemployed). The magnitude of the effects is, however, the same whether the base case is alternative 2 or 4.

Table 8.4.1 Estimation results of multinomial logit models for employment for welfare recipients in Los Angeles

	Model 1		Model 2		Model 3	
	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
(Appearing for numbered choice)						
constant [1]	2.171 ***	8.30	1.948 ***	6.82	2.078 ***	6.42
constant [2]	2.012 ***	7.56	1.911 ***	6.54	1.981 ***	5.92
constant [3]	-0.636 *	-1.70	-0.927 **	-2.32	-0.875 **	-1.99
age18_25 [1]	-0.255	-1.31	-0.243	-1.25	-0.237	-1.22
age18_25 [2]	-0.141	-0.68	-0.138	-0.67	-0.133	-0.64
age18_25 [3]	-0.078	-0.37	-0.066	-0.31	-0.065	-0.30
age45_ [1]	-0.128	-0.54	-0.135	-0.57	-0.133	-0.56
age45_ [2]	0.023	0.09	0.020	0.08	0.021	0.08
age45_ [3]	0.152	0.57	0.143	0.54	0.146	0.55
black [1]	-0.991 ***	-4.18	-0.954 ***	-4.01	-0.827 ***	-2.96
black [2]	-1.231 ***	-4.86	-1.216 ***	-4.79	-1.318 ***	-4.33
black [3]	-0.041	-0.14	0.007	0.02	0.073	0.22
hispa [1]	-0.380 *	-1.69	-0.402 *	-1.78	-0.320	-1.29
hispa [2]	-0.534 **	-2.30	-0.545 **	-2.34	-0.463 *	-1.79
hispa [3]	0.272	0.94	0.243	0.84	0.276	0.89
otherr [1]	0.584	1.00	0.606	1.03	0.630	1.07
otherr [2]	0.033	0.05	0.044	0.07	0.068	0.11
otherr [3]	1.302 **	1.98	1.332 **	2.02	1.343 **	2.04
nohi [1]	-0.781 ***	-4.87	-0.784 ***	-4.88	-0.765 ***	-4.74
nohi [2]	-0.463 ***	-2.72	-0.468 ***	-2.75	-0.471 ***	-2.74
nohi [3]	-0.446 **	-2.50	-0.454 **	-2.54	-0.447 **	-2.49
siglp [1]	-1.042	-5.06	-1.011	-4.88	-1.002 ***	-4.83
siglp [2]	-1.383 ***	-6.63	-1.372 ***	-6.56	-1.355 ***	-6.46
siglp [3]	0.582 *	1.94	0.624 **	2.07	0.626 **	2.08
kidu6 [1]	-0.390 **	-2.29	-0.392 **	-2.29	-0.390 **	-2.28
kidu6 [2]	-0.108	-0.60	-0.107	-0.59	-0.116	-0.64
kidu6 [3]	-0.355 *	-1.82	-0.356 *	-1.82	-0.355 *	-1.82
ofhs30td [1]			0.350 *	1.87	0.357 *	1.85
ofhs30td [2]			0.172	0.86	0.237	1.15
ofhs30td [3]			0.453 **	2.17	0.457 **	2.12
pctbl1 [1]					-0.004	-0.81
pctbl1 [2]					0.004	0.79
pctbl1 [3]					-0.002	-0.38
pcthisp [1]					-0.003	-0.78
pcthisp [2]					-0.003	-0.86
pcthisp [3]					-0.001	-0.25
Number of observations	1,518		1,518		1,518	
Log likelihood when parameters set to zero	-2,104		-2,104		-2,104	
Log-likelihood at convergence	-1,958		-1,955		-1,952	
ρ^2	0.07		0.07		0.07	
Adjusted ρ^2	0.06		0.06		0.06	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table 8.4.1b Effects of changes in variables on employment probabilities by auto ownership for welfare recipients in Los Angeles

Variable	Description	Changes in P(Employed)			
		Auto		No auto	
AGE18_25	1: 18-25 years old; 0: otherwise	-0.03		-0.02	
AGE45_	1: >=45 years old; 0: otherwise	-0.04		0.04	
BLACK	1: Non-Hispanic black; 0: otherwise	0.12	*	0.02	
HISPA	1: Hispanic; 0: otherwise	0.04		0.07	
OTHERR	1: Other minority race; 0: otherwise	0.13		0.32	**
NOHI	1: Less than high school degree; 0: otherwise	-0.07	*	-0.11	**
SIGLP	1: Single-parent household; 0: otherwise	0.09	**	0.15	**
KIDU6	1: With child under 6 yrs. old; 0 otherwise	-0.07	*	-0.08	*
OFHS30TD	Ratio of transit to auto job accessibility (30-min. threshold)	0.03		0.09	**
PCTBL1	% Blacks	-0.08		-0.02	
PCTHISP	% Hispanics	0.01		-0.01	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level. Significance levels for auto-owning workers are from estimates of models where the base case is alternative 2 (auto, unemployed). Continuous variables were changed one standard deviation on either side of the mean vector of variables.

Figure 8.4.1 shows the simulation of changes in the conditional probability of employment given auto ownership as a function of job accessibility. The calculation is based on Model 3 for an average welfare recipient in the sample. As the graph shows, improving job accessibility of transit (relative to autos) heightens the employment probability for both autoless and auto-owning welfare recipients, but the job-access effect is greater for autoless recipients than for auto-owning recipients. This result is quantified in Table 8.4.1b. For an average welfare recipient, improving job accessibility of transit (relative to autos) by one standard deviation on either side of the mean increases the employment probability by 0.09 for a person without an auto but only by 0.03 for a person with an auto.

A real-world example of this job-access effect follows. Suppose that an average welfare recipient lives in an area in Inglewood (Tract 06037601212 in Table 8.2.3) that has a relatively low level of job accessibility of transit at 400 (the ratio of transit to auto accessibility is also low, 0.25) and has a high concentration of welfare recipients. If an average welfare recipient did not have an auto, her probability of employment would be 0.37. If this autoless welfare recipient lived in a Century City neighborhood that has a high level of job accessibility for transit users at 1110 (the ratio of transit to auto accessibility is also high, 0.79), her employment probability would be 0.43, or a 0.06 increase. (For simplicity, neighborhood characteristics are held constant at the average.) If an average welfare recipient had an auto, on the other hand, her probability of employment would be 0.56 in the area in Inglewood and 0.58 in the Century City neighborhood, or a 0.02 increase. Therefore, the employment gain by moving from the Inglewood location to the area in Century City would be greater for an autoless welfare recipient than for an auto-owning recipient. For autoless welfare recipients, job accessibility is indeed one of the most significant factors in determining employment. Among the variables tested in the model, job accessibility shows the second strongest significance, following skills (no high school diploma).

The positive effect of job accessibility of transit (relative to autos) for welfare recipients with autos probably reflects the fact that not all auto-owning recipients have full access to automobiles, and that many recipients' vehicles are old and unreliable.

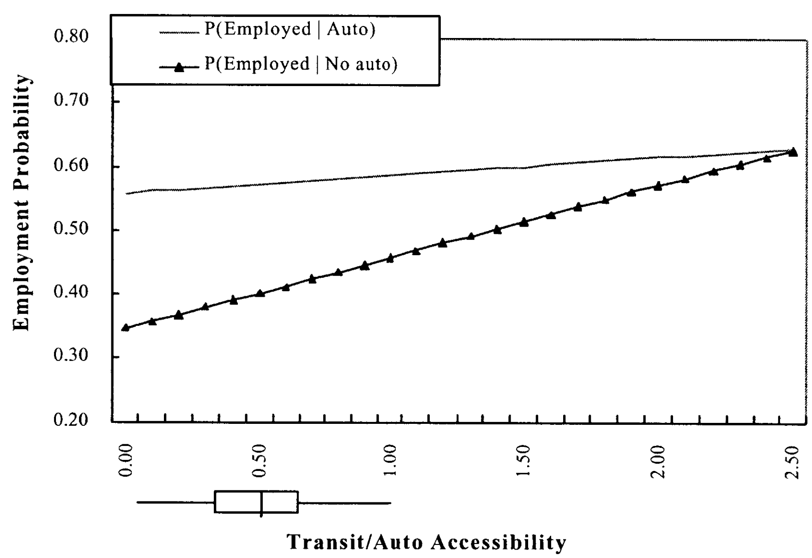

Figure 8.4.1 Effect of job access on conditional probability of employment given auto ownership for welfare recipients in Los Angeles.

Among the personal and household characteristics, education, single parenthood, and the presence of a child under 6 years old significantly affect employment for both autoless and auto-owning welfare recipients. As expected, not having a high school diploma significantly reduces the probability of employment for both types of welfare recipients. Single parenthood, on the other hand, significantly raises the employment probability, all else being equal, suggesting that single parents have a strong work incentive to support their families. Welfare recipients with a young child under 6 years old are significantly less likely to be employed than to be unemployed, reflecting that finding and keeping a job while taking care of a young child is a formidable task.

Few racial dummies have a significant impact on employment. Being African-American significantly increases the employment probability for welfare recipients with autos, and being an other-race person (OTHERR) also significantly raises the employment probability for autoless recipients. The effects of the other racial dummies are not significant but all positive. The positive effects of the minority races may contradict the traditional view. The results for the Hispanic race and the other race (OTHERR) are, however, overall consistent with the results for general low-skilled workers in Los Angeles in Chapter 7, and therefore they may be specific to Los Angeles. The results for the African-American race, on the other hand, are inconsistent. For general low-skilled workers in Los Angeles, being African-American significantly lowers the likelihood that workers gain employment, while it raises the likelihood for welfare recipients. The positive effect of the African-American race may be specific to welfare recipients in Los Angeles. That overall minority welfare recipients in Los Angeles do well in employment is perhaps related to the great racial diversity in this area. Racial barriers may be much less prominent in Los Angeles, where 57% of population are non-white, than in most other metropolitan areas.

The estimated coefficients of the neighborhood variables are all insignificant. It is interesting to find that even at the tract level, the job-access effect for autoless welfare recipients has greater magnitude and significance than do the neighborhood variables.

8.4.2 Earnings

The estimation results of the three MNL models examining the likelihood of earning $4,500 or more per year are presented in Table 8.4.2. The dependent variable, EAR45A6, is described in Figure 8.3.2 and Table 8.1.1.

As in the case of the employment models, the personal and household characteristics and job-access variable are not highly sensitive to the model specifications, and they retain signs and significance, with the exception of the Hispanic race (HISPA) and the other race (OTHERR). The HISPA coefficient for alternative 4 becomes insignificant in Model 3, and the OTHERR coefficient for alternative 1 becomes positive in Model 2. The changes in the coefficients of these two variables, however, are minor.

Below, I interpret the results based on Model 3, which includes all the variables. To make interpretations easier, I show Table 8.4.2b that simulates the variables' effects on the conditional probability of earning $4,500 or more per year given auto ownership. The calculation is made for an average welfare recipient in the sample.[27]

The result of the job-access variable (OFHS30TD) is illustrated in Figures 8.4.2a and 8.4.2b, in which the probabilities are calculated for an average welfare recipient in the sample. Improving job accessibility for transit (relative to autos) raises the likelihood of earning $4,500 or more per year for both autoless and auto-owning welfare recipients, but the effect is greater for autoless welfare recipients than for auto-owning recipients. This result is consistent with the result for the employment models. Compared to the effects on the employment probability, however, the job-access effects on the probability of earning at least $4,500 per year are small, and they are not statistically significant. These findings suggest that improving job accessibility for transit users helps autoless welfare recipients get jobs, but it does not make much difference in obtaining full-time or well-paying jobs.

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[27] The significance of each variable's effect for a person without an auto is given by the significance of alternative 4 (no auto, earned ≥ $4,500) relative to alternative 6 (no auto, unemployed), and the significance for a person having an auto is given by the significance of alternative 1 (auto, earned ≥ $4,500) relative to alternative 3 (auto, unemployed).

Table 8.4.2 Estimation results of multinomial logit models for earnings for welfare recipients in Los Angeles

	Model 1		Model 2		Model 3	
	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic
(Appearing for numbered choice)						
constant [1]	1.708 ***	5.63	1.583 ***	4.78	1.478 ***	3.91
constant [2]	1.403 ***	4.45	1.332 ***	3.84	1.450 ***	3.71
constant [3]	2.379 ***	8.40	2.327 ***	7.51	2.409 ***	6.89
constant [4]	-0.343	-0.83	-0.496	-1.13	-0.678	-1.36
constant [5]	-1.611 ***	-2.95	-1.586 ***	-2.78	-1.601 ***	-2.63
age18_25 [1]	-0.315	-1.32	-0.308	-1.29	-0.309	-1.30
age18_25 [2]	0.290	1.20	0.293	1.21	0.299	1.23
age18_25 [3]	-0.166	-0.74	-0.165	-0.74	-0.161	-0.72
age18_25 [4]	0.028	0.11	0.037	0.14	0.025	0.10
age18_25 [5]	0.324	1.30	0.324	1.30	0.327	1.31
age45_ [1]	-0.519 *	-1.90	-0.523 *	-1.91	-0.530 *	-1.93
age45_ [2]	-0.542 *	-1.74	-0.544 *	-1.75	-0.542 *	-1.74
age45_ [3]	-0.018	-0.07	-0.020	-0.08	-0.017	-0.07
age45_ [4]	-0.043	-0.14	-0.047	-0.16	-0.047	-0.16
age45_ [5]	-0.826 **	-2.09	-0.825 **	-2.09	-0.827 **	-2.09
black [1]	-0.455	-1.61	-0.434	-1.53	-0.516	-1.54
black [2]	-0.956 ***	-3.26	-0.944 ***	-3.21	-0.872 **	-2.49
black [3]	-1.234 ***	-4.82	-1.225 ***	-4.78	-1.247 ***	-4.08
black [4]	0.315	0.87	0.341	0.94	0.344	0.84
black [5]	0.237	0.65	0.234	0.64	0.152	0.37
hispa [1]	0.163	0.61	0.150	0.57	0.067	0.23
hispa [2]	-0.317	-1.17	-0.324	-1.19	-0.233	-0.78
hispa [3]	-0.601 **	-2.54	-0.607 **	-2.55	-0.524 **	-2.00
hispa [4]	0.664 *	1.88	0.649 *	1.84	0.510	1.35
hispa [5]	0.350	0.97	0.354	0.98	0.367	0.96
otherr [1]	-0.011	-0.02	0.001	0.00	-0.022	-0.04
otherr [2]	-0.675	-1.06	-0.669	-1.05	-0.644	-1.01
otherr [3]	-0.266	-0.53	-0.262	-0.52	-0.239	-0.48
otherr [4]	-0.347	-0.40	-0.334	-0.39	-0.371	-0.43
otherr [5]	0.547	0.77	0.544	0.76	0.539	0.76
nohi [1]	-0.669 ***	-3.53	-0.669 ***	-3.53	-0.682 ***	-3.57
nohi [2]	-0.614 ***	-3.03	-0.616 ***	-3.03	-0.599 ***	-2.93
nohi [3]	-0.628 ***	-3.53	-0.631 ***	-3.54	-0.624 ***	-3.47
nohi [4]	-0.498 **	-2.33	-0.500 **	-2.34	-0.515 **	-2.39
nohi [5]	-0.186	-0.87	-0.184	-0.86	-0.188	-0.87
siglp [1]	-1.542 ***	-6.39	-1.526 ***	-6.31	-1.533 ***	-6.32
siglp [2]	-1.171 ***	-4.50	-1.162 ***	-4.45	-1.149 ***	-4.39
siglp [3]	-1.470 ***	-6.37	-1.465 ***	-6.33	-1.450 ***	-6.25
siglp [4]	-0.475	-1.55	-0.455	-1.48	-0.468	-1.52
siglp [5]	0.888 *	1.90	0.884 *	1.90	0.892 *	1.91
kidu6 [1]	-0.273	-1.35	-0.274	-1.36	-0.275	-1.36
kidu6 [2]	-0.320	-1.46	-0.319	-1.46	-0.321	-1.47
kidu6 [3]	-0.165	-0.87	-0.165	-0.86	-0.170	-0.89
kidu6 [4]	-0.225	-0.97	-0.225	-0.97	-0.220	-0.95
kidu6 [5]	-0.238	-1.02	-0.240	-1.03	-0.243	-1.04
ofhs30td [1]			0.192	0.93	0.192	0.91
ofhs30td [2]			0.114	0.51	0.129	0.56
ofhs30td [3]			0.085	0.42	0.119	0.58
ofhs30td [4]			0.236	1.00	0.192	0.79
ofhs30td [5]			-0.044	-0.16	-0.015	-0.05
pctbl1 [1]					0.002	0.37
pctbl1 [2]					-0.002	-0.29
pctbl1 [3]					0.001	0.27
pctbl1 [4]					-0.001	-0.19
pctbl1 [5]					0.003	0.48
pcthisp [1]					0.003	0.59
pcthisp [2]					-0.003	-0.69
pcthisp [3]					-0.003	-0.76
pcthisp [4]					0.005	1.04
pcthisp [5]					-0.001	-0.13
Number of observations	1.518		1.518		1.518	
Log likelihood when parameters set to zero	-2,722		-2,722		-2,722	
Log-likelihood at convergence	-2.519		-2.518		-2.515	
ρ^2	0.07		0.07		0.08	
Adjusted ρ^2	0.06		0.06		0.05	

Note: ***Significant at the 0.01 level: **significant at the 0.05 level: *significant at the 0.10 level.

Table 8.4.2b Effects of changes in variables on probabilities of earning $4,500 or more per year for welfare recipients in Los Angeles

Variable	Description	Changes in P(>=$4,500) Auto		No auto	
AGE18_25	1: 18-25 years old; 0: otherwise	-0.07		-0.02	
AGE45_	1: >=45 years old; 0: otherwise	-0.07	**	0.03	
BLACK	1: Non-Hispanic black; 0: otherwise	0.13	**	0.06	
HISPA	1: Hispanic; 0: otherwise	0.11	**	0.08	
OTHERR	1: Other minority race; 0: otherwise	0.08		-0.10	
NOHI	1: Less than high school degree; 0: otherwise	-0.01		-0.09	**
SIGLP	1: Single-parent household; 0: otherwise	-0.04		-0.15	
KIDU6	1: With child under 6 yrs. old; 0 otherwise	-0.01		-0.03	
OFHS30TD	Ratio of transit to auto job accessibility (30-min. threshold)	0.01		0.03	
PCTBL1	% Blacks	0.02		-0.02	
PCTHISP	% Hispanics	0.06		0.06	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.
Significance levels for auto-owning workers are from estimates of models where the base case is alternative 3 (auto, unemployed). Significance levels for autoless workers are from estimates of models where the base case is alternative 6 (no auto, unemployed). Continuous variables were changed one standard deviation on either side of the mean vector of variables.

Few variables associated with human capital significantly affect the likelihood that a person earns $4,500 or more per year. For autoless welfare recipients, only educational attainment matters significantly; if an average welfare recipient does not have a high school diploma, her probability of attaining annual earnings of $4,500 or higher is lessened by 0.09. Interestingly, for an average welfare recipient with an auto, not having a high school diploma decreases the probability by only 0.01 and this effect is not significant.

For welfare recipients owning autos, the variables for the age range of 45 or older, African-American race, and Hispanic race have significant impacts on the likelihood of earning $4,500 or more per year. For a welfare recipient with an auto, being 45 or older significantly reduces the probability of earning at least $4,500 per year, and being African-American or Hispanic significantly raises this probability. As in the case of the employment model, none of the neighborhood characteristics has a significant effect.

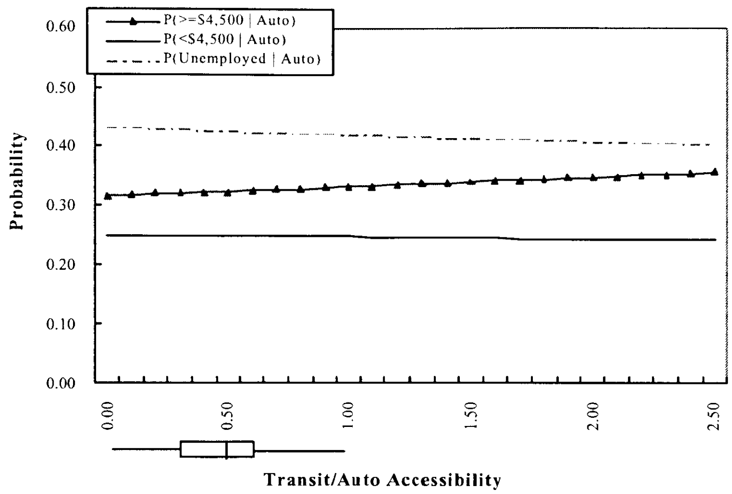

Figure 8.4.2a Effect of job access on conditional probability of earning $4,500 or more per year conditional on having an auto for welfare recipients in Los Angeles.

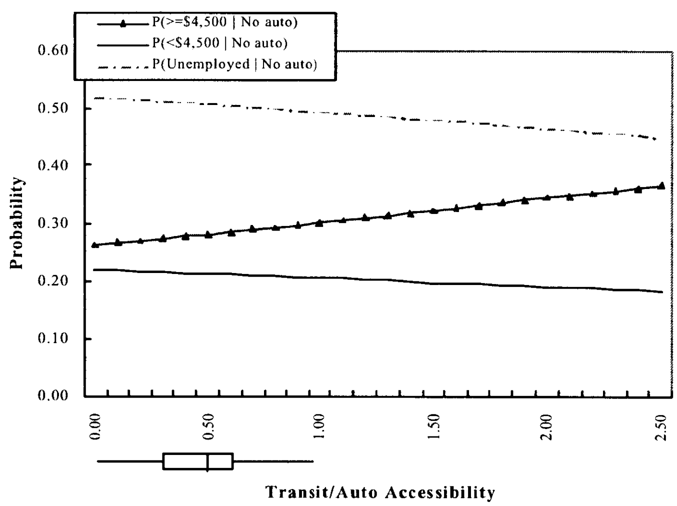

Figure 8.4.2b Effect of job access on conditional probabilities of earning $4,500 or more per year conditional on not having an auto for welfare recipients in Los Angeles.

It is interesting to find that for autoless welfare recipients, being an other-race person (OTHERR) decreases the probability of earning at least $4,500 per year (this effect is not significant, however) but significantly increases the probability of employment. This result suggests that other-race welfare recipients without autos are significantly more likely to get a job but are less likely to obtain and keep a full-time or decent-paying job. A similar result is found for single parenthood (SIGLP). For both autoless and auto-owning welfare recipients, being a single parent significantly increases the probability of employment but lowers the likelihood of earning $4,500 or more per year (although the latter effect is not significant). Perhaps single parents are facing strong pressure to obtain a job to support their families, but getting and holding a full-time job is extremely difficult while taking care of children.

8.5 SENSITIVITY ANALYSES

For each of the employment and earnings models, I tested sensitivity to the alternative job-access measures that use different travel time thresholds of 15, 30, and 45 minutes. I also tested sensitivity to the first alternative job-access measurement reviewed in Section 2.2.2, the jobs-per-area measurement. The second alternative measurement, the simple jobs-to-workers-per-area ratio, is not tested since recent data on female job seekers who are low-skilled are not available at this time. The third alternative measurement, commuting time, is also not examined since commuting time is not available in the data set. Table 8.5.1 shows the definition and descriptive statistics of the tested alternative job-access measurements.

Table 8.5.1 Alternative job-access measurements for welfare recipients in Los Angeles

		Statistics					
Variable	Description	Total		With auto		Without auto	
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
OFHS15TD	Ratio of transit to auto job accessibility (15-min. threshold)	0.71	0.82	0.76	0.87	0.64	0.74
OFHS30TD	Ratio of transit to auto job accessibility (30-min. threshold)	0.58	0.43	0.60	0.46	0.55	0.38
OFHS45TD	Ratio of transit to auto job accessibility (45-min. threshold)	0.66	0.36	0.65	0.36	0.67	0.36
LNFHSPSM	Natural logarithm of jobs per square miles	6.01	1.12	5.94	1.15	6.09	1.06

8.5.1 Employment Probability

Table 8.5.2a presents the estimated results of the employment models that use the three different travel time thresholds—15, 30, and 45 minutes. The estimated coefficients of the job-access variables are highly sensitive. As the travel time threshold increases, the job-access effect for autoless welfare recipients becomes greater, while the effect for welfare recipients with autos becomes smaller. The job-access effect for autoless welfare recipients is not significant for the 15-minute threshold, but the effect is significant for the 30- and 45-minute thresholds. One may argue that the use of the 15-minute threshold is more appropriate since travel time of welfare recipients would be shorter than that of general workers, since welfare mothers would desire to work nearby. Using 1990 Public Use Microdata Samples (PUMS), I investigated the mean commuting time for persons who are poor female householders in the labor force, with a child less than 6 years old (as proxy for the welfare population). I found that for this population in Los Angeles County, the mean transit commuting time was 44 minutes, much longer than expected, and the mean auto commuting time was 23 minutes.[28] This result suggests that welfare mothers seek to work close to home, but in reality 15 minutes is not feasible for most transit users. The use of the 30-minute threshold for my models therefore is reasonable.

The estimation result using the jobs-per-area measurement (LNFHSPSM) is reported in Table 8.5.2b. Note that this alternative job-access measurement does not take travel modes into account. When the jobs-per-area measurement is used, the job-access effect on the employment probability for autoless welfare recipients remains positive but becomes insignificant. The effect for auto-owning recipients, on the other hand, becomes negative and significant.

[28] For total workers, the mean commuting times of transit users and auto users in Los Angeles County were, respectively, 42 and 26 minutes.

