CSIS Discussion Paper No. 69

# Spatio-Temporal Dimensions of Commuting Inequality Between Car and Public Transit: The Case of San Francisco

by

Mizuki Kawabata[a*] and Qing Shen[b]

March, 2006

[a*] Corresponding author. Center for Spatial Information Science, University of Tokyo
5-1-5 Kashiwano-ha Kashiwa-shi Chiba, 277-8568, Japan
Email: mizuki@csis.u-tokyo.ac.jp
[b] School of Architecture, Planning, and Preservation, University of Maryland
College Park, MD 20742, USA
Email: qshen@umd.edu

**Abstract**

The issue of equity is increasingly recognized as an essential component of sustainable development and transportation. Utilizing 1990 and 2000 spatial data and GIS, we conduct a spatial and temporal examination of commuting inequality between car and public transit in the San Francisco Bay Area. Results visualized in the maps show considerable inequality in job accessibility and commuting time between car and public transit and among locations within the metropolitan area. The visualized results also show substantial spatial variations in the temporal changes in job accessibility and commuting time for car as well as for public transit. Results from OLS and spatial regression models indicate that in both 1990 and 2000 greater job accessibility is significantly associated with shorter commuting time for driving alone as well as for public transit, but the degree of this association is considerably greater for public transit than for driving alone.

# 1 Introduction

The issue of equity is increasingly recognized as an essential component of sustainable development and transportation (Banister, 2002; Deakin, 2001, 2002; FHWA, 2001; Johnston and Garry, 2003; Richardson, 2005; Steg and Gifford, 2005). Researchers and policymakers have come to agree worldwide with the notion that sprawling, auto-oriented urban development is unsustainable, where a critical issue is inequality in job access and commuting to work between car and public transit users. In geographically dispersed, low-density US metropolitan areas, for example, the number of accessible job opportunities, referred to hereafter as job accessibility, is considerably lower for public transit users than for car users (Hess, 2005; Kawabata, 2003b; Kawabata and Shen, 2006; Shen 1998). A growing body of research in fact suggests that in highly auto-oriented metropolitan areas, lack of access to a car is a barrier to participation in economic activities (Blumenberg, 2004; Cervero *et al.*, 2002; Gurley and Bruce, 2005; Kawabata, 2003a; Sanchez, 1999; Taylor and Ong, 1995). It is also reported that people who use public transit spend much more time commuting than people who use cars (Kasarda, 1995; Taylor and Ong, 1995).

Under these circumstances, however, a limited number of studies have so far focused on the spatial and temporal dimensions of commuting inequality between car and public transit. Much is known about the presence of substantial spatial variations in commuting time within a metropolitan area (Shen, 2000), but little is known about the potential presence of spatial variations in commuting time when the two travel modes, car and public transit, are differentiated. Given the considerable car/public transit disparity in job accessibility, one might suspect that location is a more important factor associated with commuting time for people who use public transit than for people who use cars. Nevertheless, the extent to which the association between urban spatial structure and commuting time differs between car and public transit is not yet fully understood. Neither the existence of temporal changes in this association nor the differences in changes, if any, between car and public transit has been sufficiently investigated. The spatial and temporal dimensions of commuting by car vis-à-vis public transit are a relatively under-researched area partly because data on commuting time sorted by travel mode for small geographic areas are not readily available.

The recent advances in and simplification of spatial data and Geographic Information Systems (GIS) have allowed us to further explore this research area. Thus, by making use of 1990 and 2000 spatial data and GIS, we examine the spatial and temporal dimensions of commuting inequality between car and public transit. The study area is the San Francisco Bay Area, which has a relatively high level of public transit usage with a slight increase in the proportion of public transit commuters occurring in the 1990s; this was the first such increase since 1960.

We specifically consider the relevant situations mentioned above and examine car/public transit inequality with the following two lines of questions. The first line of question is whether there are substantial spatial and temporal variations in job accessibility and commuting time within the metropolitan area. To answer this question, we calculate and visualize job accessibility and commuting time for car and public transit users separately. In measuring job accessibility, our study takes into account spatial variations in the supply and demand sides of the labor market (i.e., jobs and workers) as well as the distinction between the travel modes (i.e., car and public transit), which have rarely been simultaneously addressed. The second line of questions are whether the association between job accessibility and commuting time is greater for public transit than for driving alone and also whether this association changed between 1990 and 2000. To answer these questions, we examine ordinary least squares (OLS) and also two typical spatial regression models which take into account spatial autocorrelation, spatial lag and spatial error models. We address the spatial regression models since the presence of considerable spatial autocorrelation is suggested by regression diagnostics. The application of spatial regression models is rarely conducted in this area of research and therefore is a unique methodological feature in this study. It has to be noted that the subject of this study is not to identify causal relationships between job accessibility and commuting time but to examine car/public transit differences in the association between job accessibility and commuting time. Here, the spatial unit of the analyses is the regional travel analysis zone (RTAZ), a rather disaggregated area serving the purpose of this research.

The remainder of this article starts with a review of related research in Section 2. We subsequently describe the study area and methodology in Section 3 and Section 4, respectively. Results are then presented in Section 5, and conclusions are given in Section 6.

# 2 Prior Research

## *2.1 Job Access and Transportation*

Geographical separation between workplace and residence, often called spatial mismatch in academic literature, has garnered considerable attention since Kain (1968) introduced it as a possible explanation for concentrated urban poverty. Kain hypothesized that residential segregation and employment suburbanization deteriorate minority workers' job opportunities and aggravate their employment outcomes. Since Kain's study, a considerable number of studies have been conducted to examine spatial mismatch, and scholars provide summaries and reviews (Blumenberg and Manville, 2004; Glaeser *et al.*, 2004; Holzer, 1991; Ihlanfeldt and Sjoquist, 1998; Kain, 1992).