Table 8.5.2a Estimation results of multinomial logit models for employment using alternative travel-time thresholds for welfare recipients in Los Angeles

	15 min.			30 min.			45 min.		
	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
(Appearing for numbered choice)									
constant [1]	2.216	***	6.94	2.078	***	6.42	2.226	***	6.84
constant [2]	2.112	***	6.38	1.981	***	5.92	2.043	***	6.07
constant [3]	-0.649		-1.51	-0.875	**	-1.99	-0.861	**	-1.97
age18_25 [1]	-0.247		-1.28	-0.237		-1.22	-0.250		-1.29
age18_25 [2]	-0.141		-0.68	-0.133		-0.64	-0.140		-0.68
age18_25 [3]	-0.080		-0.37	-0.065		-0.30	-0.096		-0.45
age45_ [1]	-0.128		-0.53	-0.133		-0.56	-0.128		-0.53
age45_ [2]	0.025		0.10	0.021		0.08	0.023		0.09
age45_ [3]	0.154		0.58	0.146		0.55	0.150		0.56
black [1]	-0.834	***	-2.98	-0.827	***	-2.96	-0.836	***	-2.99
black [2]	-1.332	***	-4.38	-1.318	***	-4.33	-1.325	***	-4.35
black [3]	0.055		0.16	0.073		0.22	0.110		0.32
hispa [1]	-0.317		-1.28	-0.320		-1.29	-0.320		-1.29
hispa [2]	-0.468	*	-1.81	-0.463	*	-1.79	-0.465	*	-1.80
hispa [3]	0.277		0.90	0.276		0.89	0.302		0.97
otherr [1]	0.626		1.06	0.630		1.07	0.599		1.02
otherr [2]	0.047		0.08	0.068		0.11	0.046		0.07
otherr [3]	1.321	**	2.00	1.343	**	2.04	1.300	**	1.97
nohi [1]	-0.756	***	-4.68	-0.765	***	-4.74	-0.762	***	-4.72
nohi [2]	-0.470	***	-2.73	-0.471	***	-2.74	-0.468	***	-2.72
nohi [3]	-0.438	**	-2.44	-0.447	**	-2.49	-0.443	**	-2.46
siglp [1]	-1.023	***	-4.94	-1.002	***	-4.83	-1.034	***	-5.01
siglp [2]	-1.376	***	-6.56	-1.355	***	-6.46	-1.372	***	-6.56
siglp [3]	0.589	**	1.96	0.626	**	2.08	0.590	**	1.96
kidu6 [1]	-0.386	**	-2.26	-0.390	**	-2.28	-0.386	**	-2.26
kidu6 [2]	-0.116		-0.64	-0.116		-0.64	-0.114		-0.63
kidu6 [3]	-0.351	*	-1.80	-0.355	*	-1.82	-0.342	*	-1.75
ofhstd [1]	0.059		0.61	0.357	*	1.85	0.121		0.50
ofhstd [2]	0.004		0.04	0.237		1.15	0.137		0.54
ofhstd [3]	0.041		0.36	0.457	**	2.12	0.494	**	2.04
pctbl1 [1]	-0.004		-0.90	-0.004		-0.81	-0.005		-1.06
pctbl1 [2]	0.004		0.69	0.004		0.79	0.003		0.64
pctbl1 [3]	-0.003		-0.54	-0.002		-0.38	-0.004		-0.83
pcthisp [1]	-0.002		-0.58	-0.003		-0.78	-0.002		-0.66
pcthisp [2]	-0.003		-0.74	-0.003		-0.86	-0.003		-0.82
pcthisp [3]	0.000		-0.04	-0.001		-0.25	-0.002		-0.41
Number of observations	1,518			1,518			1,518		
Log likelihood when parameters set to zero	-2,104.4			-2,104.4			-2,104.4		
Log-likelihood at convergence	-1,954.7			-1,952.2			-1,952.3		
ρ^2	0.07			0.07			0.07		
Adjusted ρ^2	0.05			0.06			0.06		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table 8.5.2b Estimation results for of multinomial logit models for employment using alternative access measurement for welfare recipients in Los Angeles

	Ratio of transit to auto job accessibility (30-min)			Jobs per square mile		
	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
(Appearing for numbered choice)						
constant [1]	2.078	***	6.42	3.342	***	6.62
constant [2]	1.981	***	5.92	2.580	***	4.81
constant [3]	-0.875	**	-1.99	-1.352	*	-2.09
age18_25 [1]	-0.237		-1.22	-0.282		-1.44
age18_25 [2]	-0.133		-0.64	-0.157		-0.76
age18_25 [3]	-0.065		-0.30	-0.047		-0.22
age45_ [1]	-0.133		-0.56	-0.104		-0.44
age45_ [2]	0.021		0.08	0.036		0.14
age45_ [3]	0.146		0.55	0.148		0.56
black [1]	-0.827	***	-2.96	-0.830	***	-2.96
black [2]	-1.318	***	-4.33	-1.311	***	-4.29
black [3]	0.073		0.22	0.038		0.11
hispa [1]	-0.320		-1.29	-0.321		-1.29
hispa [2]	-0.463	*	-1.79	-0.450	*	-1.73
hispa [3]	0.276		0.89	0.256		0.82
otherr [1]	0.630		1.07	0.639		1.09
otherr [2]	0.068		0.11	0.091		0.15
otherr [3]	1.343	**	2.04	1.282	*	1.94
nohi [1]	-0.765	***	-4.74	-0.775	***	-4.78
nohi [2]	-0.471	***	-2.74	-0.492	***	-2.85
nohi [3]	-0.447	**	-2.49	-0.425	**	-2.36
siglp [1]	-1.002	***	-4.83	-1.060	***	-5.11
siglp [2]	-1.355	***	-6.46	-1.402	***	-6.68
siglp [3]	0.626	**	2.08	0.592	**	1.96
kidu6 [1]	-0.390	**	-2.28	-0.387	**	-2.26
kidu6 [2]	-0.116		-0.64	-0.126		-0.70
kidu6 [3]	-0.355	*	-1.82	-0.371	*	-1.90
ofhs30td [1]	0.357	*	1.85			
ofhs30td [2]	0.237		1.15			
ofhs30td [3]	0.457	**	2.12			
lnfhspsm [1]				-0.186	***	-2.76
lnfhspsm [2]				-0.087		-1.21
lnfhspsm [3]				0.120		1.50
pctbl1 [1]	-0.004		-0.81	-0.006		-1.17
pctbl1 [2]	0.004		0.79	0.004		0.72
pctbl1 [3]	-0.002		-0.38	-0.002		-0.41
pcthisp [1]	-0.003		-0.78	-0.001		-0.19
pcthisp [2]	-0.003		-0.86	-0.002		-0.45
pcthisp [3]	-0.001		-0.25	0.000		-0.07
Number of observations	1,518			1,512		
Log likelihood when parameters set to zero	-2,104			-2,096		
Log-likelihood at convergence	-1,952			-1,939		
ρ^2	0.07			0.08		
Adjusted ρ^2	0.06			0.06		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

8.5.2 Earnings

Table 8.5.3a shows the estimated earnings models that use the three different travel-time thresholds. The job-access coefficients are somewhat sensitive, but the estimates indicate that in all three models the job-access effects on the conditional probability of earning at least \$4,500 per year given auto ownership are positive. As in the case of the employment models, for autoless welfare recipients the magnitude of the job-access effect becomes greater as the travel-time threshold lengthens, but none of these effects is significant.

The estimated result using the jobs-per-area measurement (LNFHSPSM) is presented in Table 8.5.3b. When the jobs-per-area measurement is used, the job-access effect on the likelihood of attaining \$4,500 or more per year becomes smaller for both autoless and auto-owning welfare recipients.

Table 8.5.3a Estimation results of multinomial logit models for earnings using alternative travel-time thresholds for welfare recipients in Los Angeles

	15 min.		30 min.		45 min.	
	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic
(Appearing for numbered choice)						
constant [1]	1.515 ***	4.07	1.478 ***	3.91	1.530 ***	4.05
constant [2]	1.731 ***	4.46	1.450 ***	3.71	1.560 ***	3.99
constant [3]	2.478 ***	7.18	2.409 ***	6.89	2.622 ***	7.45
constant [4]	-0.558	-1.15	-0.678	-1.36	-0.705	-1.43
constant [5]	-1.424 **	-2.35	-1.601 ***	-2.63	-1.530 **	-2.51
age18_25 [1]	-0.313	-1.32	-0.309	-1.30	-0.318	-1.33
age18_25 [2]	0.293	1.20	0.299	1.23	0.296	1.22
age18_25 [3]	-0.162	-0.72	-0.161	-0.72	-0.168	-0.75
age18_25 [4]	0.017	0.07	0.025	0.10	0.007	0.03
age18_25 [5]	0.332	1.32	0.327	1.31	0.330	1.32
age45_ [1]	-0.527 *	-1.92	-0.530 *	-1.93	-0.529 *	-1.93
age45_ [2]	-0.535 *	-1.72	-0.542 *	-1.74	-0.538 *	-1.73
age45_ [3]	-0.014	-0.06	-0.017	-0.07	-0.007	-0.03
age45_ [4]	-0.043	-0.14	-0.047	-0.16	-0.043	-0.14
age45_ [5]	-0.824 **	-2.08	-0.827 **	-2.09	-0.825 **	-2.09
black [1]	-0.507	-1.51	-0.516	-1.54	-0.510	-1.52
black [2]	-0.903 ***	-2.59	-0.872 **	-2.49	-0.886 **	-2.53
black [3]	-1.256 ***	-4.10	-1.247 ***	-4.08	-1.270 ***	-4.15
black [4]	0.335	0.82	0.344	0.84	0.382	0.93
black [5]	0.125	0.30	0.152	0.37	0.137	0.33
hispa [1]	0.082	0.28	0.067	0.23	0.076	0.26
hispa [2]	-0.243	-0.81	-0.233	-0.78	-0.235	-0.78
hispa [3]	-0.520 **	-1.99	-0.524 **	-2.00	-0.527 **	-2.01
hispa [4]	0.514	1.36	0.510	1.35	0.538	1.42
hispa [5]	0.380	0.99	0.367	0.96	0.362	0.94
otherr [1]	-0.004	-0.01	-0.022	-0.04	-0.038	-0.07
otherr [2]	-0.721	-1.13	-0.644	-1.01	-0.645	-1.01
otherr [3]	-0.247	-0.49	-0.239	-0.48	-0.222	-0.44
otherr [4]	-0.384	-0.44	-0.371	-0.43	-0.388	-0.45
otherr [5]	0.497	0.70	0.539	0.76	0.547	0.77
nohi [1]	-0.670 ***	-3.50	-0.682 ***	-3.57	-0.677 ***	-3.54
nohi [2]	-0.622 ***	-3.03	-0.599 ***	-2.93	-0.598 ***	-2.92
nohi [3]	-0.621 ***	-3.45	-0.624 ***	-3.47	-0.630 ***	-3.50
nohi [4]	-0.513 **	-2.38	-0.515 **	-2.39	-0.514 **	-2.39
nohi [5]	-0.201	-0.93	-0.188	-0.87	-0.188	-0.87
siglp [1]	-1.541 ***	-6.35	-1.533 ***	-6.32	-1.549 ***	-6.41
siglp [2]	-1.204 ***	-4.60	-1.149 ***	-4.39	-1.161 ***	-4.45
siglp [3]	-1.458 ***	-6.29	-1.450 ***	-6.25	-1.470 ***	-6.36
siglp [4]	-0.488	-1.59	-0.468	-1.52	-0.489	-1.59
siglp [5]	0.868 *	1.86	0.892 *	1.91	0.891 *	1.91
kidu6 [1]	-0.272	-1.35	-0.275	-1.36	-0.274	-1.36
kidu6 [2]	-0.333	-1.52	-0.321	-1.47	-0.321	-1.47
kidu6 [3]	-0.170	-0.89	-0.170	-0.89	-0.170	-0.89
kidu6 [4]	-0.218	-0.94	-0.220	-0.95	-0.215	-0.93
kidu6 [5]	-0.260	-1.11	-0.243	-1.04	-0.247	-1.06
ofhstd [1]	0.049	0.46	0.192	0.91	0.093	0.40
ofhstd [2]	-0.204	-1.58	0.129	0.56	-0.086	-0.33
ofhstd [3]	-0.016	-0.15	0.119	0.58	-0.296	-1.19
ofhstd [4]	-0.010	-0.08	0.192	0.79	0.251	1.03
ofhstd [5]	-0.288 *	-1.71	-0.015	-0.05	-0.166	-0.52
pctbl1 [1]	0.002	0.39	0.002	0.37	0.002	0.26
pctbl1 [2]	-0.004	-0.59	-0.002	-0.29	-0.002	-0.30
pctbl1 [3]	0.001	0.23	0.001	0.27	0.002	0.32
pctbl1 [4]	-0.002	-0.28	-0.001	-0.19	-0.002	-0.37
pctbl1 [5]	0.002	0.32	0.003	0.48	0.003	0.54
pcthisp [1]	0.003	0.69	0.003	0.59	0.003	0.63
pcthisp [2]	-0.003	-0.58	-0.003	-0.69	-0.003	-0.56
pcthisp [3]	-0.003	-0.68	-0.003	-0.76	-0.002	-0.47
pcthisp [4]	0.006	1.12	0.005	1.04	0.005	0.96
pcthisp [5]	0.000	0.01	-0.001	-0.13	0.000	-0.02
Number of observations	1.518		1.518		1.518	
Log likelihood when parameters set to zero	-2.722		-2.722		-2.722	
Log-likelihood at convergence	-2.511		-2.515		-2.513	
ρ^2	0.08		0.08		0.08	
Adjusted ρ^2	0.06		0.06		0.05	

Note: ***Significant at the 0.01 level: **significant at the 0.05 level: *significant at the 0.10 level.

Table 8.5.3b Estimation results for of multinomial logit models for eranings using alternative access measurement for welfare recipients in Los Angeles

	Ratio of transit to auto job accessibility (30-min)			Jobs per square mile		
	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant [1]	1.478	***	3.91	2.930	***	4.81
constant [2]	1.450	***	3.71	3.360	***	5.36
constant [3]	2.409	***	6.89	3.632	***	6.32
constant [4]	-0.678		-1.36	-0.744		-0.97
constant [5]	-1.601	***	-2.63	-0.391		-0.48
age18_25 [1]	-0.309		-1.30	-0.362		-1.51
age18_25 [2]	0.299		1.23	0.239		0.98
age18_25 [3]	-0.161		-0.72	-0.209		-0.93
age18_25 [4]	0.025		0.10	0.013		0.05
age18_25 [5]	0.327		1.31	0.294		1.17
age45_ [1]	-0.530	*	-1.93	-0.496	*	-1.81
age45_ [2]	-0.542	*	-1.74	-0.524	*	-1.68
age45_ [3]	-0.017		-0.07	0.001		0.00
age45_ [4]	-0.047		-0.16	-0.054		-0.18
age45_ [5]	-0.827	**	-2.09	-0.818	**	-2.07
black [1]	-0.516		-1.54	-0.469		-1.39
black [2]	-0.872	**	-2.49	-0.879	**	-2.51
black [3]	-1.247	***	-4.08	-1.227	***	-3.98
black [4]	0.344		0.84	0.350		0.85
black [5]	0.152		0.37	0.160		0.39
hispa [1]	0.067		0.23	0.123		0.41
hispa [2]	-0.233		-0.78	-0.229		-0.76
hispa [3]	-0.524	**	-2.00	-0.490	*	-1.85
hispa [4]	0.510		1.35	0.549		1.45
hispa [5]	0.367		0.96	0.386		1.00
otherr [1]	-0.022		-0.04	0.040		0.07
otherr [2]	-0.644		-1.01	-0.616		-0.96
otherr [3]	-0.239		-0.48	-0.192		-0.38
otherr [4]	-0.371		-0.43	-0.372		-0.43
otherr [5]	0.539		0.76	0.568		0.79
nohi [1]	-0.682	***	-3.57	-0.705	***	-3.67
nohi [2]	-0.599	***	-2.93	-0.631	***	-3.06
nohi [3]	-0.624	***	-3.47	-0.668	***	-3.69
nohi [4]	-0.515	**	-2.39	-0.524	**	-2.42
nohi [5]	-0.188		-0.87	-0.212		-0.98
siglp [1]	-1.533	***	-6.32	-1.577	***	-6.48
siglp [2]	-1.149	***	-4.39	-1.198	***	-4.56
siglp [3]	-1.450	***	-6.25	-1.500	***	-6.45
siglp [4]	-0.468		-1.52	-0.484		-1.57
siglp [5]	0.892	*	1.91	0.872	*	1.87
kidu6 [1]	-0.275		-1.36	-0.251		-1.23
kidu6 [2]	-0.321		-1.47	-0.318		-1.44
kidu6 [3]	-0.170		-0.89	-0.170		-0.88
kidu6 [4]	-0.220		-0.95	-0.210		-0.91
kidu6 [5]	-0.243		-1.04	-0.232		-0.99
ofhs30td [1]	0.192		0.91			
ofhs30td [2]	0.129		0.56			
ofhs30td [3]	0.119		0.58			
ofhs30td [4]	0.192		0.79			
ofhs30td [5]	-0.015		-0.05			
lnfhspsm [1]				-0.231	***	-2.85
lnfhspsm [2]				-0.309	***	-3.65
lnfhspsm [3]				-0.196	***	-2.58
lnfhspsm [4]				0.030		0.31
lnfhspsm [5]				-0.200	**	-2.11
pctbl1 [1]	0.002		0.37	0.000		0.01
pctbl1 [2]	-0.002		-0.29	-0.004		-0.58
pctbl1 [3]	0.001		0.27	0.000		0.07
pctbl1 [4]	-0.001		-0.19	-0.002		-0.25
pctbl1 [5]	0.003		0.48	0.002		0.28
pcthisp [1]	0.003		0.59	0.004		0.91
pcthisp [2]	-0.003		-0.69	-0.001		-0.28
pcthisp [3]	-0.003		-0.76	-0.002		-0.39
pcthisp [4]	0.005		1.04	0.005		1.03
pcthisp [5]	-0.001		-0.13	0.000		-0.01
Number of observations	1,518			1,513		
Log likelihood when parameters set to zero	-2,722			-2,711		
Log-likelihood at convergence	-2,515			-2,496		
ρ^2	0.08			0.08		
Adjusted ρ^2	0.06			0.06		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

8.6 CHAPTER SUMMARY

The empirical results using the survey in Los Angeles showed that higher job accessibility of transit (relative to autos) had a significant and positive effect on the employment probability for autoless welfare recipients. The simulations further revealed that the job-access effect was greater for autoless welfare recipients than for recipients having autos. For instance, increasing job accessibility of transit (relative to autos) by one standard deviation on either side of the mean would enhance the average welfare recipient's employment probability by 0.09 for an autoless person but by only 0.03 for an auto-owning person. Indeed, for autoless welfare recipients, the job-access effect showed the second greatest significance, following skills (education). For welfare recipients having autos, on the other hand, the job-access effect was positive but not significant, and the significant factors were skills, single parenthood, the presence of a child under 6 years old, and the African-American race. The job-access effect on the probability of earning $4,500 or more per year was also positive but not statistically significant. The above results together suggest that improving job accessibility for transit users helps autoless welfare recipients' transition to work, but this job accessibility alone does not guarantee stable jobs.

Among the variables, skills would appear to be the most prevalently important factor, especially for autoless welfare recipients. All else being equal, not having a high school diploma lowers the employment probability of an average autoless recipient by 0.11 and reduces her likelihood of earning at least $4,500 per year by 0.09. An interesting finding is that minority members overall did well in the employment outcomes. This result is perhaps owing to the multiethnic nature of Los Angeles, where racial barriers may be substantially lower than those in most other areas in this country. Another interesting finding is that controlling for auto ownership, single parents were significantly more likely to be employed than to be unemployed, probably because of strong work pressure, but being a single parent lowers the probability of earning $4,500 or more per year. This result suggests the great difficulty of single parents, most of whom are women, in getting and holding full-time or well-paying jobs.

The empirical findings indicated that for autoless welfare recipients, the job-access effect on employment was significant and greater than were the neighborhood effects even at the tract level. This result is consistent with the results for general low-skilled workers at the level of PUMAs. Policy implications identified by the empirical findings are discussed in the next chapter.

Chapter 9: Conclusion

In the auto-oriented, spatially dispersed U.S. metropolitan areas, workers without autos have severely limited spatial mobility, experiencing a considerable disadvantage in accessing employment opportunities. Concentrating on low-skilled workers and welfare recipients without autos, I found that improving job accessibility for transit users made a significant difference in enabling these disadvantaged people to obtain and keep jobs in the two highly auto-dependent metropolitan areas, San Francisco and Los Angeles. In this concluding chapter, I first summarize findings in the preceding chapters, then discuss policy implications based on the empirical results, and finally, suggest future research directions.

9.1 SUMMARY OF FINDINGS

The analysis of this dissertation is broadly categorized into three parts, each focusing on persons without autos. The first part investigated socioeconomic and transportation characteristics of individual low-skilled workers (Chapter 4); the second part examined geographies of the low-skilled labor market (Chapters 5 and 6); and the third part analyzed job-access effects on employment outcomes for the two disadvantaged worker groups: low-skilled workers and welfare recipients (Chapters 7 and 8).

Preceding the analysis, I first in Chapter 3 provided basic information about the urban structures of the three study areas: the Boston Primary Metropolitan Statistical Area (PMSA), the nine-county San Francisco Bay Area, and Los Angeles County. While the San Francisco Bay Area and Los Angeles County are large metropolitan areas with 6,900 and 4,100 square miles of land, respectively, Boston is a much more compact area having 1,800 square miles of land.

An important feature of the study areas is auto dependency, which is a good indicator of the sprawling and auto-oriented nature of urban structures. Although in all three metropolitan areas the great majority own autos and use auto for commuting, Boston is less auto-dependent than are San Francisco and Los Angeles. In Boston, autoless households accounted for 17% and persons who commuted by public transportation constituted 14% of workers. San Francisco and Los Angeles, on the other hand, are more auto-dependent metropolitan areas, where only 11% of each area were autoless households and only 9% and 7%, respectively, used public transportation to get to work. Note that the city of San Francisco with well-developed transit systems had high proportions of autoless households and transit commuters, 31% and 34%, respectively. These proportions for the entire San Francisco Bay Area were low because transit networks were poorly developed in the Bay Area other than the city of San Francisco; that area constitutes 99% of the Bay Area.

Examining characteristics of individual workers by skill and auto ownership, Chapter 4 exhibited the markedly low socioeconomic profile of low-skilled workers without autos. Compared to the other general populations, low-skilled autoless workers were far more likely to be members of female-headed households and members of minority groups, and also are much more likely to be poor and unemployed. Moreover, their household incomes and personal earnings were extremely low. The statistics showed that of low-skilled autoless workers in the study areas, 37%-50% were in female-headed households; 54%-72% belonged to minority groups; 24%-39% were in poverty; and 18%-23% were unemployed. The median household incomes and the median personal earnings of low-skilled autoless workers in the study areas were approximately $19,000-$23,000 and $9,000-$11,000, respectively. Workers who were both low-skilled and autoless were indeed among the most disadvantaged worker groups in the urban labor market.

Among low-skilled workers in the study areas, auto dependency was highest in San Francisco, second highest in Los Angeles, and lowest in Boston. Of low-skilled workers, the proportion of autoless persons was only 9% in San Francisco and 12% in Los Angeles, while the proportion in Boston was relatively high, 16%. Among those who were low-skilled, the proportions of auto commuters in San Francisco and Los Angeles were 77% and 75%, respectively, whereas the proportion of auto commuters in Boston was lower, 69%.

It was interesting to find that for low-skilled workers without autos in the study areas, although the dominant mode of travel was public transportation, 27%-31% commuted by auto, and roughly half of them carpooled to work. For low-skilled workers with autos in the three areas, on the other hand, although 9%-12% used public transportation, the great majority, 77%-81%, used autos to get to work. These figures suggest greater preference for autos over public transportation, which conversely reflects the difficulty of using public transportation as a mode of travel.

The geographies of the low-skilled labor market were explored in Chapters 5 and 6. Chapter 5 first examined how low-skilled workers and jobs were spatially distributed within and across the metropolitan areas. To investigate whether the distributions were unique to the low-skilled group, the distributions were compared with those of their counterparts, the high-skilled group.

The tabulated statistics of workers and jobs for the dichotomy between the central city and the suburbs indicated that in all three areas, workers were more suburbanized than jobs. The statistics also indicated that low-skilled workers were slightly more concentrated in the central cities than high-skilled workers in Boston and Los Angeles (no difference for San Francisco), but low-skilled jobs were more decentralized than were high-skilled jobs. The resulting jobs-to-workers ratios were higher in the central cities than in the suburbs for both low-skilled and high-skilled groups. Within the central cities, however, the jobs-to-workers ratios for the low-skilled group were lower than those for the high-skilled group; conversely, the ratios in the suburbs were higher for the low-skilled group than for the high-skilled group, but this difference was relatively small. These results indicated that in terms of job opportunities, the central-city areas offered more of a geographical advantage than did the suburban areas for low-skilled as well as for high-skilled workers, but such a geographical advantage was reduced for the low-skilled cohort.

The distributions of workers and jobs were also presented in maps in three dimensions. With 3D maps, it was possible to show more spatially disaggregated pictures of the distributions and to highlight great spatial variability. Such information could not be conveyed effectively by tables or 2D maps. The 3D maps revealed that despite the substantial suburbanization of employment, areas around the CBDs still had high concentrations of jobs, providing greater job opportunities than most suburban areas. Workers were also highly concentrated around the central-city areas but were more decentralized than jobs. The 3D maps also indicated that the distributional patterns for the low-skilled group resembled those for the high-skilled group. Although these findings were consistent across the three metropolitan areas, the distributional patterns varied across the three metropolitan areas.

Boston had a distinctive urban core, having both workers and jobs centered around the city of Boston. Jobs were, however, far more concentrated around the CBD than were workers. San Francisco showed a more polycentric metropolitan structure. While the city of San Francisco, particularly around the northeastern parts of the city (e.g., Union Square), had the highest concentrations of workers and jobs, workers and jobs also clustered in areas surrounding the San Francisco Bay (e.g., downtown Oakland and downtown San Jose). Los Angeles, on the other hand, had less conspicuous urban cores with workers and jobs being widely distributed in the southern sections of Los Angeles County. Still, areas around downtown Los Angeles provided markedly high concentrations of jobs.

With the 3D maps, Chapter 5 showed clearly the limitations of using the jobs-to-workers-per-area ratio as a measurement of job accessibility for small geographic areas like TAZ. One limitation is that the jobs-to-workers-per-area ratio tends to overestimate job accessibility in an area that has a large number of workers residing nearby. For example, Boston's CBD, downtown San Jose, and Los Angeles' Terminal Island and Long Beach Airport had exceptionally high jobs-to-workers-per-area ratios. These ratios were likely to overestimate job accessibility because even though these areas provided relatively large numbers of jobs, many workers living outside these areas were likely to commute to fill those jobs. Conversely, low jobs-to-workers-per-area ratios in areas near CBDs (e.g., the city of Cambridge near Boston's CBD) were likely to underestimate true job accessibility since workers in those areas actually had many jobs nearby.

Another limitation of the jobs-to-workers-per-area ratio is in a situation where an area has a small number of jobs but an even smaller number of workers. For instance, the large area to the east of Livermore City in the San Francisco Bay Area and the large area at the south part of Angeles National Forest had relatively high ratios, but job opportunities there were in fact not plentiful.

In Chapter 6, improved measures that better represent job accessibility were computed by incorporating job openings, job seekers, and transportation. The measures were based on Shen's formulas (2001) that take into account supply and demand of the labor market and travel modes. The presented measures were essentially the ratios of job openings to job seekers, but unlike the simple jobs-to-workers-per-area ratio, these measures incorporated job openings and job seekers not only within an area of residence but also in zones beyond that area, depending on travel costs and travel modes. Each measure therefore can be considered the number of spatially accessible job openings per job seeker in a given zone.

The tabulated and visualized measures indicated that in all three study areas, job accessibility for transit users was considerably lower than that for auto users, suggesting that workers who depend on public transportation face much lower levels of accessible job opportunities than workers who have access to autos. For instance, a typical low-skilled transit commuter in a typical zone in Boston's suburbs had a low access measure of 0.02 jobs per job seeker, but a typical low-skilled auto commuter in this same suburban zone had a much higher access measure of 0.27 jobs per job seeker.

The measures also indicated that, contrary to the perception of many spatial mismatch studies, central-city areas still offered more of a geographical advantage in accessing employment opportunities than suburban areas, despite the substantial suburbanization of employment. For example, a typical low-skilled transit commuter had an access measure of 0.08 jobs per job seeker in a typical zone in the city of Boston but had an access measure of only 0.02 in a typical suburban zone in Boston.

The geographical disparities, however, were much smaller than the auto/transit disparities, suggesting that the mode of travel had greater importance in determining job accessibility than location. These findings from the three areas were consistent with the findings of Shen (2001). These results together suggested that spatial mismatch was in fact greater in suburban areas than in central-city areas, and further that spatial mismatch might be a serious problem for autoless workers, particularly for those who lived in suburban areas.

The analysis proceeded to one of the major parts of this dissertation, Chapter 7. Focusing on low-skilled workers without autos, in this chapter I incorporated the improved job-access measures into statistical models to estimate job-access effects on employment outcomes. The employment outcomes examined were the probability of employment, the probability of working 30 or more hours per week, and earnings. In order to deal with the sample selection problem, multinomial logit (MNL) and the Heckman correction method were employed as the analytical methods.

The empirical results indicated that for low-skilled autoless workers in San Francisco and Los Angeles, job accessibility for transit users had significant and positive effects on the employment probability and the probability of working full-time (30 or more hours per week), but the job-access effects were not significant in Boston. Further, the job-access effects were consistently greater for autoless workers than for auto-owning workers in San Francisco and Los Angeles. In Boston, on the other hand, the auto/no auto differences were relatively minor, and none of the job-access effects was significant. Earnings were also raised by greater job accessibility for transit users, but this effect was significant in Los Angeles only.

A question raised in this study was whether the job-access effect for autoless workers varied across metropolitan areas with different urban spatial structures. The results indicated that job accessibility for transit users played a more important role in employment outcomes in San Francisco and Los Angeles, more highly auto-dependent areas, than in Boston, a more compact area with relatively well-developed transit systems. A closer look at the metropolitan variations indicated that for each of the three employment outcomes, the magnitude of the job-access effect for autoless workers was greatest in San Francisco, but the significance was strongest in Los Angeles. The magnitude and significance of the job-access effects in Boston were almost always smallest. Further, the auto/no-auto disparities in the job-access effects were largely greater in San Francisco and Los Angeles than in Boston.

In Chapter 8, the analytical framework developed in Chapter 7 was applied to examine the job-access effect on employment outcomes for another disadvantaged group, autoless welfare recipients in Los Angeles. For this group, employment outcomes examined were the following: the probability of employment and the probability of earning $4,500 or more per year. Using MNL, I found that for welfare recipients without autos, higher job accessibility of transit (relative to autos) significantly raised the employment probability for autoless welfare recipients. I also found that the job-access effect was greater for autoless welfare recipients than for auto-owning recipients. These results were therefore consistent with the results for general low-skilled workers. The job-access effect on the probability of earning at least $4,500 per year, however, was positive but not statistically significant for autoless as well as auto-owning welfare recipients. These findings suggest that improving job accessibility for transit users would help autoless welfare recipients' transition to work, but such improvement alone would not make much difference in getting or retaining full-time jobs.

The empirical findings together suggest that spatial mismatch is in fact the problem for autoless workers in suburban areas where jobs are dispersed and public transportation is poorly developed. The findings also suggest that spatial mismatch is more likely to be an employment barrier for those who live in suburban areas than for those who live in central-city areas, which contradicts the dominant view among spatial mismatch researchers.

9.2 SUGGESTIONS FOR GENERAL MOBILITY PROGRAMS

The empirical findings from this dissertation hold important policy implications, particularly for the spatial mobility improvements commonly recommended for disadvantaged workers. Generally, the spatial mobility approaches can be placed into three categories: (1) housing dispersal—helping workers move near jobs (e.g., Kain 1992; Rosenbaum and Popkin 1991); (2) economic development—creating jobs near workers (e.g., Giloth 1998; Porter 1997); and (3) transportation mobility—improving public transportation services and encouraging auto ownership (e.g., Hughes 1995; Sawicki and Moody 2000).

The first approach, housing dispersal, focuses on disadvantaged people in inner cities and tries to help them move to suburban areas. An example is the Gautreax program in Chicago that was begun in late 1970s. This program has helped low-income African-American families move to various locations in the Chicago area. Examining this program, Rosenbaum and Popkin (1991) showed that those program participants who moved to the suburbs experienced increased employment rates. My dissertation's implication for the housing dispersal approach is that for autoless workers in highly auto-dependent areas, moving people to suburban areas would in fact worsen their employment prospects. For autoless workers, areas around the central cities, which still offer relatively high concentrations of jobs and relatively well-developed transit services, provide higher job accessibility than do most suburban areas.

Using the estimates in Chapter 7, I examine whether or not the housing dispersal program actually increases employment outcomes for low-skilled autoless workers. For each of the San Francisco Bay Area and Los Angeles County, the following four areas are selected: a high poverty area, a moderate poverty area, a moderately affluent area, and a highly affluent area. Table 9.2.1 lists the four areas (PUMAs) for San Francisco and Los Angeles, and Figures 9.2.1 and 9.2.2 map the locations of these areas.[29] I present two sample cases that show (1) to what extent employment outcomes would change if a low-skilled person were moved from a high poverty area to a highly affluent area and (2) from a moderate poverty area to a moderately affluent area.

[29] Generally, researchers define a high poverty neighborhood as an area where 40% or more of residents are poor. Since there is no PUMA with a poverty rate of 40% or greater in the samples, I select a PUMA with a poverty rate that is equal to or greater than the 95th percentile in the distribution of poverty rates as a high poverty area, and a PUMA with a poverty rate that is about the 75th percentile (upper quartile) as a moderate poverty area. I select a PUMA with a median household income that is about the 75th percentile in the distribution of median household incomes as a moderate affluent area, and a PUMA with a median household income that is about or greater than the 90th percentile as a highly affluent area.

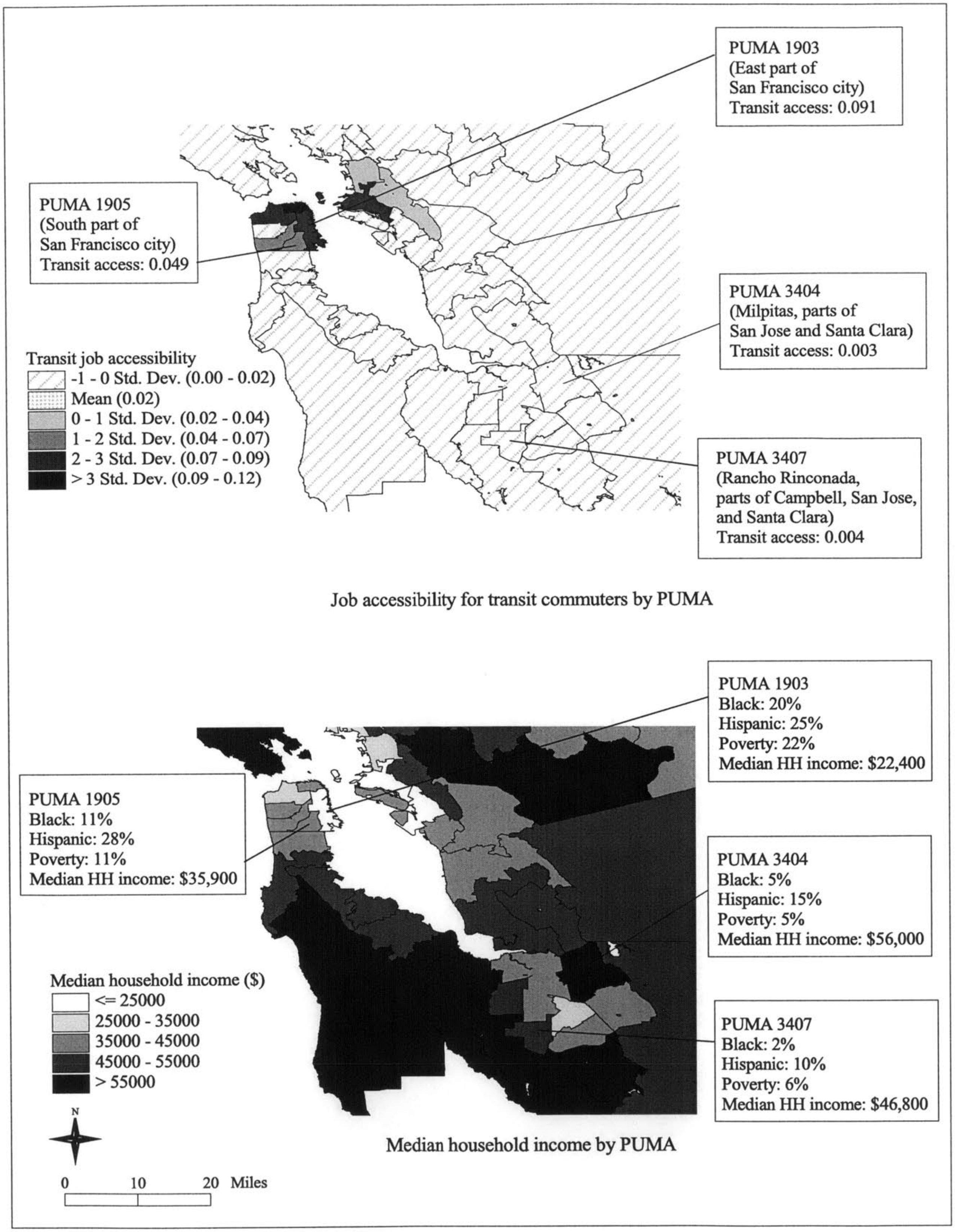

Figure 9.2.1 Neighborhood characteristics of sample PUMAs in San Francisco

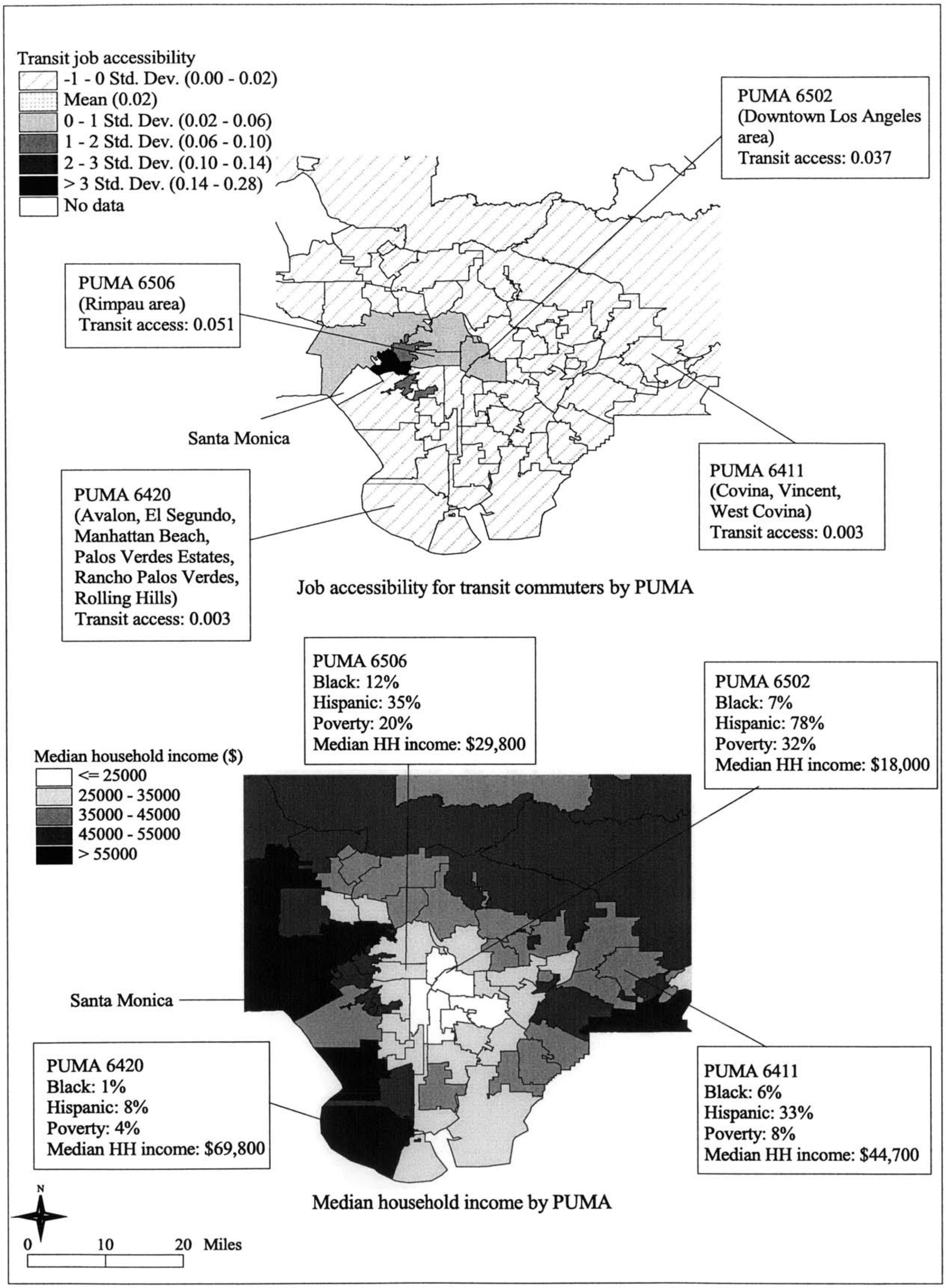

Figure 9.2.2 Neighborhood characteristics of sample PUMAs in Los Angeles

Table 9.2.1 Neighborhood characteristics of sample PUMAs

PUMA	Area	Percent Blacks	Percent Hispanics	Percent poor persons	Median HH income	Accessibility for transit	Accessibility for autos	Transit/auto accessibility
San Francisco								
1903	East part of San Francisco city	20%	25%	22%	$22,400	0.091	0.436	0.209
1905	South part of San Francisco city	11%	28%	11%	$35,900	0.049	0.399	0.123
3407	Rancho Rinconada and parts of Campbell, San Jose, and Santa Clara	2%	10%	6%	$46,800	0.004	0.178	0.023
3404	Milpitas and parts of San Jose and Santa Clara	5%	15%	5%	$56,000	0.003	0.183	0.015
Los Angeles								
6502	Downtown Los Angeles area	7%	78%	32%	$18,000	0.037	0.293	0.125
6506	Rimpau area	12%	35%	20%	$29,800	0.051	0.265	0.193
6411	Covina, Vincent, West Covina	6%	33%	8%	$44,700	0.003	0.144	0.022
6420	Avalon, El Segundo, Manhattan Beach, Palos Verdes Estates, Rancho Palos Verdes, Rolling Hills	1%	8%	4%	$69,800	0.003	0.130	0.023

The sample cases are reported in Table 9.2.2. Note that the probabilities are calculated for a low-skilled man 25-55 years old in a male-headed household. The sample cases show that if a low-skilled autoless man were moved from a high poverty area to a highly affluent area, his employment probability and probability of working full-time (30 or more hours per week) would indeed decrease. For example, suppose that a low-skilled Hispanic man without an auto is moved from the east part of San Francisco city to the Milpitas area. The former area is a central-city neighborhood with a high poverty rate (22%) and a high level of job accessibility for transit users (0.091); the latter area is an affluent suburban neighborhood with a low poverty rate (5%) and a low level of job accessibility for transit users (0.003). With this move, his employment probability would decrease by 0.06 and his probability of working full-time would decrease by 0.07. This result is largely because for low-skilled autoless workers the magnitude of the positive job-access effect on the employment outcomes is large. Similar results also apply to the cases where a low-skilled autoless man were moved from a moderate poverty area to a moderately affluent area; the former area has greater job accessibility for transit users than the latter.

For a low-skilled man with an auto, on other hand, the housing dispersal program could increase employment outcomes if the person were moved from a high poverty area to a highly affluent area. Suppose, for instance, that a low-skilled Hispanic man in Los Angeles were moved from the downtown Los Angeles area to the Rancho Palos Verdes area. The former area has a high poverty rate (32%) and a high level of job accessibility for transit users (0.037); the latter area has a low poverty rate (4%) and a low level of job accessibility for transit users (0.003). With this move, his employment probability would increase by 0.03, although his probability of working full-time would not change. This result is largely because for low-skilled workers with autos the magnitude of the positive job-access effect on the employment outcomes is smaller than that of the negative poverty effect. The simulation shows, however, that if a low-skilled man with an auto were moved from a moderate poverty area to a moderately affluent area, his employment outcomes would not increase, and would rather be likely to decrease.

Table 9.2.2 Changes in employment outcomes for a low-skilled man by moving from a poverty area to an affluent area

		P(Employed)			P(Worked >= 30 hrs.)		
		Before move	After move	Change	Before move	After move	Change
From a high poverty area to a highly affluent area							
San Francisco: from PUMA 1903 to PUMA 3404							
Black	No auto	0.74	0.64	-0.10	0.71	0.60	-0.11
	Auto	0.83	0.88	0.05	0.80	0.82	0.02
Hispanic	No auto	0.89	0.83	-0.06	0.83	0.76	-0.07
	Auto	0.90	0.93	0.03	0.88	0.88	0.00
Los Angeles: from PUMA 6502 to PUMA 6420							
Black	No auto	0.75	0.72	-0.03	0.68	0.63	-0.05
	Auto	0.82	0.87	0.05	0.78	0.78	0.00
Hispanic	No auto	0.89	0.88	-0.01	0.85	0.82	-0.03
	Auto	0.90	0.93	0.03	0.88	0.88	0.00
From a moderate poverty area to a moderately affluent area							
San Francisco: from PUMA 1905 to PUMA 3407							
Black	No auto	0.72	0.65	-0.07	0.71	0.60	-0.11
	Auto	0.88	0.87	-0.01	0.84	0.81	-0.03
Hispanic	No auto	0.88	0.84	-0.04	0.84	0.75	-0.09
	Auto	0.93	0.93	0.00	0.90	0.87	-0.03
Los Angeles: from PUMA 6506 to PUMA 6411							
Black	No auto	0.77	0.72	-0.05	0.70	0.65	-0.05
	Auto	0.86	0.86	0.00	0.80	0.79	-0.01
Hispanic	No auto	0.90	0.88	-0.02	0.86	0.84	-0.02
	Auto	0.92	0.92	0.00	0.89	0.89	0.00

Note: The probabilities are calculated for a low-skilled man 25-55 years old in a male-headed household.

The above sample cases suggest that for low-skilled autoless workers, the housing dispersal program would actually lower their employment outcomes. For low-skilled auto-owning workers, on the other hand, the housing dispersal program could enhance their employment prospects if workers were moved from a high poverty neighborhood to a highly affluent neighborhood, but the program would not be likely to increase their employment outcomes if the workers were moved from a moderate poverty area to a moderately affluent area. Note that in the above sample cases and discussion focus only on the employment outcomes, and benefits from better suburban neighborhoods' characteristics, such as less crime and better schools, are not considered. Note also that since auto insurance costs are usually lower in affluent suburban areas with less crime than in central-city areas with more crime, some low-skilled autoless workers who are moved from inner cities to affluent suburban neighborhoods may be able to buy autos and enjoy employment gains.

Returning to the discussion of this dissertation's implications for the three general mobility approaches: the second mobility approach, economic development, helps increase job opportunities, which in turn improves job accessibility. However, unless targeted areas are located near workers' homes or adequate transportation services are provided (e.g., shuttle bus and vanpooling services), economic development in suburban areas is unlikely to be effective for workers without autos. Due to the insufficient coverage inherent in most transit networks, suburban jobs are not easily accessible for those who do not have autos. From a practical point of view, it is not easy to implement economic development programs that cover extensive suburban areas where people and jobs are sparsely distributed. Economic development targeted at central-city areas, on the other hand, would be more helpful in increasing accessible employment opportunities for autoless workers, although such economic development would not be helpful for autoless workers in suburban areas.

Finally, the empirical results suggest that the third approach, transportation mobility, should be strongly encouraged for workers without autos, particularly for those who live in transit-scarce suburban areas. Two major programs that aim at improving transportation mobility are improving public transportation services and encouraging auto ownership. Since the transportation mobility programs are closely related to the empirical findings in this dissertation, in the next section I discuss the transportation mobility programs in more detail.

9.3 SUGGESTIONS FOR TRANSPORTATION MOBILITY PROGRAMS

The empirical results suggested that in two highly auto-dependent areas, the San Francisco Bay Area and Los Angeles County, improving job accessibility for transit users significantly augments disadvantaged workers without autos obtain and keep jobs. To understand the significance of such improvement, I first present sample cases that show to what extent the improvement in job accessibility for transit users enhances employment outcomes for autoless workers. I then discuss specific transportation mobility programs that would improve transit mobility and job accessibility.

9.3.1 Sample Cases for Low-Skilled Workers and Welfare Recipients

<u>*Sample Cases for Low-Skilled Workers*</u>

To present the sample cases for low-skilled workers, I select two PUMAs that had high concentrations of low-skilled persons in each of the San Francisco and Los Angeles metropolitan areas. Figures 9.3.1 and 9.3.2 identify the locations and neighborhood characteristics of those PUMAs, along with maps showing spatial variations in job accessibility for transit commuters.

For the San Francisco Bay Area, PUMAs 3409 and 3405 (each includes parts of San Jose and Santa Clara) are selected. Among the 48 PUMAs in the Bay Area, these two PUMAs had the highest proportions of low-skilled persons (37% and 36%, respectively) and also had the highest proportions of Hispanic residents (44% and 43%, respectively). While PUMA 3409 had a moderate level of job accessibility for transit users at 0.017 (the ratio of transit to auto accessibility also was moderate, 0.076), PUMA 3405 had a low level of job accessibility for transit users at 0.004 (the ratio of transit to auto accessibility also was low, 0.024).

For Los Angeles County, PUMA 5600 (Florence-Graham, Huntington Park, and Walnut Park) and PUMA 6404 (Bell, Bell Gardens, Commerce, Cudahy, Maywood, and Vernon) are selected. These PUMAs had exceedingly high proportions of low-skilled persons (71% and 69%, respectively), and, similar to the two PUMAs selected for San Francisco, these PUMAs had quite high proportions of Hispanic residents (84% and 88%, respectively).

Based on the model estimates in Chapter 7, I next calculate changes in the employment outcomes by improving transit accessibility from the current level to the level for an area with relatively high job accessibility for transit users. Note that unless otherwise mentioned, the probabilities are calculated for a low-skilled man 22-55 years old in a male-headed household. Note also that to make simulations simple, auto job accessibility is held constant. The simulated outcomes are summarized in Table 9.3.1.

Table 9.3.1 Changes in employment outcomes for a low-skilled man in areas with high concentrations of low-skilled persons

Area	Race	Auto ownership	P(Employed) Before change	After change	After - Before	P(Worked >= 30 hrs.) Before change	After change	After - Before
San Francisco								
PUMA 3409	Hispanic	No auto	0.86	0.93	0.06	0.83	0.91	0.08
Parts of San Jose,		Auto	0.89	0.93	0.03	0.89	0.92	0.03
Parts of Santa Clara	Black	No auto	0.70	0.82	0.13	0.68	0.82	0.14
		Auto	0.81	0.87	0.06	0.81	0.86	0.05
PUMA 3405	Hispanic	No auto	0.84	0.93	0.09	0.81	0.92	0.11
Parts of San Jose,		Auto	0.91	0.95	0.04	0.90	0.93	0.03
Parts of Santa Clara	Black	No auto	0.66	0.83	0.17	0.65	0.84	0.19
		Auto	0.84	0.91	0.06	0.83	0.89	0.06
Los Angeles								
PUMA 5600	Hispanic	No auto	0.88	0.91	0.03	0.85	0.88	0.03
Florence-Graham,		Auto	0.90	0.91	0.01	0.88	0.89	0.01
Huntington Park,	Black	No auto	0.72	0.78	0.05	0.67	0.73	0.06
Walnut Park		Auto	0.82	0.83	0.02	0.78	0.80	0.01
PUMA 6406	Hispanic	No auto	0.87	0.91	0.03	0.84	0.88	0.04
Bell, Bell Gardens,		Auto	0.90	0.91	0.01	0.88	0.89	0.01
Commerce, Cudahy,								
Maywood, Vernon								

Note: The probabilities are calculated for a low-skilled man 25-55 years old in a male-headed household.

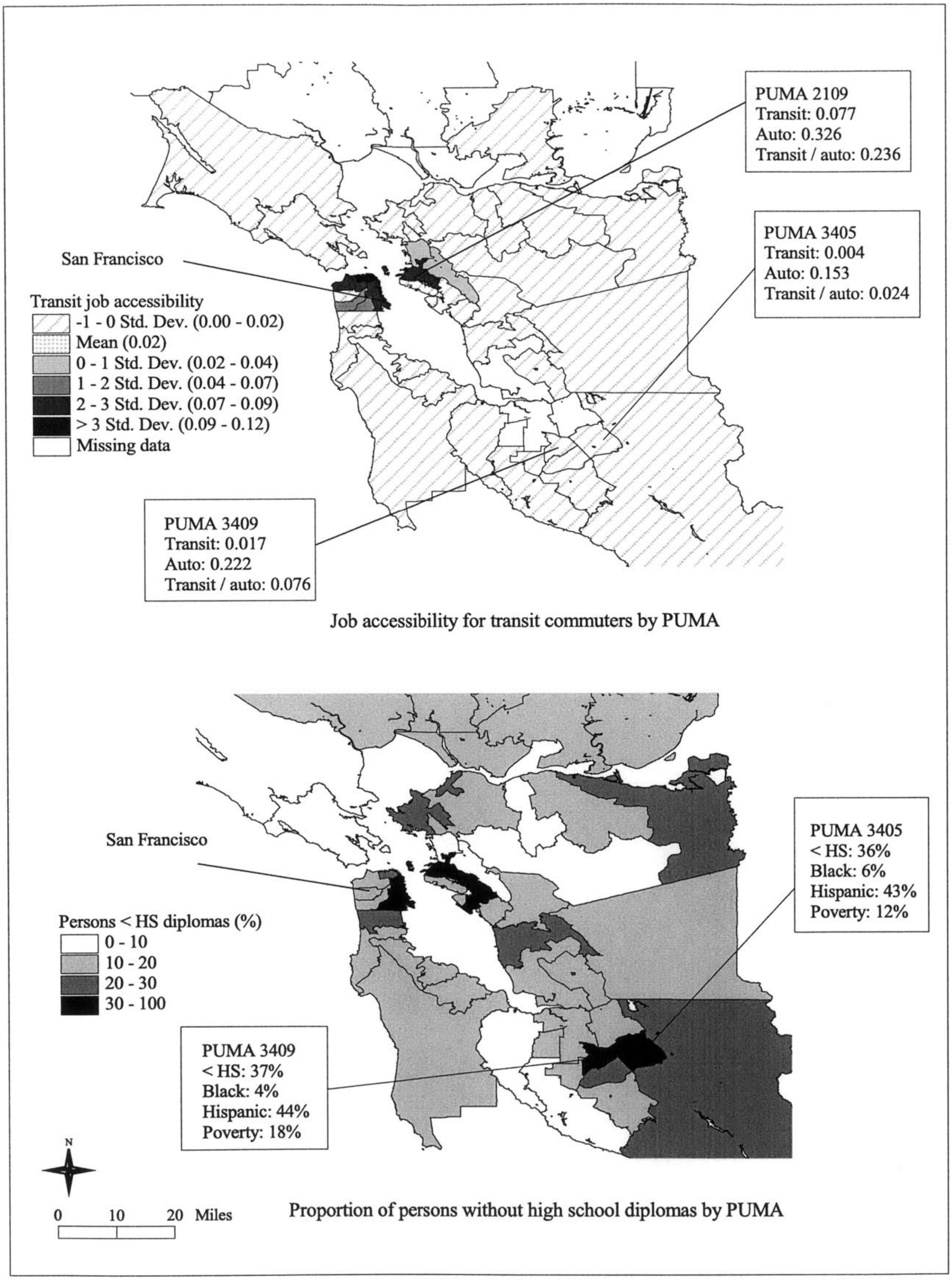

Figure 9.3.1 Locations of sample cases for low-skilled workers in San Francisco

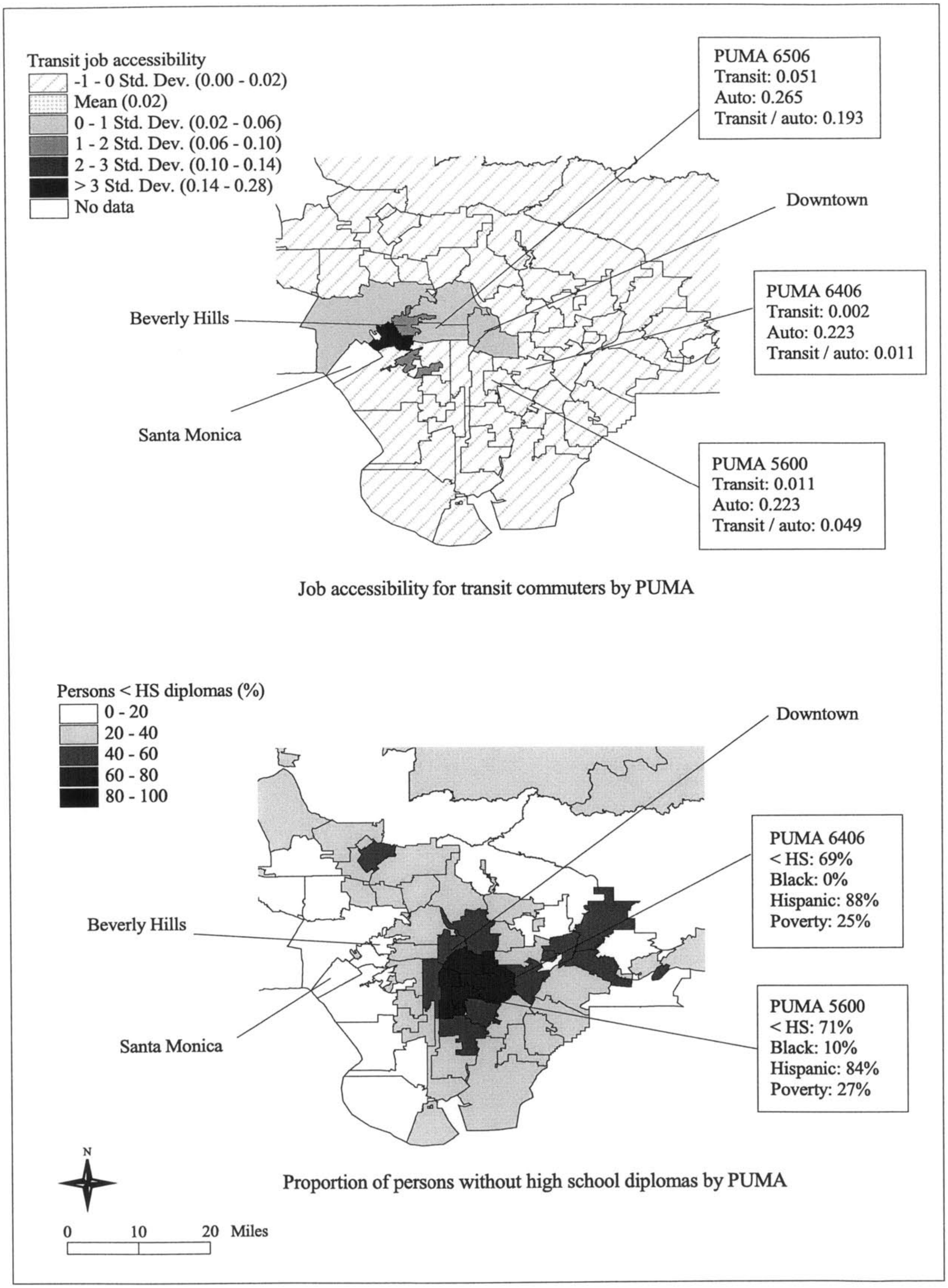

Figure 9.3.2 Locations of sample cases for low-skilled workers in Los Angeles

Cases for San Francisco:

Suppose that job accessibility for transit commuters in PUMA 3409 (parts of San Jose and Santa Clara) is improved from the current level of 0.017 to 0.052, which yields a relatively high ratio of transit to auto accessibility for downtown Oakland (see Figure 9.3.1). In this scenario, the simulated employment outcomes are as follows:

- if a person were a low-skilled Hispanic man and did not have an auto, his employment probability would rise from 0.86 to 0.93 (a 0.07 increase), and his probability of working full-time (30 or more hours per week) would increase from 0.83 to 0.91 (a 0.08 increase);
- if the same Hispanic man had an auto, the magnitude of the effects would be smaller; the employment probability would increase from 0.89 to 0.93 (a 0.04 increase), and the probability of working full-time would increase from 0.89 to 0.92 (a 0.03 increase);
- if a person were a low-skilled African-American man and did not have an auto, his employment probability would increase from 0.70 to 0.82 (a 0.12 increase), and his probability of working full-time would increase from 0.68 to 0.82 (a 0.14 increase);
- if the same African-American man had an auto, the magnitude of the effects would be smaller; the employment probability would increase from 0.81 to 0.87 (a 0.06 increase), and his probability of working full-time would increase from 0.81 to 0.86 (a 0.05 increase).

Likewise, suppose that job accessibility for transit users in PUMA 3405 (other parts of San Jose and Santa Clara) is improved from 0.004 to 0.036, which again generates a ratio of transit to auto accessibility for downtown Oakland. In this case, the simulated probabilities based on the models are as follows:

- if a person were a low-skilled Hispanic man and did not have an auto, his employment probability would improve from 0.84 to 0.93 (a 0.09 increase), and his probability of working full-time would increase from 0.81 to 0.92 (a 0.11 increase);
- if the same Hispanic man had an auto, the employment probability would increase from 0.91 to 0.95 (a 0.04 increase), and his probability of working full-time would

rise from 0.90 to 0.93 (a 0.03 increase);

- if a person were a low-skilled African-American man and did not have an auto, his employment probability would improve from 0.66 to 0.83 (a 0.17 increase), and his probability of working full-time would increase from 0.65 to 0.84 (a 0.19 increase);
- if the same African-American man had an auto, the employment probability would rise from 0.84 to 0.91 (a 0.07 increase), and the probability of working full-time would increase from 0.83 to 0.89 (a 0.06 increase).

Cases for Los Angeles:

Suppose that job accessibility for transit users in PUMA 5600 (Florence-Graham, Huntington Park, and Walnut Park) is enhanced from 0.011 to 0.043, which yields a ratio of transit to auto accessibility for the area between downtown Los Angeles and Beverly Hills (see Figure 9.3.2). In this situation, the simulated probabilities based on the models are as follows:

- if a person were a low-skilled Hispanic man and did not have an auto, his employment probability would increase from 0.88 to 0.91 (a 0.03 increase), and his probability of working full-time would improve from 0.85 to 0.88 (a 0.03 increase);
- if the same Hispanic man had an auto, the employment probability would increase from 0.90 to 0.91 (a 0.01 increase), and the probability of working full-time would rise from 0.88 to 0.89 (a 0.01 increase);
- if a person were a low-skilled African-American man and did not have an auto, his employment probability would increase from 0.72 to 0.78 (a 0.06 increase), and his probability of working full-time would increase from 0.67 to 0.73 (a 0.06 increase);
- if the same African-American man had an auto, the employment probability would increase from 0.82 to 0.83 (a 0.01 increase), and the probability of working full-time would increase from 0.78 to 0.80 (a 0.02 increase).

In terms of another hypothetical situation in Los Angeles, suppose that job accessibility for transit users in PUMA 6406 (Bell, Bell Gardens, Commerce, Cudahy, Maywood, and Vernon) is improved from 0.002 to 0.043, which results in a ratio of transit to auto accessibility in the area between downtown Los Angeles and Beverly Hills. In this scenario, the simulated probabilities based on the models are as follows:

- if a person were a low-skilled Hispanic man and did not have an auto, his employment probability would climbs from 0.87 to 0.91 (a 0.04 increase), and his probability of working full-time would increase from 0.84 to 0.88 (a 0.04 increase);
- if the same Hispanic man had an auto, the employment probability would increase from 0.90 to 0.91 (a 0.01 increase), and the probability of working full-time would increase from 0.88 to 0.89 (a 0.01 increase).[30]

At first glance, these simulated increases in the employment outcomes may appear small. However, given the fact that the unemployment rate for low-skilled autoless men was 0.18 for San Francisco and 0.17 for Los Angeles (which 1990 PUMS indicate), the simulated 0.06-0.17 and 0.03-0.05 increases in the employment probability for San Francisco and Los Angeles, respectively, could be considered substantial gains. Likewise, given the fact that the proportion of low-skilled autoless men who work fewer than 30 hours per week was 0.26 for San Francisco and 0.22 for Los Angeles (which 1990 PUMS indicate), the simulated 0.08-0.19 and 0.03-0.06 increases in the probability of working full-time for San Francisco and Los Angeles, respectively, would indicate considerable gains.

Rough estimates provide a quick understanding of what these figures indicate. According to 1990 PUMS, there were about 22,500 low-skilled autoless men in the nine-county San Francisco Bay Area and about 86,000 in Los Angeles County. For simplicity, suppose that these sample cases were applied to each of the metropolitan areas as a whole. If the employment probability increased by, for example, 0.11 in San Francisco, approximately 2,500 unemployed low-skilled autoless men would become employed. If the employment probability increased by, for instance, 0.04 in Los Angles, about 3,400 unemployed low-skilled autoless men would obtain jobs. If the probability of working full-time increased by 0.13 in San Francisco, approximately 2,900 low-skilled autoless men would obtain full-time jobs. If the probability of working full-time increased by 0.04 in Los Angeles, additional about 3,400 low-skilled autoless men would work full-time.

[30] Since the proportion of African-American residents in this PUMA 6404 is 0%, the simulation for an African-American man is not presented.

It should be noted that improved job accessibility for transit users not only benefits low-skilled autoless men, a relatively small population, but also benefits a larger population including auto-owning men as well as women. For example, according to 1990 PUMS, there were about 239,500 low-skilled men with autos in the nine-county San Francisco Bay Area and about 662,500 in Los Angeles County. If the employment probability increased by, for instance, 0.05 in San Francisco, roughly 12,000 low-skilled men with autos would get jobs. If the employment probability increased by, for example, 0.01 in Los Angeles, about 6,600 low-skilled auto-owning men would obtain jobs. If the probability of working full-time increased by 0.04 in San Francisco, about 9,600 low-skilled auto-owning men would get full-time jobs. If the probability of working full-time increased by 0.01 in Los Angeles, approximately 6,600 low-skilled men with autos would obtain full-time jobs.

These results suggest that in San Francisco and Los Angeles, improving job accessibility for transit users enhances employment outcomes for autoless workers as well as for auto-owning workers. Further, although the magnitude of such enhancement is greater for autoless workers than for auto-owning workers, the number of people who experience increased employment outcomes would be greater for auto-owning workers than for autoless workers.

Sample Cases for Welfare Recipients

For the welfare recipient sample cases, I select two census tracts, tracts 601212 and 602502, which had high concentrations of welfare recipients (individual adults on welfare in the CTNA survey described in Chapter 8) in Los Angeles. The locations and neighborhood characteristics of these census tracts are indicated in Figure 9.3.3. Tract 601212 is a part of Inglewood, and tract 602502 is a part of Hawthorne. The two tracts had relatively low job accessibility for transit commuters, 400 and 495, respectively (the ratios of transit to auto accessibility also were relatively low, 0.25 and 0.35, respectively).

Using the model estimates in Chapter 8, I calculate changes in the employment probabilities by improving transit accessibility from the current level to the level for tract 269500 that is located around Century City and had relatively high transit accessibility. Note that the probabilities are calculated for an adult on welfare who is 25-45 years old, in a single-parent household, without a high school diploma, and with a child under 6 years of age. The simulated probabilities are presented in Table 9.3.2.

Table 9.3.2 Changes in employment probabilities for a welfare recipient in Los Angeles

Area	Race	P(Employed | no auto)			P(Employed | auto)		
		Before change	After change	After - Before	Before change	After change	After - Before
Tract 601212	Hispanic	0.31	0.37	0.06	0.45	0.46	0.02
Part of Inglewood	Black	0.27	0.32	0.05	0.53	0.55	0.02
Tract 602502	Hispanic	0.33	0.37	0.05	0.44	0.45	0.01
Part of Hawthorne	Black	0.28	0.33	0.04	0.53	0.54	0.01

Note: The probabilities are calculated for an adult on welfare who is 25-45 years old, in a single-parent household, without a high school diploma, and with a child under 6 years of age.

Tract 601212 (an area in Inglewood):

Suppose that job accessibility for transit commuters in tract 601212 is improved from the current level of 400 to 1284, which yields a relatively high ratio of transit to auto accessibility for an area around Century City (see Figure 9.3.3). In this scenario, the simulated employment probabilities are as follows:

- if a welfare recipient were Hispanic and did not have an auto, her employment probability would increase from 0.31 to 0.37 (a 0.06 increase);
- if the same Hispanic welfare recipient had an auto, the increase would be smaller; her employment probability would increase from 0.45 to 0.46 (a 0.01 increase);
- if a welfare recipient were African-American and did not have an auto, her employment probability would rise from 0.27 to 0.32 (a 0.05 increase);
- if the same African-American welfare recipient had an auto, the magnitude of the increase would be smaller; her employment probability would increase from 0.53 to 0.55 (a 0.02 increase).

Tract 602502 (an area in Hawthorne):

Suppose that job accessibility for transit commuters in tract 602502 is improved from the current level of 495 to 1110, which generates a comparatively high ratio of transit to auto accessibility for the area around Century City. In this case, the simulated probabilities of employment are as follows:

- if a welfare recipient were Hispanic and did not have an auto, her employment probability would rise from 0.33 to 0.37 (a 0.04 increase);
- if, the same Hispanic welfare recipient had an auto her employment probability would increase from 0.45 to 0.46 (a 0.01 increase);
- if a welfare recipient were African-American and did not have an auto, her employment probability would rise from 0.28 to 0.33 (a 0.05 increase);
- if the same African-American welfare recipient had an auto, her employment probability would increase from 0.53 to 0.54 (a 0.01 increase).

These sample cases indicate that in Los Angeles, a highly auto-dependent area, improving job accessibility for transit users augments employment outcomes for both autoless and auto-owning welfare recipients.

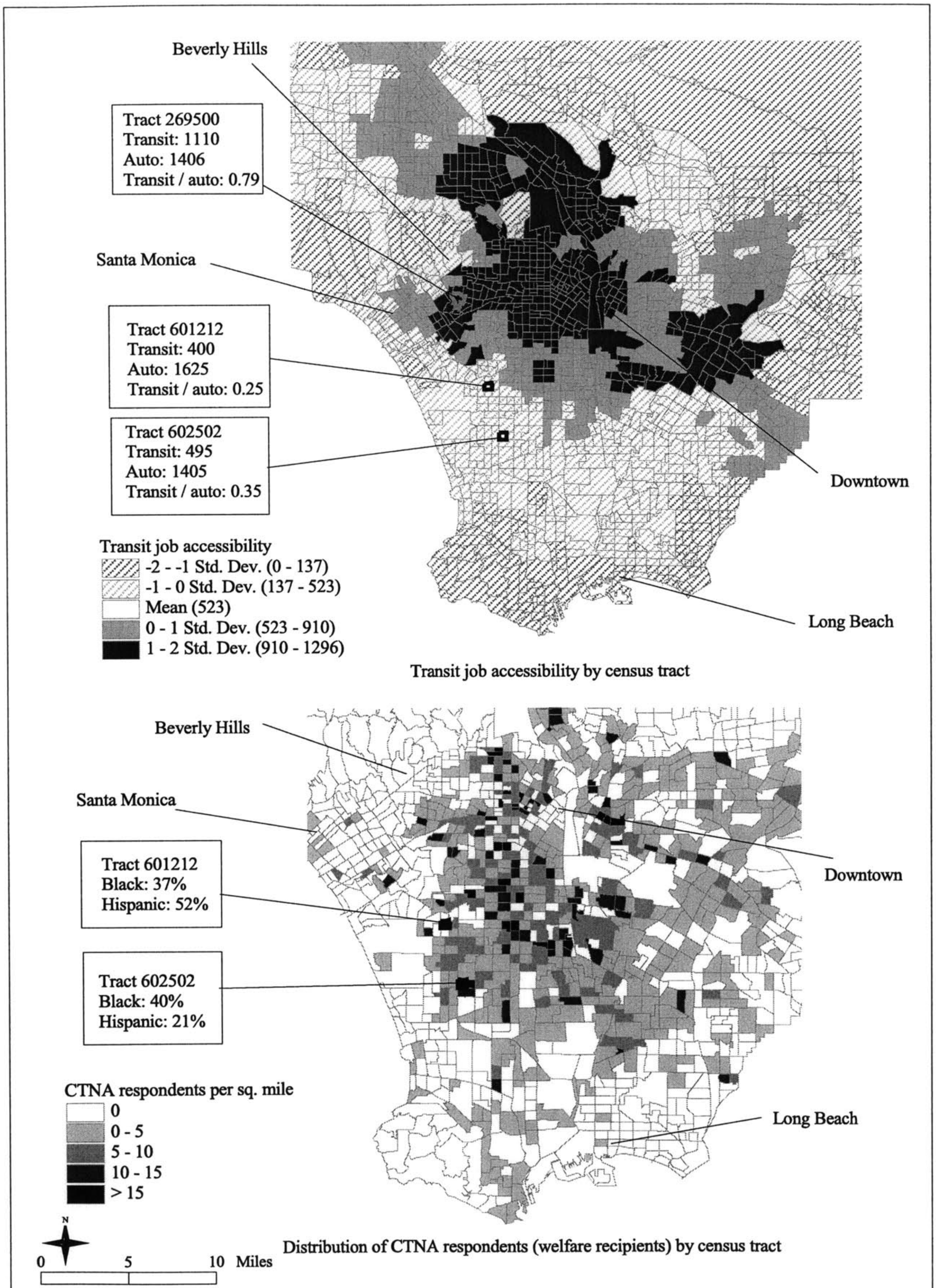

Figure 9.3.3 Locations of sample cases for welfare recipients in Los Angeles

9.3.2 Improving Mobility and Accessibility for Workers without Autos

The empirical findings and the sample cases above suggest that current levels of transit mobility and job accessibility are inadequate, and that improving job accessibility for transit users is one of the effective strategies to enhance employment prospects for disadvantaged workers without autos. Given the continuing suburbanization, already low job accessibility for people without autos is likely to decline further, and the auto/transit disparity in job accessibility is likely to widen. There is clearly a need for improving transit mobility and job accessibility.

Note that such improvements are valuable not only to disadvantaged people without autos, who now are a small population, but also to a larger population including people with autos. Although the people who benefit most are likely to be those who depend on public transportation, people who have autos but cannot use them anytime would also benefit greatly. For example, a household with multiple adults with only one car available is common among low-income people; if an adult in such a household uses the auto for commuting, the other adults cannot use the auto unless they have similar work schedules and proximate workplaces. Improved transit services that can be used by the general public, such as greater frequency and connectivity of transit systems, provide greater transportation options to all people. Improving transit mobility also helps non-work trips, such as trips to medical centers and shops. In addition, improved transportation mobility benefits employers who can have access to a larger pool of potential employees.

The importance of transportation mobility programs is drawing increasing attention, particularly since the welfare reform in 1996, which promotes welfare-to-work transition. Currently, a variety of programs are being planned and implemented. In the following, I present a few specific programs that would improve mobility and job accessibility for persons who do not have access to autos.

Improving Existing Transit Systems

Before developing new transportation mobility programs, planners should first consider utilizing existing transit services. Improving existing transportation services can generally be implemented at lower cost than establishing new services in isolation, and they can reduce duplicated and uncoordinated services. One example of such improvements is to extend fixed-route bus and rail services, which facilitate not only traditional city-to-city and suburb-to-city commuting but also city-to-suburb commuting. As more and more jobs are created in the suburbs, providing services for city-to-suburb commuting, or reverse commuting, has become a popular approach. For example, expanding routes to growing suburban employment centers and shopping centers increases accessible employment opportunities for disadvantaged people. Utilizing existing transit systems to accommodate now popular suburb-to-suburb commuting is not easy, however.

Another example is to extend service hours and to increase frequency of services that enhance the usability of fixed-route services. The extension of service hours help, for instance, many low-skilled workers who work second and third shifts, since transit services often do not operate during the late evening or early morning. Increased frequency would enable people to use fixed-route services for a wider variety of trip purposes, such as job training, schools, childcare, and health care. Increased frequency is also helpful in reducing overcrowding and waiting time. Conducting a survey of welfare recipients in Los Angeles, Ong et al (2001) found that of those who used public transportation, 60% experienced buses passing by sometimes, very often, or always, and 27% said that one of the biggest problems in using transit systems was infrequent service or waiting (their average waiting time was 22.5 minutes). Crowding was reported by 27%, and 21% mentioned the bus not running on schedule. Safety was also an issue, especially for women and children; the same survey data indicated that 55% of transit users felt unsafe at least sometimes. Interestingly, even with these problems, 40% of survey respondents stated that public transportation was a feasible trip option.

The significance of these problems would vary from place to place, but improving transit services to accommodate these concerns would be helpful for many local people who do not have access to autos.

Utilizing Existing Vehicles

One of the cost-effective programs is to cross-utilize existing vehicles. For example, a number of communities offer transportation services for elderly or disabled people. During the times they are not used, the vehicles for these transportation services could be used for disadvantaged people without access to autos. Another possibility is to use school buses for transporting parents who need mobility assistance. When the buses are not in use, they may be used to transport the parents to job-related places, such as job training centers and second or third shift work. For instance, Ohio is active in encouraging the use of school buses for job access services.

Vanpooling and Ridesharing Services

Vanpooling and ridesharing services offer the convenience and speed of automobiles for workers who have similar commuting schedules. Since, in general, transit systems are poorly developed in suburban areas, these services would be helpful particularly for city-to-suburb or suburb-to-suburb commuting. Additionally, the services can be adjusted to meet specific transportation needs such as childcare stops. Various vanpooling and ridesharing programs are currently being offered. For example, CARAVAN in Massachusetts works with employers, job training and placement agencies, and transportation providers to offer statewide vanpooling and ride matching services for commuters (http://www.commute.com/). In the Chicago area, the Pace Vanpool Incentive Program provides economical transportation for people who either live or work near each other (http://www.pacebus.com/). In this unique program, vans are owned, maintained, and insured by Pace, a local bus company, but are driven by volunteers who themselves are commuters. The volunteer drivers receive some benefits, including no monthly fee and personal use of the vans up to 300 miles per month during non-work hours. The program offers vanpool participants a guaranteed ride home program; that is, if a participant needs alternative transportation in case of emergency, Pace reimburses the expense up to $100 per year. This program would be helpful particularly for parents with young children.

Bus Rapid Transit

Bus Rapid Transit (BRT) is an innovative approach to improving transit mobility in urban areas. Buses of BRT are equipped with intelligent transportation systems technology and run on urban arterials or city streets that are reserved for BRT; they therefore combine the flexibility of buses and the quality of rail transit. While trains provide relatively fast and reliable transportation mobility, adding expensive and inflexible railroads is becoming less viable in the dispersing urban structures in the U.S. Compared to rail systems, buses are more flexible and much less expensive, but buses are often unbearably slow due to traffic congestion, frequent traffic signals, and frequent stops for picking up and dropping off passengers. The relatively fast and flexible BRT increases mobility and connectivity, having potential to stimulate economic development and improve job accessibility. Currently, BRT projects are being implemented in 17 areas in the U.S., including Boston, Cleveland, and Los Angeles.

Assisting with Transportation Costs

Subsidizing transit expenses, such as bus and rail passes and vouchers, is helpful for low-income people who depend on public transit. It is, however, important that the passes and vouchers allow people to make several transfers between different routes and services, since paying multiple fares can discourage low-income people from finding and keeping jobs. In some areas, different transportation providers offer various transportation services, making fare structures complex and imposing a financial burden on low-income people who need to transfer to and from different services. Simplifying fare structures and coordinating the transportation services is helpful not only for low-income people but also for the general population.

Transportation Provisions for Economic Development

When economic development efforts are combined with transportation programs, job accessibility as well as transportation mobility are greatly improved. For example, the ongoing Urban Ring project conducted by the Massachusetts Bay Transportation Authority and the Federal Transit Administration plans to connect urban ring corridors in Boston, which is expected to promote economic growth in the urban area.

Smart Growth and Transit Oriented Development (TOD)

More long-term improvement of job accessibility for transit users can be expected from the implementation of Smart Growth and Transit Oriented Development (TOD), which have garnered considerable attention in recent years. Current decentralized urban structures are greatly due to political complacency and the realization of American dreams (e.g., owning autos and single-family housing). Many planners and policy makers, however, now agree that such decentralized structures have serious social costs, including excessive auto dependency (which aggravates congestion and pollution), lack of accessible activities for children and the elderly, and loss of communities.

By encouraging more compact development and discouraging suburban sprawl, Smart Growth is advocated to mitigate these problems and to create more livable communities. Most smart growth proponents recommend the following approaches: providing more transportation options, increasing land use mix, and promoting densification. Developing or redeveloping more compact areas that integrate and balance residential, commercial, and civic functions would reduce spatial separation and the travel costs associated with excessive auto dependency and long travels. In such areas, non-auto modes are more viable options and likely to be used more, even among people with autos. Additionally, such development patterns would increase areas' opportunities, activities, and attractiveness.

Closely related to Smart Growth, Transit-Oriented Development (TOD) promotes compact, transit and pedestrian-oriented development that increases urban environmental benefits, including reduction in sprawl and automobile use and encouragement of urban vitality and attractiveness. Generally, TOD is designed to cluster urban functions and amenities around transit stops; for example, housing, businesses, and shops, together with the pedestrian- and amenity-rich neighborhoods, are developed around transit stops.

Improving Access to Childcare Facilities

Having access to childcare is critical for welfare recipients as well as working parents to be able to obtain and retain jobs. Going to and from childcare facilities is a daily activity and is a formidable task for people without available autos. Especially when childcare facilities are not accessible on the route to the workplace, childcare considerations can significantly impede these people from working. Planners therefore must not only consider connecting people to jobs but also support them in accessing childcare facilities. Promoting vanpooling services described earlier or locating childcare centers near transit hubs are two possible solutions.

Coordination among Organizations

Successful transportation programs require coordination and collaboration efforts among various organizations such as transportation, human resource, social service, and job placement agencies. Without such efforts, transportation programs could be fragmented and misunderstand the nature of the job access problem. Working closely with other agencies, on the one hand, transportation planners can gain valuable information about the transportation needs of the target population and thus can create programs that actually meet those needs. On the other hand, human resource, social service, and job placement agencies can be better informed about available transportation services and resources.

Providing Information about Available Transportation Resources

Lack of knowledge about available transportation services is common among job seekers as well as job counselors. With more and more transportation alternatives provided, it becomes difficult to know them all. For instance, finding a good route using a complex bus system is challenging. People are, in general, familiar with transportation services in their neighborhoods but are unfamiliar with other areas where their potential jobs may be located. A planning case reviewed by the Office of Planning in the Federal Transit Administration (2001) indicates that difficulty in understanding available transportation services is one of the significant barriers to using transit for low-income people in the Washington DC metropolitan area. The review also suggests that job placement counselors often do not know the transit service area.

It would be helpful to gather information about the available transportation services and provide mini brochures, maps, and web pages that describe those services at a glance. It also would be helpful to place transportation service coordinators who help workers find and obtain available transportation resources. Cooperating with employers and transportation providers, transportation coordinators also could arrange and operate such transportation services as vanpools.

Employer Involvement

Getting employers' cooperation is essential for successful job access programs. Working with employers, transportation planners could identify job opportunities and transportation requirements and thus would incorporate such considerations into their planning process. Employers themselves could be transportation providers, for example, by operating or arranging shuttle and vanpooling services that link homes and workplaces or link workplaces and transit stations. Employers also could subsidize transportation costs, which can be promoted by tax incentives. For instance, the Taxpayer Relief Act of 1997 allows employers to offer transportation expenditures of up to $65 per month as a tax-free employee benefit.

Summary

Since transportation needs vary among different individuals in different locations, planners must consider a wide range of service alternatives to accommodate the various needs. For example, transportation needs and concerns change as people proceed from job training to part-time, full-time, and long-term jobs. Those who are receiving job training or those who are looking for jobs need temporary short-term transportation, while those who are working on a regular time schedule need short-term or long-term transportation to worksites. Many working parents and welfare recipients need transportation that allows them to make multiple trips a day, including trips to schools, childcare centers, and workplaces. Transportation needs also vary from place to place. For instance, the need for improving transit mobility would be much greater in sprawling and heavily auto-dependent areas than in more compact areas with well-developed transit systems. Clearly, one solution will not work, and a variety of flexible and sustainable transportation options is needed to increase the likelihood that a greater number of people will be able to find, obtain, and retain jobs.

It is, however, difficult to finance capital and operational costs of the various transportation services. The areas that need transportation assistance most are transit-scarce suburban neighborhoods where jobs and workers are sparsely distributed and multiple trips are often required. In such suburbs, providing new transit routes cannot be easily justified. Planners are aware of the value for such provision but are often unable to afford the costs.

Planners could, however, utilize the government funds that are allowed to use for job access planning. The funding sources for transportation assistance have been increasingly available particularly since the 1996 welfare reform, which has funded programs that would promote welfare-to-work transition. For example, the Bridges to Work program promoted by the U.S. Department of Housing and Urban Development, and Access to Jobs initiative funded by the U.S. Department of Transportation have been developing a variety of transportation mobility programs to help low-income people participate in work activity.

This dissertation focused primarily on the transportation mobility programs for disadvantaged workers without autos. Transportation, however, is not the only barrier. Multiple barriers are common among disadvantaged people, and there are a number of other barriers such as work experience, race, and health. Transportation mobility programs must be well integrated into various other public policies and services to be truly successful in helping disadvantaged people advance in the labor market.

9.4 RESEARCH DIRECTIONS

In this final section, I discuss methodological issues that need to be clarified as well as future research that would further explore the problems addressed in this study.

Endogeneity Problem

One limitation to the analysis in Chapters 7 and 8 is potential endogeneity between residential choices and employment outcomes; that is, an improvement in employment outcomes might enable workers to change their residential locations. In such situations, the estimated job-access effects were likely to be biased. In order to avoid this endogeneity problem, many spatial mismatch studies focus on youths living at home because youths' residential locations are largely predetermined by their parents (e.g., Ihlanfeldt and Sjoquist, 1991; Raphael, 1998). The inclusion of only low-skilled workers or welfare recipients, however, was likely to reduce the bias, since, compared to the other populations, these groups have limited resources to finance transaction costs associated with moving, and therefore they would be more restricted in choosing residential locations. Still, more refined models could provide more accurate estimates.

Note that auto ownership and employment outcomes are also likely to be jointly endogenous; that is, higher employment outcomes are likely to encourage auto ownership. Therefore, if a model is estimated only for those who own autos or for those who do not have autos, estimated parameters are likely to involve selectivity bias. This dissertation, however, uniquely dealt with this problem by employing multinomial logit models that incorporated both auto ownership and employment outcomes as dependent variables.

Spatial Resolution

The analysis in Chapter 7 has another limitation that comes from the size of the geographic unit, PUMA. Since PUMAs are rather large for defining neighborhoods, the estimated job-access variables might not capture the full effects. Unfortunately, individual-level data for small geographic areas are not publicly available and are usually protected under strict confidentiality agreements. The possible bias from the use of PUMAs, however, could be minor since the size of neighborhoods defining job accessibility could be relatively large.

Access Measures

In this study, accessibility was measured in terms of employment opportunities with respect to residences. Worksites, however, are not the only destinations in daily life. Access measures could be improved greatly by incorporating other important destinations, such as childcare centers, job training centers, and shopping centers.

Richer Datasets

There is clearly a need for more detailed data. Most needed are detailed individual-level data for small geographic areas, which would enable us to conduct more in-depth analyses. Since such data are not publicly available, researchers often rely on survey data. Conducting a survey, however, is expensive and restricted to limited areas, and the confidentiality issue always comes with a survey that is related to human subjects. For a researcher who has not been involved in the related project, obtaining permission to use confidential survey data is very difficult. With the generosity of Professor Ong at UCLA, I was fortunately able to obtain permission to use the confidential survey data on welfare recipients in Los Angeles. Nonetheless, to conduct comprehensive analyses, more detailed and extensive data are needed.

For the evaluation of the effectiveness of job-access planning, longitudinal data would be particularly valuable, although the collection of these data is extremely costly.

Comparison of Time Periods

With the exception of Chapter 8, which used data for 1998-2000, the analysis in this dissertation was largely based on the rather old 1990 data. Currently, needed data for the year 2000 are not completely available, but once they are made available, I plan to conduct similar research. One study that would be important to examine is the comparison of 1990 and 2000 job-access measures calculated in Chapter 6. The computation of access measures for the years before 1990 is difficult since necessary data for those years are in most cases not completely available, and the data do not provide comprehensive GIS data. Since the 1990 and 2000 census data are computer- and GIS-friendly, the comparison of the 1990 and 2000 measures can be readily carried out. This dissertation showed that despite substantial suburbanization, central-city areas still offered a geographical advantage in accessing job opportunities. Such a geographical advantage for central-city areas, however, is likely to have lessened substantially over recent decades. Additionally, given the continuing suburbanization, the auto/transit discrepancy in job accessibility is likely to have been growing. These likely situations can be examined by comparing the job-access measures for 1990 and 2000.

Another important study would be to compare 1990 and 2000 results from the analysis in Chapter 7, which examines the job-access effects on employment outcomes for low-skilled workers without autos. Since the analysis uses census-based PUMS data, which are available every decade, such a study can also be easily conducted. Additionally, with the comprehensive PUMS data, extensive metropolitan comparisons are feasible.

Definition of Low Skills

Since the focus groups were among the most disadvantaged people, in this dissertation low-skilled workers were defined as workers without high school degrees, people in the lowest educational category. The empirical results, however, might be sensitive to different definitions; for example, if the low-skilled category were defined as having high school diplomas but no advanced degrees, the results might differ significantly. The exploration of the alternative definitions of the skill categories is of interest to our future research.

Extension of Study Areas

Since the analytical framework developed in this study can be readily applied to further research, the empirical analysis conducted in this study can be extended to include more study areas. There is considerable regional variation in urban structures in the U.S., and the nature of the job-access problem varies from place to place. The comparison of Boston, San Francisco, and Los Angeles improved understanding of the variation between the major eastern and western metropolitan areas. The access barriers for autoless workers, however, are likely to be worse in much more auto-dependent areas like Phoenix, Dallas, and Detroit. Comparative studies that add these areas in the South and Midwest would provide a more comprehensive picture of metropolitan variation in the job-access problem.

Policy Evaluations

Currently, various programs that target improving job accessibility are being implemented. The efficacy of these programs, however, is not well studied. To make the programs more effective, cost and benefit analyses and more research examining whether the programs actually generate positive employment outcomes are needed. Such efforts are becoming particularly important for programs aiming at welfare-to-work. In the process of reauthorization of the 1996 welfare reform, President Bush is planning to reinforce work requirements for welfare recipients, which will put states under even stronger pressure to reduce welfare caseloads. The comprehensive program evaluations described above would help planners and policy makers formulate effective job-access strategies.

To summarize, future research should generate more in-depth insights into the nature of the job-access problem and should provide useful data for making effective programs that help disadvantaged populations to be successful in getting and keeping jobs.

Appendix A: Results of Sensitivity Analysis in Chapter 7

Table a.1 Estimation results for employment using alternative access measures in Boston

	L30TD		LNJPAL		JWRATIOL	
	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
(Appearing for numbered choice)						
constant [1]	5.764 ***	25.06	6.695 ***	13.50	5.942 ***	23.36
constant [2]	3.470 ***	14.14	4.602 ***	8.58	3.946 ***	13.82
constant [3]	1.602 ***	6.45	1.379 **	2.57	1.581 ***	5.82
age16_ 25 [1]	-0.337 **	-2.40	-0.337 **	-2.39	-0.324 **	-2.31
age16_ 25 [2]	0.142	0.90	0.140	0.89	0.159	1.01
age16_ 25 [3]	-0.470 ***	-3.07	-0.467 ***	-3.05	-0.473 ***	-3.09
age55_65 [1]	1.153 ***	3.85	1.155 ***	3.86	1.150 ***	3.84
age55_65 [2]	0.631 *	1.95	0.635 **	1.96	0.625 *	1.93
age55_65 [3]	1.411 ***	4.62	1.406 ***	4.60	1.410 ***	4.61
female [1]	0.330 **	2.39	0.340 **	2.46	0.334 **	2.41
female [2]	-0.085	-0.55	-0.074	-0.48	-0.081	-0.52
female [3]	0.293 **	1.98	0.292 **	1.97	0.295 **	2.00
femhh [1]	-1.932 ***	-13.44	-1.925 ***	-13.41	-1.928 ***	-13.43
femhh [2]	-1.694 ***	-10.21	-1.685 ***	-10.17	-1.692 ***	-10.20
femhh [3]	-0.546 ***	-3.56	-0.543 ***	-3.54	-0.546 ***	-3.55
nhblack [1]	-0.788 ***	-3.70	-0.769 ***	-3.61	-0.808 ***	-3.77
nhblack [2]	-0.600 **	-2.37	-0.577 **	-2.27	-0.626 **	-2.46
nhblack [3]	-0.466 **	-2.03	-0.473 **	-2.06	-0.474 **	-2.05
hispa [1]	-1.074 ***	-5.00	-1.070 ***	-4.98	-1.088 ***	-5.07
hispa [2]	-0.833 ***	-3.32	-0.829 ***	-3.31	-0.836 ***	-3.33
hispa [3]	-0.228	-1.01	-0.241	-1.06	-0.233	-1.03
asiapc [1]	-0.708 **	-2.36	-0.763 **	-2.55	-0.745 **	-2.48
asiapc [2]	-0.989 ***	-2.74	-1.041 ***	-2.89	-0.992 ***	-2.74
asiapc [3]	-0.066	-0.21	-0.072	-0.23	-0.073	-0.23
otherr [1]	-1.782 ***	-6.91	-1.799 ***	-6.98	-1.800 ***	-6.98
otherr [2]	-1.574 ***	-4.74	-1.597 ***	-4.81	-1.611 ***	-4.85
otherr [3]	-0.784 ***	-2.87	-0.788 ***	-2.88	-0.794 ***	-2.90
l30td [1]	-5.402 ***	-3.98				
l30td [2]	-6.109 ***	-3.74				
l30td [3]	-0.118	-0.08				
lnjpal [1]			-0.231 **	-2.31		
lnjpal [2]			-0.282 **	-2.57		
lnjpal [3]			0.047	0.44		
jwratiol [1]					-0.288 **	-2.14
jwratiol [2]					-0.603 ***	-3.62
jwratiol [3]					0.020	0.14
nhbl_pt [1]	0.010	1.54	0.018 ***	3.00	0.018 ***	2.98
nhbl_pt [2]	0.010	1.29	0.018 **	2.54	0.016 **	2.28
nhbl_pt [3]	-0.007	-1.03	-0.006	-0.96	-0.006	-1.00
hisp_pt [1]	-0.069 *	-1.92	-0.057	-1.61	-0.069 *	-1.93
hisp_pt [2]	-0.075 *	-1.86	-0.061	-1.52	-0.082 **	-2.04
hisp_pt [3]	0.015	0.38	0.018	0.49	0.017	0.44
povty_pt [1]	-0.072 ***	-3.05	-0.095 ***	-4.16	-0.107 ***	-5.18
povty_pt [2]	-0.045	-1.60	-0.066 **	-2.48	-0.078 ***	-3.21
povty_pt [3]	0.000	0.01	-0.008	-0.33	-0.003	-0.12
Number of observations	7,811		7,811		7,811	
Log likelihood when parameters set to zero	-10,828		-10,828		-10,828	
Log-likelihood at convergence	-5,378		-5,391		-5,391	
ρ^2	0.50		0.50		0.50	
Adjusted ρ^2	0.50		0.50		0.50	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.2 Estimation results for employment using alternative access measures in San Francisco

	L30TD			LNJPAL			JWRATIOL		
	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
(Appearing for numbered choice)									
constant [1]	5.808	***	27.06	5.341	***	15.92	5.648	***	27.83
constant [2]	2.974	***	13.20	2.654	***	7.53	2.802	***	12.98
constant [3]	1.675	***	7.19	0.251		0.67	1.948	***	8.96
age16_ 25 [1]	-0.321	**	-2.49	-0.284	**	-2.21	-0.278	**	-2.16
age16_ 25 [2]	0.384	***	2.81	0.426	***	3.12	0.434	***	3.18
age16_ 25 [3]	-0.329	**	-2.33	-0.332	**	-2.35	-0.351	**	-2.49
age55_65 [1]	0.783	***	3.26	0.759	***	3.17	0.754	***	3.15
age55_65 [2]	0.463	*	1.81	0.439	*	1.72	0.428	*	1.67
age55_65 [3]	0.889	***	3.58	0.893	***	3.59	0.908	***	3.66
female [1]	-0.034		-0.27	-0.028		-0.22	-0.034		-0.27
female [2]	-0.002		-0.02	0.006		0.05	-0.001		-0.01
female [3]	-0.104		-0.77	-0.099		-0.73	-0.104		-0.77
femhh [1]	-1.336	***	-10.34	-1.330	***	-10.32	-1.339	***	-10.38
femhh [2]	-0.950	***	-6.82	-0.939	***	-6.77	-0.956	***	-6.88
femhh [3]	-0.273	*	-1.95	-0.302	**	-2.16	-0.297	**	-2.13
nhblack [1]	-1.524	***	-8.16	-1.585	***	-8.54	-1.607	***	-8.61
nhblack [2]	-0.841	***	-4.17	-0.915	***	-4.57	-0.940	***	-4.67
nhblack [3]	-1.117	***	-5.32	-1.094	***	-5.21	-1.088	***	-5.18
hispa [1]	-0.616	***	-2.86	-0.762	***	-3.58	-0.706	***	-3.28
hispa [2]	-0.583	**	-2.51	-0.764	***	-3.32	-0.703	***	-3.03
hispa [3]	-0.092		-0.40	0.007		0.03	0.039		0.17
asiapc [1]	-0.361	*	-1.83	-0.615	***	-3.23	-0.629	***	-3.32
asiapc [2]	-0.230		-1.10	-0.513	**	-2.53	-0.551	***	-2.73
asiapc [3]	0.026		0.12	0.029		0.14	0.166		0.82
otherr [1]	-0.339	*	-1.66	-0.372	*	-1.83	-0.388	*	-1.90
otherr [2]	-0.242		-1.13	-0.280		-1.31	-0.296		-1.38
otherr [3]	-0.035		-0.16	-0.036		-0.17	-0.018		-0.08
l30td [1]	-9.308	***	-5.16						
l30td [2]	-12.034	***	-6.18						
l30td [3]	4.444	**	2.29						
lnjpal [1]				0.057		0.79			
lnjpal [2]				0.001		0.01			
lnjpal [3]				0.398	***	5.03			
jwratiol [1]							-0.320	***	-3.21
jwratiol [2]							-0.397	***	-3.57
jwratiol [3]							-0.228	**	-2.16
nhbl_pt [1]	0.002		0.22	0.033	***	4.31	0.014	*	1.67
nhbl_pt [2]	-0.001		-0.16	0.032	***	3.90	0.013		1.42
nhbl_pt [3]	-0.013		-1.36	-0.003		-0.31	-0.045	***	-4.86
hisp_pt [1]	-0.003		-0.29	0.039	***	5.44	0.029	***	3.80
hisp_pt [2]	-0.007		-0.60	0.043	***	5.62	0.031	***	3.83
hisp_pt [3]	0.006		0.51	-0.004		-0.47	-0.027	***	-3.36
povty_pt [1]	-0.027		-0.85	-0.176	***	-7.80	-0.108	***	-4.46
povty_pt [2]	0.032		0.96	-0.137	***	-5.69	-0.070	***	-2.67
povty_pt [3]	-0.015		-0.45	-0.033		-1.32	0.103	***	3.90
Number of observations	16,212			16,212			16,212		
Log likelihood when parameters set to zero	-22,475			-22,475			-22,475		
Log-likelihood at convergence	-10,006			-10,115			-10,157		
ρ^2	0.56			0.55			0.55		
Adjusted ρ^2	0.55			0.55			0.55		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.3 Estimation results for employment using alternative access measurements in Los Angeles

	L30TD			LNJPAL			JWRATIOL		
	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
(Appearing for numbered choice)									
constant [1]	5.338	***	47.49	6.516	***	20.14	5.223	***	48.46
constant [2]	2.700	***	22.57	3.737	***	10.93	2.534	***	21.97
constant [3]	1.694	***	13.90	0.976	***	2.78	1.831	***	15.79
age16_25 [1]	-0.627	***	-10.24	-0.629	***	-10.28	-0.627	***	-10.25
age16_25 [2]	0.102		1.55	0.100		1.52	0.101		1.54
age16_25 [3]	-0.452	***	-6.80	-0.452	***	-6.80	-0.453	***	-6.82
age55_65 [1]	0.326	**	2.55	0.326	**	2.54	0.322	**	2.51
age55_65 [2]	0.080		0.58	0.078		0.56	0.075		0.54
age55_65 [3]	0.294	**	2.15	0.298	**	2.19	0.299	**	2.19
female [1]	-0.121	**	-1.97	-0.121	**	-1.97	-0.123	**	-2.00
female [2]	0.079		1.19	0.078		1.18	0.076		1.15
female [3]	-0.239	***	-3.59	-0.234	***	-3.52	-0.232	***	-3.50
femhh [1]	-1.296	***	-20.68	-1.293	***	-20.63	-1.296	***	-20.67
femhh [2]	-1.111	***	-16.01	-1.107	***	-15.96	-1.110	***	-16.00
femhh [3]	-0.252	***	-3.73	-0.256	***	-3.79	-0.257	***	-3.79
nhblack [1]	-1.025	***	-9.29	-1.025	***	-9.30	-1.012	***	-9.14
nhblack [2]	-0.335	***	-2.81	-0.336	***	-2.82	-0.323	***	-2.70
nhblack [3]	-0.772	***	-6.18	-0.765	***	-6.12	-0.756	***	-6.03
hispa [1]	-0.183	**	-2.13	-0.182	**	-2.13	-0.168	*	-1.94
hispa [2]	-0.176	*	-1.89	-0.185	**	-1.99	-0.168	*	-1.79
hispa [3]	0.246	***	2.67	0.262	***	2.86	0.288	***	3.09
asiapc [1]	0.215		1.30	0.229		1.39	0.231		1.40
asiapc [2]	0.174		1.00	0.186		1.06	0.191		1.09
asiapc [3]	0.154		0.87	0.151		0.85	0.168		0.95
otherr [1]	-0.102		-1.31	-0.104		-1.34	-0.087		-1.12
otherr [2]	-0.135		-1.63	-0.137		-1.65	-0.120		-1.44
otherr [3]	0.232	***	2.77	0.235	***	2.81	0.244	***	2.89
l30td [1]	-0.911	*	-1.75						
l30td [2]	-1.673	***	-2.87						
l30td [3]	1.906	***	3.52						
lnjpal [1]				-0.215	***	-4.14			
lnjpal [2]				-0.198	***	-3.60			
lnjpal [3]				0.155	***	2.75			
jwratiol [1]							0.054		1.62
jwratiol [2]							0.058		1.57
jwratiol [3]							0.065	*	1.86
nhbl_pt [1]	0.025	***	8.83	0.023	***	8.33	0.028	***	10.11
nhbl_pt [2]	0.025	***	8.15	0.024	***	8.11	0.029	***	9.72
nhbl_pt [3]	0.000		-0.08	-0.001		-0.45	-0.003		-1.11
hisp_pt [1]	0.017	***	7.39	0.019	***	8.83	0.019	***	8.77
hisp_pt [2]	0.019	***	7.62	0.022	***	9.46	0.021	***	9.41
hisp_pt [3]	0.001		0.38	-0.003		-1.38	-0.003		-1.32
povty_pt [1]	-0.106	***	-17.44	-0.098	***	-15.29	-0.112	***	-19.27
povty_pt [2]	-0.093	***	-14.17	-0.088	***	-12.90	-0.102	***	-16.26
povty_pt [3]	-0.005		-0.73	-0.006		-0.81	0.002		0.32
Number of observations	56,044			56,044			56,044		
Log likelihood when	-77,693			-77,693			-77,693		
Log-likelihood at convergence	-39,481			-39,463			-39,565		
ρ^2	0.49			0.49			0.49		
Adjusted ρ^2	0.49			0.49			0.49		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.4 Estimation results for working hours using alternative access measures in Boston

	L30TD		LNJPAL		JWRATIOL	
	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic	Coefficient estimate	t-statistic
(Appearing for numbered choice)						
constant [1]	5.545 ***	24.05	6.365 ***	12.73	5.757 ***	22.50
constant [2]	3.635 ***	15.28	4.756 ***	9.27	3.754 ***	13.97
constant [3]	3.408 ***	13.95	4.559 ***	8.50	3.879 ***	13.63
constant [4]	1.403 ***	5.47	0.933 *	1.66	1.366 ***	4.87
constant [5]	-0.189	-0.61	0.165	0.25	-0.144	-0.42
age16_25 [1]	-1.261 ***	-8.62	-1.261 ***	-8.63	-1.255 ***	-8.59
age16_25 [2]	1.420 ***	9.32	1.418 ***	9.32	1.429 ***	9.39
age16_25 [3]	0.245	1.54	0.242	1.53	0.254	1.60
age16_25 [4]	-0.778 ***	-4.67	-0.773 ***	-4.64	-0.779 ***	-4.68
age16_25 [5]	0.312	1.59	0.310	1.58	0.312	1.59
age55_65 [1]	1.158 ***	3.86	1.159 ***	3.87	1.154 ***	3.85
age55_65 [2]	1.387 ***	4.47	1.394 ***	4.49	1.387 ***	4.47
age55_65 [3]	0.656 **	2.03	0.660 **	2.04	0.650 **	2.01
age55_65 [4]	1.420 ***	4.59	1.415 ***	4.57	1.418 ***	4.59
age55_65 [5]	1.457 ***	4.20	1.452 ***	4.19	1.456 ***	4.20
female [1]	-0.039	-0.28	-0.031	-0.22	-0.040	-0.28
female [2]	1.058 ***	7.19	1.067 ***	7.26	1.056 ***	7.18
female [3]	0.003	0.02	0.013	0.08	0.001	0.01
female [4]	0.080	0.51	0.077	0.49	0.083	0.53
female [5]	0.694 ***	3.65	0.697 ***	3.66	0.695 ***	3.65
femhh [1]	-1.816 ***	-12.39	-1.810 ***	-12.37	-1.813 ***	-12.38
femhh [2]	-2.074 ***	-13.39	-2.063 ***	-13.34	-2.067 ***	-13.36
femhh [3]	-1.727 ***	-10.37	-1.717 ***	-10.33	-1.723 ***	-10.36
femhh [4]	-0.586 ***	-3.64	-0.582 ***	-3.61	-0.586 ***	-3.64
femhh [5]	-0.406 **	-2.10	-0.404 **	-2.09	-0.406 **	-2.10
nhblack [1]	-0.724 ***	-3.33	-0.708 ***	-3.25	-0.743 ***	-3.40
nhblack [2]	-0.844 ***	-3.53	-0.818 ***	-3.41	-0.863 ***	-3.59
nhblack [3]	-0.595 **	-2.35	-0.570 **	-2.25	-0.619 **	-2.44
nhblack [4]	-0.390	-1.62	-0.402 *	-1.67	-0.398 *	-1.64
nhblack [5]	-0.615 **	-2.05	-0.611 **	-2.04	-0.626 **	-2.07
hispa [1]	-0.891 ***	-4.08	-0.887 ***	-4.07	-0.901 ***	-4.12
hispa [2]	-1.466 ***	-5.97	-1.465 ***	-5.97	-1.487 ***	-6.06
hispa [3]	-0.843 ***	-3.36	-0.840 **	-3.35	-0.844 ***	-3.36
hispa [4]	-0.187	-0.79	-0.205	-0.87	-0.190	-0.81
hispa [5]	-0.264	-0.93	-0.263	-0.92	-0.269	-0.94
asiapc [1]	-0.555 *	-1.84	-0.607 **	-2.01	-0.576 *	-1.90
asiapc [2]	-1.173 ***	-3.54	-1.225 ***	-3.71	-1.220 ***	-3.68
asiapc [3]	-1.010 ***	-2.80	-1.058 ***	-2.94	-1.010 ***	-2.79
asiapc [4]	0.035	0.11	0.028	0.09	0.029	0.09
asiapc [5]	-0.322	-0.81	-0.326	-0.82	-0.326	-0.81
otherr [1]	-1.697 ***	-6.36	-1.709 ***	-6.40	-1.714 ***	-6.42
otherr [2]	-1.944 ***	-6.31	-1.974 ***	-6.41	-1.967 ***	-6.39
otherr [3]	-1.584 ***	-4.77	-1.607 ***	-4.84	-1.620 ***	-4.88
otherr [4]	-0.899 ***	-3.03	-0.901 ***	-3.03	-0.909 ***	-3.06
otherr [5]	-0.522	-1.52	-0.528	-1.54	-0.530	-1.54
l30td [1]	-5.013 ***	-3.63				
l30td [2]	-6.465 ***	-4.25				
l30td [3]	-6.176 ***	-3.77				
l30td [4]	0.277	0.19				
l30td [5]	-1.116	-0.64				
lnjpal [1]			-0.204 **	-2.02		
lnjpal [2]			-0.279 ***	-2.68		
lnjpal [3]			-0.286 ***	-2.60		
lnjpal [4]			0.103	0.91		
lnjpal [5]			-0.086	-0.64		
jwratiol [1]					-0.320 **	-2.34
jwratiol [2]					-0.236	-1.59
jwratiol [3]					-0.595 ***	-3.58
jwratiol [4]					0.047	0.32
jwratiol [5]					-0.080	-0.46
nhbl_pt [1]	0.009	1.38	0.017 ***	2.77	0.016 **	2.56
nhbl_pt [2]	0.010	1.32	0.018 ***	2.71	0.020 ***	2.92
nhbl_pt [3]	0.010	1.29	0.018 **	2.55	0.016 **	2.30
nhbl_pt [4]	-0.007	-0.90	-0.005	-0.81	-0.006	-0.93
nhbl_pt [5]	-0.010	-1.14	-0.009	-1.11	-0.008	-1.04

hisp_pt [1]	-0.055	-1.52	-0.044	-1.25	-0.057	-1.57
hisp_pt [2]	-0.089 **	-2.31	-0.073 *	-1.94	-0.083 **	-2.18
hisp_pt [3]	-0.074 **	-1.85	-0.060	-1.50	-0.080 **	-2.00
hisp_pt [4]	0.027	0.68	0.031	0.78	0.030	0.75
hisp_pt [5]	-0.008	-0.17	-0.004	-0.08	-0.007	-0.15
povty_pt [1]	-0.071 ***	-2.93	-0.093 ***	-4.02	-0.101 ***	-4.78
povty_pt [2]	-0.075 ***	-2.86	-0.101 ***	-4.01	-0.122 ***	-5.30
povty_pt [3]	-0.045	-1.61	-0.067 **	-2.50	-0.079 ***	-3.26
povty_pt [4]	-0.007	-0.28	-0.018	-0.72	-0.008	-0.34
povty_pt [5]	0.019	0.64	0.018	0.62	0.013	0.48
Number of observations	7,811		7,811		7,811	
Log likelihood when parameters set to zero	-13,995		-13,995		-13,995	
Log-likelihood at convergence	-8,585		-8,597		-8,598	
ρ^2	0.39		0.39		0.39	
Adjusted ρ^2	0.38		0.38		0.38	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level

Table a.5 Estimation results for working hours using alternative access measures in San Francisco

	L30TD			LNJPAL			JWRATIOL		
	Coefficient estimate		t-statistic	Coefficient estimate		t-statistic	Coefficient estimate		t-statistic
(Appearing for numbered choice)									
constant [1]	5.629	***	26.30	5.078	***	15.15	5.488	***	27.08
constant [2]	3.449	***	15.47	3.345	***	9.61	3.226	***	15.05
constant [3]	2.978	***	13.30	2.671	***	7.60	2.808	***	13.07
constant [4]	1.567	***	6.66	0.087		0.23	1.874	***	8.55
constant [5]	-0.725	**	-2.19	-1.868	***	-3.41	-0.610	**	-1.96
age16_25 [1]	-0.775	***	-5.96	-0.742	***	-5.73	-0.739	***	-5.70
age16_25 [2]	1.410	***	10.25	1.443	***	10.53	1.446	***	10.54
age16_25 [3]	0.388	***	2.83	0.428	***	3.13	0.431	***	3.15
age16_25 [4]	-0.485	***	-3.34	-0.495	***	-3.42	-0.508	***	-3.51
age16_25 [5]	0.434	**	2.13	0.435	**	2.14	0.427	**	2.10
age55_65 [1]	0.755	***	3.15	0.730	***	3.04	0.725	***	3.03
age55_65 [2]	1.219	***	4.85	1.205	***	4.80	1.191	***	4.74
age55_65 [3]	0.460	*	1.80	0.436	*	1.71	0.424	*	1.66
age55_65 [4]	0.798	***	3.18	0.800	***	3.19	0.819	***	3.27
age55_65 [5]	1.414	***	4.72	1.417	***	4.73	1.430	***	4.78
female [1]	-0.221	*	-1.75	-0.217	*	-1.72	-0.224	*	-1.78
female [2]	0.647	***	4.91	0.655	***	4.98	0.647	***	4.92
female [3]	0.027		0.20	0.034		0.26	0.024		0.18
female [4]	-0.246	*	-1.78	-0.243	*	-1.75	-0.246	*	-1.78
female [5]	0.497	***	2.58	0.501	***	2.60	0.498	***	2.59
femhh [1]	-1.296	***	-9.97	-1.291	***	-9.96	-1.299	***	-10.01
femhh [2]	-1.428	***	-10.30	-1.415	***	-10.23	-1.428	***	-10.32
femhh [3]	-0.956	***	-6.86	-0.945	***	-6.80	-0.960	***	-6.91
femhh [4]	-0.304	**	-2.13	-0.334	**	-2.34	-0.328	**	-2.30
femhh [5]	-0.076		-0.39	-0.095		-0.49	-0.095		-0.49
nhblack [1]	-1.500	***	-7.96	-1.560	***	-8.33	-1.584	***	-8.41
nhblack [2]	-1.576	***	-7.65	-1.631	***	-7.96	-1.650	***	-8.02
nhblack [3]	-0.840	***	-4.17	-0.914	***	-4.57	-0.937	***	-4.66
nhblack [4]	-1.104	***	-5.11	-1.073	***	-4.98	-1.069	***	-4.96
nhblack [5]	-1.169	***	-3.62	-1.169	***	-3.62	-1.167	***	-3.62
hispa [1]	-0.549	**	-2.54	-0.694	***	-3.25	-0.635	***	-2.94
hispa [2]	-0.773	***	-3.39	-0.918	***	-4.07	-0.867	***	-3.81
hispa [3]	-0.587	**	-2.53	-0.768	***	-3.34	-0.707	***	-3.05
hispa [4]	-0.108		-0.46	0.000		0.00	0.034		0.15
hispa [5]	0.074		0.24	0.123		0.39	0.146		0.46
asiapc [1]	-0.281		-1.42	-0.539	***	-2.82	-0.547	***	-2.88
asiapc [2]	-0.608	***	-2.94	-0.826	***	-4.13	-0.862	***	-4.33
asiapc [3]	-0.240		-1.15	-0.521	**	-2.57	-0.558	***	-2.76
asiapc [4]	-0.013		-0.06	0.002		0.01	0.147		0.72
asiapc [5]	0.294		1.05	0.251		0.93	0.348		1.30
otherr [1]	-0.211		-1.04	-0.244		-1.20	-0.258		-1.26
otherr [2]	-0.873	***	-4.05	-0.904	***	-4.19	-0.921	***	-4.27
otherr [3]	-0.253		-1.18	-0.290		-1.36	-0.304		-1.42
otherr [4]	0.008		0.04	0.009		0.04	0.027		0.12
otherr [5]	-0.208		-0.63	-0.205		-0.62	-0.190		-0.58
l30td [1]	-9.165	***	-5.07						
l30td [2]	-9.282	***	-4.86						
l30td [3]	-12.002	***	-6.17						
l30td [4]	5.023	**	2.54						
l30td [5]	1.732		0.66						
lnjpal [1]				0.080		1.11			
lnjpal [2]				-0.036		-0.49			
lnjpal [3]				-0.002		-0.02			
lnjpal [4]				0.419	***	5.21			
lnjpal [5]				0.296	***	2.70			
jwratiol [1]							-0.343	***	-3.43
jwratiol [2]							-0.217	**	-1.97
jwratiol [3]							-0.391	***	-3.52
jwratiol [4]							-0.235	**	-2.20
jwratiol [5]							-0.185		-1.24
nhbl_pt [1]	0.003		0.29	0.035	***	4.51	0.013		1.56
nhbl_pt [2]	0.002		0.24	0.027	***	3.25	0.018	**	1.97
nhbl_pt [3]	-0.002		-0.16	0.032	***	3.87	0.013		1.43
nhbl_pt [4]	-0.013		-1.29	-0.002		-0.24	-0.047	***	-4.94
nhbl_pt [5]	-0.014		-0.97	-0.004		-0.27	-0.034	**	-2.48

hisp_pt [1]	0.002		0.17	0.044	***	6.13	0.032	***	4.24
hisp_pt [2]	-0.021	*	-1.91	0.017	**	2.24	0.014	*	1.73
hisp_pt [3]	-0.007		-0.64	0.042	***	5.51	0.031	***	3.79
hisp_pt [4]	0.011		0.95	0.000		-0.04	-0.025	***	-3.05
hisp_pt [5]	-0.019		-1.13	-0.019		-1.62	-0.037	***	-3.27
povty_pt [1]	-0.026		-0.84	-0.179	***	-7.90	-0.102	***	-4.19
povty_pt [2]	-0.037		-1.12	-0.165	***	-6.81	-0.132	***	-5.05
povty_pt [3]	0.031		0.94	-0.137	***	-5.67	-0.071	***	-2.71
povty_pt [4]	-0.023		-0.65	-0.037		-1.48	0.105	***	3.90
povty_pt [5]	0.020		0.42	-0.011		-0.31	0.091	**	2.37
Number of observations	16,212			16,212			16,212		
Log likelihood when parameters set to zero	-29,048			-29,048			-29,048		
Log-likelihood at convergence	-15,613			-15,711			-15,762		
ρ^2	0.46			0.46			0.46		
Adjusted ρ^2	0.46			0.46			0.46		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.6 Estimation results for working hours using alternative access measurements in Los Angeles

	L30TD		LNJPAL		JWRATIOL	
	Coefficient estimate	*t* -statistic	Coefficient estimate	*t* -statistic	Coefficient estimate	*t* -statistic
(Appearing for numbered choice)						
constant [1]	5.219 ***	46.44	6.314 ***	19.43	5.104 ***	47.37
constant [2]	2.778 ***	22.88	4.343 ***	12.70	2.667 ***	22.48
constant [3]	2.699 ***	22.61	3.757 ***	10.96	2.533 ***	22.01
constant [4]	1.608 ***	13.09	0.814 **	2.29	1.770 ***	15.16
constant [5]	-0.945 ***	-4.66	-1.068 *	-1.82	-1.016 ***	-5.25
age16_25 [1]	-0.796 ***	-12.93	-0.797 ***	-12.96	-0.796 ***	-12.94
age16_25 [2]	0.597 ***	8.71	0.593 ***	8.66	0.596 ***	8.71
age16_25 [3]	0.104	1.59	0.103	1.57	0.104	1.59
age16_25 [4]	-0.493 ***	-7.32	-0.493 ***	-7.33	-0.494 ***	-7.34
age16_25 [5]	-0.154	-1.33	-0.154	-1.33	-0.156	-1.35
age55_65 [1]	0.296 **	2.30	0.295 **	2.30	0.292 **	2.27
age55_65 [2]	0.751 ***	5.45	0.752 ***	5.46	0.747 ***	5.42
age55_65 [3]	0.080	0.58	0.078	0.56	0.075	0.54
age55_65 [4]	0.243 *	1.76	0.248 *	1.80	0.250 *	1.81
age55_65 [5]	0.709 ***	3.66	0.708 ***	3.66	0.705 ***	3.64
female [1]	-0.235 ***	-3.82	-0.235 ***	-3.81	-0.238 ***	-3.85
female [2]	0.685 ***	10.06	0.684 ***	10.05	0.682 ***	10.03
female [3]	0.085	1.28	0.084	1.28	0.082	1.24
female [4]	-0.311 ***	-4.61	-0.306 ***	-4.55	-0.303 ***	-4.51
female [5]	0.323 ***	2.86	0.324 ***	2.87	0.323 ***	2.86
femhh [1]	-1.287 ***	-20.48	-1.285 ***	-20.43	-1.287 ***	-20.47
femhh [2]	-1.309 ***	-18.01	-1.303 ***	-17.92	-1.308 ***	-18.00
femhh [3]	-1.111 ***	-16.02	-1.108 ***	-15.98	-1.110 ***	-16.01
femhh [4]	-0.274 ***	-4.00	-0.278 ***	-4.07	-0.278 ***	-4.07
femhh [5]	-0.038	-0.33	-0.040	-0.36	-0.041	-0.36
nhblack [1]	-1.058 ***	-9.52	-1.059 ***	-9.54	-1.044 ***	-9.37
nhblack [2]	-0.804 ***	-6.22	-0.804 ***	-6.22	-0.791 ***	-6.10
nhblack [3]	-0.335 ***	-2.80	-0.337 ***	-2.83	-0.322 ***	-2.69
nhblack [4]	-0.843 ***	-6.60	-0.836 ***	-6.55	-0.828 ***	-6.47
nhblack [5]	-0.216	-0.98	-0.211	-0.95	-0.179	-0.81
hispa [1]	-0.137	-1.59	-0.138	-1.61	-0.123	-1.41
hispa [2]	-0.475 ***	-4.89	-0.463 ***	-4.78	-0.461 ***	-4.70
hispa [3]	-0.177 *	-1.90	-0.186 **	-2.00	-0.170 *	-1.80
hispa [4]	0.254 ***	2.74	0.272 ***	2.94	0.294 ***	3.13
hispa [5]	0.214	1.38	0.218	1.41	0.282 *	1.78
asiapc [1]	0.176	1.06	0.187	1.13	0.191	1.16
asiapc [2]	0.454 ***	2.63	0.482 ***	2.79	0.470 ***	2.71
asiapc [3]	0.176	1.01	0.188	1.07	0.193	1.10
asiapc [4]	0.034	0.19	0.030	0.17	0.046	0.26
asiapc [5]	0.873 ***	3.65	0.874 ***	3.66	0.912 ***	3.80
otherr [1]	-0.048	-0.62	-0.050	-0.65	-0.033	-0.43
otherr [2]	-0.510 ***	-5.95	-0.508 ***	-5.93	-0.496 ***	-5.75
otherr [3]	-0.137 *	-1.66	-0.139 *	-1.68	-0.122	-1.46
otherr [4]	0.243 ***	2.87	0.247 ***	2.92	0.252 ***	2.97
otherr [5]	0.169	1.16	0.169	1.16	0.202	1.38
l30td [1]	-0.917 *	-1.75				
l30td [2]	-0.899	-1.60				
l30td [3]	-1.667 ***	-2.85				
l30td [4]	2.075 ***	3.80				
l30td [5]	0.402	0.48				
lnjpal [1]			-0.200 ***	-3.83		
lnjpal [2]			-0.287 ***	-5.19		
lnjpal [3]			-0.202 ***	-3.65		
lnjpal [4]			0.171 ***	2.99		
lnjpal [5]			0.029	0.30		
jwratiol [1]					0.054	1.61
jwratiol [2]					0.049	1.23
jwratiol [3]					0.057	1.57
jwratiol [4]					0.059 *	1.66
jwratiol [5]					0.126 **	2.31
nhbl_pt [1]	0.026 ***	9.19	0.015 **	2.45	0.029 ***	10.48
nhbl_pt [2]	0.017 ***	5.46	0.017 ***	2.61	0.020 ***	6.47
nhbl_pt [3]	0.025 ***	8.15	0.016 **	2.25	0.029 ***	9.71
nhbl_pt [4]	0.002	0.51	-0.008	-1.15	-0.002	-0.66
nhbl_pt [5]	-0.017 ***	-3.13	-0.008	-1.03	-0.016 ***	-2.90

hisp_pt [1]	0.018	***	7.89	-0.078	**	-2.14	0.020	***	9.30
hisp_pt [2]	0.009	***	3.64	-0.107	***	-2.80	0.011	***	4.63
hisp_pt [3]	0.019	***	7.61	-0.099	**	-2.47	0.021	***	9.39
hisp_pt [4]	0.002		0.92	0.021		0.52	-0.002		-0.88
hisp_pt [5]	-0.011	**	-2.42	-0.018		-0.38	-0.011	***	-2.83
povty_pt [1]	-0.106	***	-17.37	-0.108	***	-5.21	-0.112	***	-19.21
povty_pt [2]	-0.108	***	-15.62	-0.127	***	-5.63	-0.114	***	-17.21
povty_pt [3]	-0.093	***	-14.16	-0.089	***	-3.73	-0.102	***	-16.26
povty_pt [4]	-0.007		-1.12	-0.010		-0.44	0.000		0.07
povty_pt [5]	0.021	*	1.83	0.010		0.38	0.019	*	1.70
Number of observations	56,044			56,044			56,044		
Log likelihood when parameters set to zero	-100,420			-100,420			-100,420		
Log-likelihood at convergence	-54,186			-54,163			-54,273		
ρ^2	0.46			0.46			0.46		
Adjusted ρ^2	0.46			0.46			0.46		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.7 Estimation results for earnings using alternative access measures in Boston

(Auto)	L30TD			LNJPAL			JWRATIOL		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	10.396	***	47.55	10.367	***	47.38	10.475	***	46.21
age16_25	-1.682	***	-29.51	-1.691	***	-29.34	-1.712	***	-27.89
age55_65	-0.079		-1.36	-0.090		-1.53	-0.106	*	-1.72
female	-0.517	***	-20.64	-0.516	***	-20.61	-0.513	***	-20.43
femhh	0.124	***	3.32	0.129	***	3.41	0.135	***	3.52
nhblack	-0.100	*	-1.63	-0.107	*	-1.73	-0.114	*	-1.82
hispa	-0.209	***	-2.66	-0.223	***	-2.80	-0.245	***	-2.94
asiapc	-0.225	***	-3.39	-0.235	***	-3.50	-0.246	***	-3.60
otherr	-0.226	**	-2.30	-0.233	**	-2.38	-0.246	**	-2.48
l30td	0.126		0.39						
lnjpal				0.019		1.14			
jwratiol							0.048		1.37
nhbl_pt	-0.004	**	-2.39	-0.004	**	-2.45	-0.004	**	-2.38
hisp_pt	0.004		0.56	0.003		0.50	0.004		0.58
povty_pt	0.008		1.40	0.006		1.22	0.008	*	1.65
ramda1	-0.266	**	-2.49	-0.289	***	-2.65	-0.328	***	-2.81
Number of observations	5,599			5,599			5,599		
R^2	0.45			0.45			0.45		
Adjusted R^2	0.45			0.45			0.45		

(No Auto)	L30TD			LNJPAL			JWRATIOL		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	9.675	***	11.02	10.354	***	13.61	9.884	***	13.07
age16_25	-0.732	***	-8.52	-0.765	***	-9.26	-0.743	***	-8.91
age55_65	0.037		0.25	-0.065		-0.51	0.000		0.00
female	-0.410	***	-5.52	-0.391	***	-5.35	-0.404	***	-5.52
femhh	0.034		0.31	-0.036		-0.36	0.008		0.08
nhblack	-0.062		-0.44	-0.137		-1.06	-0.085		-0.64
hispa	-0.134		-0.58	-0.302		-1.54	-0.195		-0.95
asiapc	-0.477	**	-2.57	-0.556	***	-3.15	-0.538	***	-3.05
otherr	-0.266		-1.15	-0.414	**	-2.02	-0.309		-1.46
l30td	1.059		1.37						
lnjpal				0.009		0.18			
jwratiol							0.113	*	1.74
nhbl_pt	0.006	*	1.79	0.005		1.45	0.006	*	1.90
hisp_pt	0.005		0.28	-0.002		-0.12	0.001		0.09
povty_pt	-0.012		-1.13	-0.010		-0.87	-0.011		-1.00
ramda2	-0.036		-0.14	-0.250		-1.18	-0.120		-0.54
Number of observations	780			780			780		
R^2	0.16			0.16			0.17		
Adjusted R^2	0.15			0.15			0.15		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.8 Estimation results for earnings using alternative access measures in San Francisco

(Auto)

Independent variable	L30TD Coefficient estimate		L30TD t-statistic	LNJPAL Coefficient estimate		LNJPAL t-statistic	JWRATIOL Coefficient estimate		JWRATIOL t-statistic
constant	9.820	***	33.89	9.374	***	32.44	9.536	***	32.56
age16_25	-1.333	***	-21.33	-1.274	***	-21.02	-1.267	***	-19.75
age55_65	0.138	**	2.52	0.182	***	3.44	0.190	***	3.43
female	-0.494	***	-23.09	-0.504	***	-23.80	-0.505	***	-23.51
femhh	-0.054	*	-1.94	-0.071	***	-2.58	-0.067	**	-2.41
nhblack	-0.006		-0.12	-0.015		-0.34	-0.021		-0.46
hispa	-0.111	*	-1.75	-0.060		-0.99	-0.047		-0.73
asiapc	-0.078	**	-2.42	-0.073	**	-2.40	-0.064	**	-2.10
otherr	0.042		0.50	0.120		1.47	0.131		1.52
l30td	0.207		0.67						
lnjpal				0.044	***	4.56			
jwratiol							-0.052	**	-2.32
nhbl_pt	0.003		1.58	0.006	***	3.32	0.001		0.66
hisp_pt	0.006	***	2.58	0.009	***	3.72	0.006	**	2.54
povty_pt	-0.014	***	-2.98	-0.023	***	-5.46	-0.006		-1.32
ramda1	0.001		0.01	0.133		1.03	0.150		1.09
Number of observations	12,016			12,016			12,016		
R^2	0.32			0.32			0.32		
Adjusted R^2	0.31			0.32			0.31		

(No Auto)

Independent variable	L30TD Coefficient estimate		L30TD t-statistic	LNJPAL Coefficient estimate		LNJPAL t-statistic	JWRATIOL Coefficient estimate		JWRATIOL t-statistic
constant	8.842	***	8.18	9.898	***	14.37	9.711	***	19.19
age16_25	-0.731	***	-7.80	-0.790	***	-10.19	-0.781	***	-10.36
age55_65	0.091		0.74	0.008		0.08	0.019		0.20
female	-0.277	***	-3.82	-0.246	***	-3.67	-0.250	***	-3.77
femhh	-0.070		-0.68	-0.143	*	-1.78	-0.133	*	-1.74
nhblack	-0.037		-0.28	-0.098		-0.82	-0.089		-0.75
hispa	-0.094		-0.48	-0.247	*	-1.67	-0.225	*	-1.65
asiapc	-0.219		-1.28	-0.337	***	-2.66	-0.323	***	-2.61
otherr	0.090		0.44	-0.073		-0.51	-0.051		-0.39
l30td	1.357		0.91						
lnjpal				-0.015		-0.40			
jwratiol							0.014		0.31
nhbl_pt	0.004		0.84	0.003		0.60	0.004		0.79
hisp_pt	0.008		1.41	0.004		1.00	0.004		1.16
povty_pt	-0.016		-1.15	-0.012		-0.87	-0.016		-0.93
ramda2	0.169		0.56	-0.105		-0.61	-0.069		-0.47
Number of observations	1,200			1,200			1,200		
R^2	0.12			0.12			0.12		
Adjusted R^2	0.11			0.11			0.11		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.9 Estimation results for earnings using alternative access measurements in Los Angeles

(Auto)	L30TD			LNJPAL			JWRATIOL		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	9.252	***	47.59	9.624	***	58.25	9.589	***	57.46
age16_25	-0.750	***	-43.99	-0.777	***	-50.17	-0.774	***	-50.04
age55_65	0.225	***	9.64	0.190	***	8.89	0.194	***	9.06
female	-0.446	***	-34.25	-0.429	***	-35.10	-0.430	***	-35.33
femhh	-0.085	***	-4.63	-0.059	***	-3.48	-0.061	***	-3.62
nhblack	-0.053		-1.28	0.012		0.31	0.005		0.13
hispa	-0.057		-1.17	-0.150	***	-3.59	-0.144	***	-3.50
asiapc	-0.198	***	-7.51	-0.165	***	-6.65	-0.169	***	-6.79
otherr	0.067		1.31	-0.030		-0.69	-0.023		-0.52
l30td	-0.338	***	-3.61						
lnjpal				-0.002		-0.27			
jwratiol							-0.009		-1.44
nhbl_pt	0.003	***	3.91	0.002	***	2.94	0.002	***	2.94
hisp_pt	0.004	***	4.15	0.003	***	2.92	0.003	***	3.08
povty_pt	-0.010	***	-9.74	-0.011	***	-10.99	-0.011	***	-11.50
ramda1	0.289	***	2.80	0.088		1.00	0.106		1.21
Number of observations	39,689			39,689			39,689		
R^2	0.19			0.19			0.19		
Adjusted R^2	0.19			0.19			0.19		

(No Auto)	L30TD			LNJPAL			JWRATIOL		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	8.356	***	23.85	8.612	***	20.52	8.676	***	26.79
age16_25	-0.370	***	-12.73	-0.379	***	-13.00	-0.380	***	-13.17
age55_65	0.180	***	3.82	0.172	***	3.65	0.172	***	3.66
female	-0.312	***	-10.00	-0.301	***	-9.66	-0.301	***	-9.77
femhh	0.075	*	1.66	0.050		1.09	0.047		1.08
nhblack	0.082		1.33	0.092		1.51	0.090		1.47
hispa	0.048		0.75	0.014		0.22	0.003		0.05
asiapc	-0.250	***	-3.81	-0.246	***	-3.74	-0.247	***	-3.76
otherr	0.089		1.59	0.058		1.00	0.050		0.93
l30td	0.513	**	2.26						
lnjpal				0.004		0.18			
jwratiol							-0.012		-1.03
nhbl_pt	0.003	**	2.40	0.003	**	2.17	0.003	**	1.99
hisp_pt	0.002	**	2.47	0.002	*	1.82	0.002	*	1.87
povty_pt	-0.001		-0.24	-0.003		-0.49	-0.002		-0.44
ramda2	0.284	***	2.60	0.209	*	1.88	0.200	*	1.94
Number of observations	4,808			4,808			4,808		
R^2	0.08			0.08			0.08		
Adjusted R^2	0.08			0.08			0.08		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.10 Estimation results for employment using different travel time thresholds in Boston

Independent variable	15-min threshold Coefficient estimate		*t*-statistic	30-min threshold Coefficient estimate		*t*-statistic	45-min threshold Coefficient estimate		*t*-statistic
(Appearing for numbered choice)									
constant [1]	5.719	***	25.22	5.764	***	25.06	5.981	***	24.40
constant [2]	3.438	***	14.11	3.470	***	14.14	3.660	***	14.07
constant [3]	1.594	***	6.51	1.602	***	6.45	1.604	***	6.05
age16_ 25 [1]	-0.321	**	-2.28	-0.337	**	-2.40	-0.345	**	-2.46
age16_ 25 [2]	0.161		1.03	0.142		0.90	0.141		0.90
age16_ 25 [3]	-0.474	***	-3.09	-0.470	***	-3.07	-0.467	***	-3.05
age55_65 [1]	1.153	***	3.85	1.153	***	3.85	1.166	***	3.89
age55_65 [2]	0.630	*	1.94	0.631	*	1.95	0.644	**	1.99
age55_65 [3]	1.410	***	4.61	1.411	***	4.62	1.409	***	4.61
female [1]	0.336	**	2.43	0.330	**	2.39	0.332	**	2.40
female [2]	-0.079		-0.51	-0.085		-0.55	-0.083		-0.54
female [3]	0.295	**	1.99	0.293	**	1.98	0.291	**	1.96
femhh [1]	-1.927	***	-13.43	-1.932	***	-13.44	-1.929	***	-13.42
femhh [2]	-1.691	***	-10.20	-1.694	***	-10.21	-1.690	***	-10.19
femhh [3]	-0.548	***	-3.57	-0.546	***	-3.56	-0.547	***	-3.56
nhblack [1]	-0.813	***	-3.78	-0.788	***	-3.70	-0.750	***	-3.54
nhblack [2]	-0.633	**	-2.49	-0.600	**	-2.37	-0.566	**	-2.24
nhblack [3]	-0.475	**	-2.05	-0.466	**	-2.03	-0.456	**	-2.00
hispa [1]	-1.098	***	-5.11	-1.074	***	-5.00	-1.058	***	-4.94
hispa [2]	-0.860	***	-3.43	-0.833	***	-3.32	-0.826	***	-3.30
hispa [3]	-0.233		-1.03	-0.228		-1.01	-0.227		-1.00
asiapc [1]	-0.771	**	-2.56	-0.708	**	-2.36	-0.727	**	-2.43
asiapc [2]	-1.049	***	-2.90	-0.989	***	-2.74	-1.027	***	-2.85
asiapc [3]	-0.068		-0.22	-0.066		-0.21	-0.061		-0.20
otherr [1]	-1.794	***	-6.97	-1.782	***	-6.91	-1.750	***	-6.78
otherr [2]	-1.594	***	-4.81	-1.574	***	-4.74	-1.545	***	-4.66
otherr [3]	-0.797	***	-2.91	-0.784	***	-2.87	-0.774	***	-2.84
ltd [1]	-1.221		-1.41	-5.402	***	-3.98	-5.748	***	-4.51
ltd [2]	-1.723	*	-1.67	-6.109	***	-3.74	-4.958	***	-3.44
ltd [3]	0.082		0.09	-0.118		-0.08	-0.102		-0.08
nhbl_pt [1]	0.020	***	3.41	0.010		1.54	0.013	**	2.18
nhbl_pt [2]	0.021	***	2.96	0.010		1.29	0.016	**	2.21
nhbl_pt [3]	-0.007		-1.05	-0.007		-1.03	-0.007		-1.14
hisp_pt [1]	-0.052		-1.42	-0.069	*	-1.92	-0.072	**	-2.02
hisp_pt [2]	-0.052		-1.26	-0.075	*	-1.86	-0.073	*	-1.81
hisp_pt [3]	0.016		0.41	0.015		0.38	0.013		0.35
povty_pt [1]	-0.119	***	-6.04	-0.072	***	-3.05	-0.063	***	-2.62
povty_pt [2]	-0.099	***	-4.22	-0.045		-1.60	-0.052	*	-1.82
povty_pt [3]	-0.002		-0.08	0.000		0.01	0.001		0.04
Number of observations	7,811			7,811			7,811		
Log likelihood when parameters set to zero	-10,828			-10,828			-10,828		
Log-likelihood at convergence	-5,402			-5,378			-5,369		
ρ^2	0.50			0.50			0.50		
Adjusted ρ^2	0.50			0.50			0.50		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.11 Estimation results for employment using different travel time thresholds in San Francisco

Independent variable	15-min threshold Coefficient estimate		15-min threshold *t*-statistic	30-min threshold Coefficient estimate		30-min threshold *t*-statistic	45-min threshold Coefficient estimate		45-min threshold *t*-statistic
(Appearing for numbered choice)									
constant [1]	5.570	***	27.17	5.808	***	27.06	5.644	***	25.90
constant [2]	2.683	***	12.44	2.974	***	13.20	2.766	***	12.07
constant [3]	1.905	***	8.65	1.675	***	7.19	1.574	***	6.63
age16_25 [1]	-0.290	**	-2.25	-0.321	**	-2.49	-0.293	**	-2.28
age16_25 [2]	0.420	***	3.08	0.384	***	2.81	0.417	***	3.06
age16_25 [3]	-0.349	**	-2.48	-0.329	**	-2.33	-0.340	**	-2.41
age55_65 [1]	0.774	***	3.23	0.783	***	3.26	0.769	***	3.21
age55_65 [2]	0.451	*	1.76	0.463	*	1.81	0.446	*	1.74
age55_65 [3]	0.915	***	3.69	0.889	***	3.58	0.896	***	3.61
female [1]	-0.024		-0.20	-0.034		-0.27	-0.030		-0.24
female [2]	0.009		0.07	-0.002		-0.02	0.003		0.02
female [3]	-0.101		-0.75	-0.104		-0.77	-0.095		-0.70
femhh [1]	-1.355	***	-10.46	-1.336	***	-10.34	-1.327	***	-10.30
femhh [2]	-0.969	***	-6.95	-0.950	***	-6.82	-0.941	***	-6.78
femhh [3]	-0.270	*	-1.92	-0.273	*	-1.95	-0.300	**	-2.15
nhblack [1]	-1.518	***	-8.14	-1.524	***	-8.16	-1.580	***	-8.48
nhblack [2]	-0.841	***	-4.18	-0.841	***	-4.17	-0.908	***	-4.52
nhblack [3]	-1.078	***	-5.14	-1.117	***	-5.32	-1.089	***	-5.19
hispa [1]	-0.659	***	-3.06	-0.616	***	-2.86	-0.753	***	-3.54
hispa [2]	-0.653	***	-2.81	-0.583	**	-2.51	-0.754	**	-3.28
hispa [3]	-0.011		-0.05	-0.092		-0.40	-0.019		-0.08
asiapc [1]	-0.457	**	-2.37	-0.361	*	-1.83	-0.569	***	-2.98
asiapc [2]	-0.363	*	-1.77	-0.230		-1.10	-0.476	**	-2.35
asiapc [3]	0.185		0.90	0.026		0.12	0.130		0.64
otherr [1]	-0.345	*	-1.69	-0.339	*	-1.66	-0.371	*	-1.82
otherr [2]	-0.251		-1.17	-0.242		-1.13	-0.279		-1.30
otherr [3]	-0.009		-0.04	-0.035		-0.16	-0.002		-0.01
ltd [1]	-15.874	***	-5.36	-9.308	***	-5.16	-1.217		-1.19
ltd [2]	-17.529	***	-5.25	-12.034	***	-6.18	-1.437		-1.33
ltd [3]	0.044		0.01	4.444	**	2.29	3.211	***	2.92
nhbl_pt [1]	0.001		0.15	0.002		0.22	0.028	***	4.20
nhbl_pt [2]	0.002		0.19	-0.001		-0.16	0.030	***	4.11
nhbl_pt [3]	-0.025	**	-2.57	-0.013		-1.36	-0.025	***	-3.39
hisp_pt [1]	0.013		1.56	-0.003		-0.29	0.034	***	4.52
hisp_pt [2]	0.017	*	1.89	-0.007		-0.60	0.038	***	4.84
hisp_pt [3]	-0.015	*	-1.67	0.006		0.51	-0.010		-1.22
povty_pt [1]	-0.068	***	-2.75	-0.027		-0.85	-0.148	***	-7.09
povty_pt [2]	-0.036		-1.35	0.032		0.96	-0.118	***	-5.25
povty_pt [3]	0.043		1.58	-0.015		-0.45	0.019		0.82
Number of observations	16,212			16,212			16,212		
Log likelihood when parameters set to zero	-22,475			-22,475			-22,475		
Log-likelihood at convergence	-10,088			-10,006			-10,122		
ρ^2	0.45			0.56			0.55		
Adjusted ρ^2	0.55			0.55			0.55		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.12 Estimation results for employment using alternative travel time thresholds in Los Angeles

	15-min threshold			30-min threshold			45-min threshold		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
(Appearing for numbered choice)									
constant [1]	5.368	***	45.95	5.338	***	47.49	5.389	***	47.91
constant [2]	2.752	***	22.10	2.700	***	22.57	2.741	***	22.95
constant [3]	1.739	***	13.76	1.694	***	13.90	1.576	***	12.83
age16_25 [1]	-0.626	***	-10.23	-0.627	***	-10.24	-0.626	***	-10.23
age16_25 [2]	0.102		1.56	0.102		1.55	0.102		1.55
age16_25 [3]	-0.453	***	-6.82	-0.452	***	-6.80	-0.453	***	-6.81
age55_65 [1]	0.328	**	2.56	0.326	**	2.55	0.327	**	2.55
age55_65 [2]	0.083		0.60	0.080		0.58	0.081		0.59
age55_65 [3]	0.296	**	2.17	0.294	**	2.15	0.301	**	2.21
female [1]	-0.122	**	-1.99	-0.121	**	-1.97	-0.122	**	-1.98
female [2]	0.076		1.16	0.079		1.19	0.077		1.17
female [3]	-0.234	***	-3.52	-0.239	***	-3.59	-0.235	***	-3.54
femhh [1]	-1.295	***	-20.67	-1.296	***	-20.68	-1.296	***	-20.69
femhh [2]	-1.110	***	-16.00	-1.111	***	-16.01	-1.111	***	-16.02
femhh [3]	-0.256	***	-3.79	-0.252	***	-3.73	-0.250	***	-3.69
nhblack [1]	-1.025	***	-9.29	-1.025	***	-9.29	-1.024	***	-9.26
nhblack [2]	-0.334	***	-2.80	-0.335	***	-2.81	-0.334	***	-2.80
nhblack [3]	-0.772	***	-6.18	-0.772	***	-6.18	-0.789	***	-6.29
hispa [1]	-0.189	**	-2.21	-0.183	**	-2.13	-0.152	*	-1.76
hispa [2]	-0.186	**	-2.00	-0.176	*	-1.89	-0.141		-1.51
hispa [3]	0.257	***	2.79	0.246	***	2.67	0.178	**	1.92
asiapc [1]	0.212		1.28	0.215		1.30	0.216		1.31
asiapc [2]	0.169		0.97	0.174		1.00	0.176		1.00
asiapc [3]	0.153		0.86	0.154		0.87	0.135		0.76
otherr [1]	-0.104		-1.34	-0.102		-1.31	-0.101		-1.30
otherr [2]	-0.139	*	-1.68	-0.135		-1.63	-0.133		-1.61
otherr [3]	0.235	***	2.80	0.232	***	2.77	0.221	***	2.63
ltd [1]	-1.218	*	-1.90	-0.911	*	-1.75	-2.530	***	-3.17
ltd [2]	-2.144	***	-3.05	-1.673	***	-2.87	-3.375	***	-3.91
ltd [3]	1.633	**	2.40	1.906	***	3.52	4.841	***	5.65
nhbl_pt [1]	0.025	***	8.92	0.025	***	8.83	0.024	***	8.52
nhbl_pt [2]	0.025	***	8.24	0.025	***	8.15	0.024	***	7.95
nhbl_pt [3]	-0.002		-0.70	0.000		-0.08	0.002		0.58
hisp_pt [1]	0.017	***	7.14	0.017	***	7.39	0.016	***	6.80
hisp_pt [2]	0.018	***	7.28	0.019	***	7.62	0.018	***	7.14
hisp_pt [3]	0.000		-0.17	0.001		0.38	0.003		1.24
povty_pt [1]	-0.107	***	-17.79	-0.106	***	-17.44	-0.097	***	-14.15
povty_pt [2]	-0.094	***	-14.56	-0.093	***	-14.17	-0.083	***	-11.18
povty_pt [3]	-0.001		-0.12	-0.005		-0.73	-0.020	***	-2.70
Number of observations	56,044			56,044			56,044		
Log likelihood when parameters	-77,693			-77,693			-77,693		
Log-likelihood at convergence	-39,512			-39,481			-39,379		
ρ^2	0.51			0.49			0.49		
Adjusted ρ^2	0.49			0.49			0.49		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.13 Estimation results for working hours using different travel time thresholds in Boston

	15-min threshold		30-min threshold		45-min threshold	
	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
(Appearing for numbered choice)						
constant [1]	5.511 ***	24.23	5.545 ***	24.05	5.745 ***	23.37
constant [2]	3.565 ***	15.14	3.635 ***	15.28	3.868 ***	15.32
constant [3]	3.377 ***	13.92	3.408 ***	13.95	3.600 ***	13.89
constant [4]	1.400 ***	5.53	1.403 ***	5.47	1.376 ***	5.01
constant [5]	-0.203	-0.66	-0.189	-0.61	-0.126	-0.38
age16_25 [1]	-1.251 ***	-8.57	-1.261 ***	-8.62	-1.262 ***	-8.63
age16_25 [2]	1.432 ***	9.42	1.420 ***	9.32	1.413 ***	9.28
age16_25 [3]	0.257	1.62	0.245	1.54	0.246	1.55
age16_25 [4]	-0.780 ***	-4.69	-0.778 ***	-4.67	-0.776 ***	-4.67
age16_25 [5]	0.312	1.59	0.312	1.59	0.314	1.60
age55_65 [1]	1.157 ***	3.86	1.158 ***	3.86	1.169 ***	3.90
age55_65 [2]	1.392 ***	4.49	1.387 ***	4.47	1.402 ***	4.52
age55_65 [3]	0.656 **	2.02	0.656 **	2.03	0.668 **	2.06
age55_65 [4]	1.418 ***	4.59	1.420 ***	4.59	1.417 ***	4.58
age55_65 [5]	1.456 ***	4.20	1.457 ***	4.20	1.456 ***	4.20
female [1]	-0.037	-0.26	-0.039	-0.28	-0.036	-0.25
female [2]	1.059 ***	7.20	1.058 ***	7.19	1.063 ***	7.23
female [3]	0.004	0.02	0.003	0.02	0.006	0.04
female [4]	0.082	0.52	0.080	0.51	0.077	0.49
female [5]	0.696 ***	3.66	0.694 ***	3.65	0.694 ***	3.65
femhh [1]	-1.813 ***	-12.38	-1.816 ***	-12.39	-1.814 ***	-12.38
femhh [2]	-2.066 ***	-13.36	-2.074 ***	-13.39	-2.072 ***	-13.37
femhh [3]	-1.722 ***	-10.36	-1.727 ***	-10.37	-1.723 ***	-10.36
femhh [4]	-0.588 ***	-3.65	-0.586 ***	-3.64	-0.587 ***	-3.64
femhh [5]	-0.407 **	-2.10	-0.406 **	-2.10	-0.406 **	-2.10
nhblack [1]	-0.750 ***	-3.41	-0.724 ***	-3.33	-0.691 ***	-3.19
nhblack [2]	-0.863 ***	-3.58	-0.844 ***	-3.53	-0.802 ***	-3.36
nhblack [3]	-0.624 **	-2.45	-0.595 **	-2.35	-0.561 **	-2.23
nhblack [4]	-0.398 *	-1.64	-0.390	-1.62	-0.384	-1.61
nhblack [5]	-0.629 **	-2.08	-0.615 **	-2.05	-0.601 **	-2.02
hispa [1]	-0.912 ***	-4.18	-0.891 ***	-4.08	-0.880 ***	-4.04
hispa [2]	-1.494 ***	-6.09	-1.466 ***	-5.97	-1.443 ***	-5.89
hispa [3]	-0.868 ***	-3.46	-0.843 ***	-3.36	-0.837 ***	-3.34
hispa [4]	-0.189	-0.80	-0.187	-0.79	-0.186	-0.79
hispa [5]	-0.272	-0.95	-0.264	-0.93	-0.262	-0.92
asiapc [1]	-0.602 **	-1.99	-0.555 *	-1.84	-0.579 *	-1.93
asiapc [2]	-1.244 ***	-3.76	-1.173 ***	-3.54	-1.178 ***	-3.57
asiapc [3]	-1.064 ***	-2.95	-1.010 ***	-2.80	-1.045 ***	-2.91
asiapc [4]	0.037	0.11	0.035	0.11	0.041	0.13
asiapc [5]	-0.330	-0.82	-0.322	-0.81	-0.326	-0.82
otherr [1]	-1.706 ***	-6.40	-1.697 ***	-6.36	-1.671 ***	-6.25
otherr [2]	-1.962 ***	-6.38	-1.944 ***	-6.31	-1.896 ***	-6.15
otherr [3]	-1.602 ***	-4.83	-1.584 ***	-4.77	-1.553 ***	-4.68
otherr [4]	-0.912 ***	-3.07	-0.899 ***	-3.03	-0.889 ***	-3.00
otherr [5]	-0.530	-1.55	-0.522	-1.52	-0.511	-1.49
ltd [1]	-1.448 *	-1.65	-5.013 ***	-3.63	-5.008 ***	-3.88
ltd [2]	-0.843	-0.89	-6.465 ***	-4.25	-7.176 ***	-5.28
ltd [3]	-1.686 *	-1.64	-6.176 ***	-3.77	-5.053 ***	-3.51
ltd [4]	0.203	0.22	0.277	0.19	0.427	0.30
ltd [5]	-0.418	-0.37	-1.116	-0.64	-1.175	-0.70
nhbl_pt [1]	0.018 ***	2.98	0.009	1.38	0.013 **	2.08
nhbl_pt [2]	0.022 ***	3.31	0.010	1.32	0.012 *	1.83
nhbl_pt [3]	0.021 ***	2.98	0.010	1.29	0.016 **	2.20
nhbl_pt [4]	-0.007	-1.02	-0.007	-0.90	-0.007	-1.02
nhbl_pt [5]	-0.008	-1.00	-0.010	-1.14	-0.009	-1.14
hisp_pt [1]	-0.037	-1.00	-0.055	-1.52	-0.056	-1.58
hisp_pt [2]	-0.071 *	-1.82	-0.089 **	-2.31	-0.095 **	-2.53
hisp_pt [3]	-0.051	-1.24	-0.074 **	-1.85	-0.072 *	-1.81
hisp_pt [4]	0.027	0.67	0.027	0.68	0.027	0.68
hisp_pt [5]	-0.002	-0.05	-0.008	-0.17	-0.011	-0.23
povty_pt [1]	-0.114 ***	-5.66	-0.071 ***	-2.93	-0.067 ***	-2.74
povty_pt [2]	-0.132 ***	-5.96	-0.075 ***	-2.86	-0.056 **	-2.12
povty_pt [3]	-0.100 ***	-4.25	-0.045	-1.61	-0.051 *	-1.81
povty_pt [4]	-0.006	-0.27	-0.007	-0.28	-0.008	-0.30
povty_pt [5]	0.010	0.38	0.019	0.64	0.021	0.68
Number of observations	7,811		7,811		7,811	
Log likelihood when parameters set to zero	-13,995		-13,995		-13,995	
Log-likelihood at convergence	-8,609		-8,585		-8,572	
ρ^2	0.38		0.39		0.39	
Adjusted ρ^2	0.38		0.38		0.38	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.14 Estimation results for working hours using different travel time thresholds in San Franci

	15-min threshold		30-min threshold		45-min threshold	
	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
(Appearing for numbered choice)						
constant [1]	5.397 ***	26.39	5.629 ***	26.30	5.460 ***	25.11
constant [2]	3.216 ***	15.05	3.449 ***	15.47	3.330 ***	14.69
constant [3]	2.691 ***	12.54	2.978 ***	13.30	2.776 ***	12.18
constant [4]	1.826 ***	8.22	1.567 ***	6.66	1.498 ***	6.25
constant [5]	-0.643 **	-2.04	-0.725 **	-2.19	-0.969 ***	-2.79
age16_25 [1]	-0.753 ***	-5.80	-0.775 ***	-5.96	-0.749 ***	-5.78
age16_25 [2]	1.436 ***	10.45	1.410 ***	10.25	1.434 ***	10.45
age16_25 [3]	0.416 ***	3.04	0.388 ***	2.83	0.419 ***	3.07
age16_25 [4]	-0.503 ***	-3.47	-0.485 ***	-3.34	-0.498 ***	-3.44
age16_25 [5]	0.438 **	2.15	0.434 **	2.13	0.436 **	2.15
age55_65 [1]	0.746 ***	3.11	0.755 ***	3.15	0.741 ***	3.09
age55_65 [2]	1.208 ***	4.81	1.219 ***	4.85	1.211 ***	4.82
age55_65 [3]	0.446 *	1.75	0.460 *	1.80	0.443 *	1.73
age55_65 [4]	0.826 ***	3.30	0.798 ***	3.18	0.806 ***	3.21
age55_65 [5]	1.436 ***	4.80	1.414 ***	4.72	1.415 ***	4.73
female [1]	-0.214 *	-1.70	-0.221 *	-1.75	-0.218 *	-1.73
female [2]	0.653 ***	4.96	0.647 ***	4.91	0.650 ***	4.94
female [3]	0.034	0.26	0.027	0.20	0.030	0.23
female [4]	-0.240 *	-1.74	-0.246 *	-1.78	-0.236 *	-1.71
female [5]	0.505 ***	2.63	0.497 ***	2.58	0.506 ***	2.63
femhh [1]	-1.315 ***	-10.09	-1.296 ***	-9.97	-1.287 ***	-9.93
femhh [2]	-1.441 ***	-10.37	-1.428 ***	-10.30	-1.419 ***	-10.26
femhh [3]	-0.974 ***	-6.98	-0.956 ***	-6.86	-0.947 ***	-6.82
femhh [4]	-0.301 **	-2.10	-0.304 **	-2.13	-0.331 **	-2.32
femhh [5]	-0.068	-0.35	-0.076	-0.39	-0.096	-0.49
nhblack [1]	-1.493 ***	-7.93	-1.500 ***	-7.96	-1.557 ***	-8.28
nhblack [2]	-1.573 ***	-7.65	-1.576 ***	-7.65	-1.624 ***	-7.90
nhblack [3]	-0.840 ***	-4.18	-0.840 ***	-4.17	-0.906 ***	-4.51
nhblack [4]	-1.055 ***	-4.90	-1.104 ***	-5.11	-1.071 ***	-4.97
nhblack [5]	-1.178 ***	-3.66	-1.169 ***	-3.62	-1.163 ***	-3.61
hispa [1]	-0.586 ***	-2.72	-0.549 **	-2.54	-0.686 ***	-3.21
hispa [2]	-0.827 ***	-3.63	-0.773 ***	-3.39	-0.903 ***	-4.00
hispa [3]	-0.657 **	-2.83	-0.587 **	-2.53	-0.758 ***	-3.30
hispa [4]	-0.018	-0.08	-0.108	-0.46	-0.026	-0.11
hispa [5]	0.106	0.34	0.074	0.24	0.098	0.31
asiapc [1]	-0.367 *	-1.90	-0.281	-1.42	-0.488 **	-2.56
asiapc [2]	-0.726 ***	-3.59	-0.608 ***	-2.94	-0.797 ***	-3.98
asiapc [3]	-0.371 *	-1.81	-0.240	-1.15	-0.484 **	-2.38
asiapc [4]	0.166	0.80	-0.013	-0.06	0.112	0.55
asiapc [5]	0.370	1.36	0.294	1.05	0.306	1.15
otherr [1]	-0.215	-1.05	-0.211	-1.04	-0.243	-1.19
otherr [2]	-0.880 ***	-4.08	-0.873 ***	-4.05	-0.906 ***	-4.20
otherr [3]	-0.260	-1.22	-0.253	-1.18	-0.289	-1.35
otherr [4]	0.036	0.16	0.008	0.04	0.043	0.19
otherr [5]	-0.189	-0.58	-0.208	-0.63	-0.179	-0.55
ltd [1]	-16.660 ***	-5.59	-9.165 ***	-5.07	-1.052	-1.03
ltd [2]	-11.829 ***	-3.63	-9.282 ***	-4.86	-1.846 *	-1.74
ltd [3]	-17.460 ***	-5.23	-12.002 ***	-6.17	-1.457	-1.35
ltd [4]	-0.022	-0.01	5.023 **	2.54	3.240 ***	2.91
ltd [5]	0.350	0.08	1.732	0.66	3.090 **	2.05
nhbl_pt [1]	0.001	0.07	0.003	0.29	0.029 ***	4.26
nhbl_pt [2]	0.006	0.66	0.002	0.24	0.027 ***	3.63
nhbl_pt [3]	0.002	0.19	-0.002	-0.16	0.029 ***	4.09
nhbl_pt [4]	-0.027 ***	-2.68	-0.013	-1.29	-0.026 ***	-3.46
nhbl_pt [5]	-0.015	-1.02	-0.014	-0.97	-0.018	-1.60
hisp_pt [1]	0.016 **	1.97	0.002	0.17	0.038 ***	5.15
hisp_pt [2]	0.000	-0.04	-0.021 *	-1.91	0.013 *	1.69
hisp_pt [3]	0.016 *	1.85	-0.007	-0.64	0.038 ***	4.75
hisp_pt [4]	-0.013	-1.37	0.011	0.95	-0.007	-0.91
hisp_pt [5]	-0.026 **	-2.01	-0.019	-1.13	-0.020 *	-1.77
povty_pt [1]	-0.062 **	-2.50	-0.026	-0.84	-0.148 ***	-7.06
povty_pt [2]	-0.098 ***	-3.63	-0.037	-1.12	-0.149 ***	-6.56
povty_pt [3]	-0.036	-1.37	0.031	0.94	-0.118 ***	-5.25
povty_pt [4]	0.045	1.60	-0.023	-0.65	0.019	0.81
povty_pt [5]	0.037	0.91	0.020	0.42	0.016	0.52
Number of observations	16,212		16,212		16,212	
Log likelihood when parameters set to zero	-29,048		-29,048		-29,048	
Log-likelihood at convergence	-15,692		-15,613		-15,637	
ρ^2	0.46		0.46		0.46	
Adjusted ρ^2	0.46		0.46		0.46	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.15 Estimation results for working hours using alternative travel time thresholds in Los Angeles

	15-min threshold		30-min threshold		45-min threshold	
	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
(Appearing for numbered choice)						
constant [1]	5.261 ***	45.02	5.219 ***	46.44	5.266 ***	46.84
constant [2]	2.750 ***	21.72	2.778 ***	22.88	2.837 ***	23.37
constant [3]	2.750 ***	22.12	2.699 ***	22.61	2.738 ***	22.99
constant [4]	1.657 ***	13.01	1.608 ***	13.09	1.482 ***	11.96
constant [5]	-0.922 ***	-4.40	-0.945 ***	-4.66	-0.998 ***	-4.86
age16_25 [1]	-0.796 ***	-12.93	-0.796 ***	-12.93	-0.795 ***	-12.92
age16_25 [2]	0.597 ***	8.71	0.597 ***	8.71	0.597 ***	8.72
age16_25 [3]	0.105	1.59	0.104	1.59	0.105	1.60
age16_25 [4]	-0.494 ***	-7.33	-0.493 ***	-7.32	-0.495 ***	-7.35
age16_25 [5]	-0.154	-1.33	-0.154	-1.33	-0.154	-1.33
age55_65 [1]	0.297 **	2.32	0.296 **	2.30	0.296 **	2.31
age55_65 [2]	0.749 ***	5.43	0.751 ***	5.45	0.752 ***	5.45
age55_65 [3]	0.082	0.60	0.080	0.58	0.081	0.59
age55_65 [4]	0.246 *	1.78	0.243 *	1.76	0.252 *	1.83
age55_65 [5]	0.709 ***	3.66	0.709 ***	3.66	0.709 ***	3.66
female [1]	-0.237 ***	-3.84	-0.235 ***	-3.82	-0.236 ***	-3.83
female [2]	0.683 ***	10.04	0.685 ***	10.06	0.684 ***	10.05
female [3]	0.082	1.25	0.085	1.28	0.084	1.27
female [4]	-0.305 ***	-4.53	-0.311 ***	-4.61	-0.308 ***	-4.57
female [5]	0.324 ***	2.87	0.323 ***	2.86	0.323 ***	2.86
femhh [1]	-1.286 ***	-20.47	-1.287 ***	-20.48	-1.288 ***	-20.49
femhh [2]	-1.307 ***	-17.99	-1.309 ***	-18.01	-1.310 ***	-18.03
femhh [3]	-1.110 ***	-16.01	-1.111 ***	-16.02	-1.112 ***	-16.03
femhh [4]	-0.278 ***	-4.07	-0.274 ***	-4.00	-0.271 ***	-3.96
femhh [5]	-0.039	-0.34	-0.038	-0.33	-0.037	-0.33
nhblack [1]	-1.057 ***	-9.53	-1.058 ***	-9.52	-1.056 ***	-9.50
nhblack [2]	-0.806 ***	-6.23	-0.804 ***	-6.22	-0.803 ***	-6.21
nhblack [3]	-0.334 ***	-2.80	-0.335 ***	-2.80	-0.334 ***	-2.80
nhblack [4]	-0.842 ***	-6.60	-0.843 ***	-6.60	-0.863 ***	-6.73
nhblack [5]	-0.216	-0.98	-0.216	-0.98	-0.216	-0.97
hispa [1]	-0.142 *	-1.66	-0.137	-1.59	-0.108	-1.24
hispa [2]	-0.482 ***	-4.98	-0.475 ***	-4.89	-0.438 ***	-4.47
hispa [3]	-0.187 **	-2.01	-0.177 *	-1.90	-0.143	-1.52
hispa [4]	0.266 ***	2.87	0.254 ***	2.74	0.181 **	1.94
hispa [5]	0.217	1.40	0.214	1.38	0.191	1.21
asiapc [1]	0.172	1.04	0.176	1.06	0.177	1.07
asiapc [2]	0.452 ***	2.62	0.454 ***	2.63	0.454 ***	2.63
asiapc [3]	0.171	0.97	0.176	1.01	0.178	1.02
asiapc [4]	0.034	0.19	0.034	0.19	0.011	0.06
asiapc [5]	0.871 ***	3.64	0.873 ***	3.65	0.870 ***	3.64
otherr [1]	-0.051	-0.65	-0.048	-0.62	-0.047	-0.61
otherr [2]	-0.511 ***	-5.95	-0.510 ***	-5.95	-0.508 ***	-5.93
otherr [3]	-0.141 *	-1.70	-0.137 *	-1.66	-0.135 *	-1.64
otherr [4]	0.246 ***	2.91	0.243 ***	2.87	0.230 ***	2.73
otherr [5]	0.169	1.16	0.169	1.16	0.167	1.15
ltd [1]	-1.376 **	-2.13	-0.917 *	-1.75	-2.430 ***	-3.04
ltd [2]	-0.580	-0.85	-0.899	-1.60	-2.818 ***	-3.20
ltd [3]	-2.128 ***	-3.01	-1.667 ***	-2.85	-3.359 ***	-3.89
ltd [4]	1.788 ***	2.60	2.075 ***	3.80	5.209 ***	6.03
ltd [5]	0.150	0.14	0.402	0.48	1.634	1.16
nhbl_pt [1]	0.026 ***	9.22	0.026 ***	9.19	0.025 ***	8.93
nhbl_pt [2]	0.018 ***	5.74	0.017 ***	5.46	0.016 ***	5.03
nhbl_pt [3]	0.025 ***	8.24	0.025 ***	8.15	0.024 ***	7.94
nhbl_pt [4]	0.000	-0.14	0.002	0.51	0.004	1.20
nhbl_pt [5]	-0.018 ***	-3.30	-0.017 ***	-3.13	-0.016 ***	-2.93
hisp_pt [1]	0.018 ***	7.54	0.018 ***	7.89	0.017 ***	7.35
hisp_pt [2]	0.010 ***	3.91	0.009 ***	3.64	0.008 ***	3.01
hisp_pt [3]	0.018 ***	7.27	0.019 ***	7.61	0.018 ***	7.14
hisp_pt [4]	0.001	0.33	0.002	0.92	0.005 *	1.83
hisp_pt [5]	-0.011 **	-2.55	-0.011 **	-2.42	-0.009 **	-2.15
povty_pt [1]	-0.106 ***	-17.66	-0.106 ***	-17.37	-0.098 ***	-14.16
povty_pt [2]	-0.110 ***	-16.28	-0.108 ***	-15.62	-0.097 ***	-12.48
povty_pt [3]	-0.094 ***	-14.56	-0.093 ***	-14.16	-0.083 ***	-11.19
povty_pt [4]	-0.003	-0.48	-0.007	-1.12	-0.024 ***	-3.16
povty_pt [5]	0.023 **	2.01	0.021 *	1.83	0.015	1.13
Number of observations	56.044		56.044		56.044	
Log likelihood when parameters set to zero	-100.420		-100.420		-100.420	
Log-likelihood at convergence	-54.215		-54.186		-54.084	
ρ^2	0.46		0.46		0.46	
Adjusted ρ^2	0.46		0.46		0.46	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.16 Estimation results for earnings using alternative travel time thresholds in Boston

(Auto)	15 minutes			30 minutes			45 minutes		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	10.392	***	47.54	10.396	***	47.55	10.383	***	47.48
age16_25	-1.682	***	-29.36	-1.682	***	-29.51	-1.679	***	-29.42
age55_65	-0.078		-1.35	-0.079		-1.36	-0.077		-1.33
female	-0.517	***	-20.63	-0.517	***	-20.64	-0.517	***	-20.65
femhh	0.124	***	3.31	0.124	***	3.32	0.123	***	3.30
nhblack	-0.099		-1.61	-0.100	*	-1.63	-0.099		-1.61
hispa	-0.207	***	-2.63	-0.209	***	-2.66	-0.206	***	-2.63
asiapc	-0.225	***	-3.38	-0.225	***	-3.39	-0.224	***	-3.37
otherr	-0.225	**	-2.30	-0.226	**	-2.30	-0.224	**	-2.29
ltd	0.032		0.16	0.126		0.39	0.085		0.35
nhbl_pt	-0.004	***	-2.71	-0.004	**	-2.39	-0.004	***	-2.60
hisp_pt	0.003		0.45	0.004		0.56	0.004		0.57
povty_pt	0.009	*	1.94	0.008		1.40	0.008		1.41
ramda1	-0.264	**	-2.46	-0.266	**	-2.49	-0.261	**	-2.44
Number of observations	5,599			5,599			5,599		
R^2	0.45			0.45			0.45		
Adjusted R^2	0.45			0.45			0.45		

(No Auto)	15 minutes			30 minutes			45 minutes		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	9.914	***	13.43	9.675	***	11.02	10.078	***	9.91
age16_25	-0.740	***	-8.87	-0.732	***	-8.52	-0.753	***	-8.62
age55_65	0.011		0.08	0.037		0.25	-0.024		-0.15
female	-0.403	***	-5.52	-0.410	***	-5.52	-0.399	***	-5.29
femhh	0.016		0.16	0.034		0.31	-0.007		-0.06
nhblack	-0.079		-0.60	-0.062		-0.44	-0.109		-0.74
hispa	-0.178		-0.87	-0.134		-0.58	-0.235		-0.93
asiapc	-0.540	***	-3.07	-0.477	**	-2.57	-0.514	**	-2.55
otherr	-0.295		-1.39	-0.266		-1.15	-0.358		-1.46
ltd	0.811	*	1.94	1.059		1.37	0.369		0.45
nhbl_pt	0.006	*	1.93	0.006	*	1.79	0.004		1.45
hisp_pt	-0.007		-0.42	0.005		0.28	0.002		0.09
povty_pt	-0.007		-0.65	-0.012		-1.13	-0.010		-0.92
ramda2	-0.103		-0.46	-0.036		-0.14	-0.161		-0.54
Number of observations	780			780			780		
R^2	0.17			0.16			0.16		
Adjusted R^2	0.15			0.15			0.15		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.17 Estimation results for earnings using alternative travel time thresholds in San Francisco

(Auto)	15 minutes		30 minutes		45 minutes	
Independent variable	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
constant	9.719 ***	33.43	9.820 ***	33.89	9.733 ***	34.94
age16_25	-1.312 ***	-21.00	-1.333 ***	-21.33	-1.316 ***	-21.90
age55_65	0.156 ***	2.86	0.138 **	2.52	0.152 ***	2.89
female	-0.497 ***	-23.31	-0.494 ***	-23.09	-0.496 ***	-23.49
femhh	-0.058 **	-2.09	-0.054 *	-1.94	-0.057 **	-2.09
nhblack	-0.008	-0.18	-0.006	-0.12	-0.009	-0.20
hispa	-0.088	-1.40	-0.111 *	-1.75	-0.095	-1.58
asiapc	-0.067 **	-2.14	-0.078 **	-2.42	-0.073 **	-2.39
otherr	0.072	0.85	0.042	0.50	0.066	0.81
ltd	-0.316	-0.48	0.207	0.67	0.115	0.81
nhbl_pt	0.002	1.29	0.003	1.58	0.003	1.61
hisp_pt	0.006 **	2.50	0.006 ***	2.58	0.006 ***	2.64
povty_pt	-0.011 **	-2.53	-0.014 ***	-2.98	-0.014 ***	-3.42
ramda1	0.050	0.37	0.001	0.01	0.040	0.31
Number of observations	12,016		12,016		12,016	
R^2	0.32		0.32		0.32	
Adjusted R^2	0.31		0.31		0.31	

(No Auto)	15 minutes		30 minutes		45 minutes	
Independent variable	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic	Coefficient estimate	*t*-statistic
constant	9.742 ***	16.33	8.842 ***	8.18	9.881 ***	16.08
age16_25	-0.784 ***	-9.96	-0.731 ***	-7.80	-0.791 ***	-10.19
age55_65	0.016	0.16	0.091	0.74	0.007	0.07
female	-0.249 ***	-3.72	-0.277 ***	-3.82	-0.246 ***	-3.68
femhh	-0.136 *	-1.69	-0.070	-0.68	-0.144 *	-1.81
nhblack	-0.093	-0.78	-0.037	-0.28	-0.100	-0.84
hispa	-0.229	-1.57	-0.094	-0.48	-0.243 *	-1.72
asiapc	-0.329 **	-2.56	-0.219	-1.28	-0.345 ***	-2.66
otherr	-0.058	-0.40	0.090	0.44	-0.080	-0.55
ltd	-0.140	-0.09	1.357	0.91	-0.284	-0.49
nhbl_pt	0.003	0.63	0.004	0.84	0.004	0.81
hisp_pt	0.004	0.95	0.008	1.41	0.003	0.97
povty_pt	-0.012	-0.86	-0.016	-1.15	-0.013	-0.93
ramda2	-0.079	-0.45	0.169	0.56	-0.111	-0.65
Number of observations	1,200		1,200		1,200	
R^2	0.12		0.12		0.12	
Adjusted R^2	0.11		0.11		0.11	

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

Table a.18 Estimation results for earnings using alternative travel time thresholds in Los Angeles

(Auto)	15 minutes			30 minutes			45 minutes		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	9.454	***	55.24	9.252	***	47.59	9.457	***	53.72
age16_25	-0.763	***	-48.45	-0.750	***	-43.99	-0.765	***	-47.81
age55_65	0.208	***	9.57	0.225	***	9.64	0.205	***	9.35
female	-0.437	***	-35.46	-0.446	***	-34.25	-0.437	***	-35.01
femhh	-0.071	***	-4.16	-0.085	***	-4.63	-0.070	***	-4.05
nhblack	-0.020		-0.52	-0.053		-1.28	-0.016		-0.42
hispa	-0.105	**	-2.46	-0.057		-1.17	-0.105	**	-2.36
asiapc	-0.182	***	-7.25	-0.198	***	-7.51	-0.180	***	-7.10
otherr	0.016		0.36	0.067		1.31	0.013		0.29
ltd	-0.352	***	-3.77	-0.338	***	-3.61	-0.360	***	-2.72
nhbl_pt	0.002	***	3.32	0.003	***	3.91	0.002	***	3.25
hisp_pt	0.003	***	3.41	0.004	***	4.15	0.003	***	3.43
povty_pt	-0.010	***	-10.79	-0.010	***	-9.74	-0.009	***	-8.14
ramda1	0.186	**	2.06	0.289	***	2.80	0.177	**	1.91
Number of observations	39,689			39,689			39,689		
R^2	0.19			0.19			0.19		
Adjusted R^2	0.19			0.19			0.19		

(No Auto)	15 minutes			30 minutes			45 minutes		
Independent variable	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic	Coefficient estimate		*t*-statistic
constant	8.550	***	25.24	8.356	***	23.85	8.378	***	20.96
age16_25	-0.377	***	-13.00	-0.370	***	-12.73	-0.371	***	-12.49
age55_65	0.174	***	3.70	0.180	***	3.82	0.181	***	3.80
female	-0.304	***	-9.83	-0.312	***	-10.00	-0.311	***	-9.73
femhh	0.057		1.28	0.075	*	1.66	0.074		1.51
nhblack	0.088		1.44	0.082		1.33	0.080		1.29
hispa	0.022		0.35	0.048		0.75	0.044		0.64
asiapc	-0.246	***	-3.76	-0.250	***	-3.81	-0.255	***	-3.86
otherr	0.066		1.19	0.089		1.59	0.087		1.43
ltd	0.313		1.10	0.513	**	2.26	0.453		1.20
nhbl_pt	0.003	**	2.32	0.003	**	2.40	0.003	**	2.05
hisp_pt	0.002	**	2.15	0.002	**	2.47	0.002	**	2.11
povty_pt	-0.003		-0.48	-0.001		-0.24	-0.001		-0.24
ramda2	0.229	**	2.16	0.284	***	2.60	0.283	**	2.30
Number of observations	4,808			4,808			4,808		
R^2	0.08			0.08			0.08		
Adjusted R^2	0.08			0.08			0.08		

Note: ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.10 level.

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