While Kain's original spatial mismatch theory does not address the issue of transportation, an increasing number of subsequent studies recognize the importance of travel modes in accessing employment, especially on the part of disadvantaged people such as low-skilled workers and welfare recipients. Some studies, for example, find that having access to a car significantly facilitates the transition of welfare to work (Cervero *et al*., 2002; Gurley and Bruce, 2005; Ong, 1996, 2002). The positive effect of car ownership on employment outcomes is also found for the more general population (Raphael and Rice, 2002). Results for the relationship between public transit access and employment are rather mixed, however. A study using 1990 census data in Atlanta and Portland finds that access to public transit increases nonwhite workers' labor participation (Sanchez, 1999). Another study using data on welfare recipients in six US metropolitan areas (Atlanta, Baltimore, Dallas, Denver, Milwaukee, and Portland), on the other hand, finds that transit access/service quality has no significant effect on improvement in employment status (Sanchez *et al.*, 2004).

In analyzing problems related to job access, a certain index of job accessibility is often used. Accessibility is measured in various ways depending on the purpose of research (Handy and Niemeier, 1997; Harris, 2001; Morris *et al*., 1979). A popular measurement of job accessibility uses the potential-based approach, which calculates the number of job opportunities available depending on given travel costs such as travel distance and time. The potential-based measurement of job accessibility has been developed in various forms, especially since Hansen's (1959) study on accessibility and land use in which accessibility is defined as the potential of opportunities for interaction.

In the case where spatial variation and travel-mode inequality in job access are of interest, two issues arise when measuring job accessibility. One issue is the joint incorporation of the supply and demand sides of the labor market. In many cases job accessibility is computed by incorporating the supply side (jobs) only, and the demand side (workers who compete for those jobs) is not factored in. Since jobs and workers are not uniformly distributed within a metropolitan area, job accessibility without considering the spatial distribution of workers (i.e., spatial competition) can generate a distorted picture (Harris, 2001; Shen, 1998; Van Wee *et al*., 2001; Weibull, 1976).

Another issue is the differentiation of travel modes. Job accessibility is in many instances calculated for all travel modes or only for car travel. It is known, however, that commuting time by public transit is much longer on average than commuting time by car (Kasarda, 1995; Taylor and Ong, 1995). Also, there is growing evidence that job accessibility for public transit users is markedly lower than that for car users. It is found, for example, that the ratios of the number of low-wage jobs accessible within 30 minutes by car to the number of jobs accessible by public transit are considerably high in low-income neighborhoods in Los Angeles (Blumenberg, 2004) and Erie and Niagara Counties in western New York State (Hess, 2005). When the focus is on inequality in job access between car and public transit, therefore, it is vital to differentiate between the travel modes. The differentiation of travel modes is especially important for highly auto-oriented US areas, since job accessibility for public transit in the US is extremely low compared to more transit-oriented areas--for instance, Tokyo (Kawabata and Shen, 2006) and Hong Kong (Kwok and Yeh, 2004).

While a number of studies suggest considerable disparity in job access between car and public transit in the US, the car/public disparity in recent years and its temporal changes are not yet fully explored.

### *2.2 Urban Spatial Structure and Commuting Time*

Relationships between urban spatial structure and travel patterns or behavior have been the subject of extensive research (reviews are given in, for example, Badoe and Miller, 2000; Boarnet and Crane, 2001; Cervero, 2002; Crane, 2000; Ewing and Cervero, 2001; Horner, 2004; Rouwendal and Nijkamp, 2004). Commuting patterns and their relation to urban spatial structure or land use have drawn interest as concerns about traffic congestion and environmental burdens have grown. In particular, the relationship between job and workers' housing locations and journeys to work have been actively examined and debated. One body of research measures *wasteful commuting* or *excess commuting* which represents the difference between observed and theoretical minimal commuting given real distributions of jobs and housing (Giuliano and Small, 1993; Hamilton, 1982; Merriman *et al*., 1995; Small and Song, 1992; White, 1988). Another body of research examines the relationship between jobs-housing balance and commuting. Some researchers suggest significant relationships between jobs-housing balance and travel patterns (Cervero, 1989; Nowlan and Stewart, 1991). Other researchers, on the other hand, question the relationships and the efficacy of jobs-housing balancing policy in reducing congestion (Giuliano, 1991; Giuliano and Small, 1993; Peng, 1997; Wachs *et al*., 1993).

The linkages between urban spatial structure and commuting continue to attract further investigations as urban spatial structure and travel patterns evolve over time. In particular, commuting time trends over the past few decades highlight the necessity for research using up-to-date and temporal data. Studies in the early 1990s indicate that in the US, commuting times are shrinking (Gordon *et al.*, 1991), largely unchanged (Levinson and Kumar, 1994; Taylor and Ong, 1995; Wachs *et al.*, 1993), or increasing at a modest pace (Rosetti and Eversole, 1993). The US Census 2000 data, however, indicate that during the 1990s commuting time increased in every one of the 49 metropolitan areas with populations of one million or more (McGuckin and Srinivasan, 2003). As an explanation of declining or steady commuting times despite increasing commuting distance between 1968 and 1988 for the Washington metropolitan area, Levinson and Kumar (1994) propose the rational locator hypothesis that workers adjust their job and housing locations to maintain constant commuting times. The study suggests that polycentric and suburbanized urban structure is a result of rational relocations, and that policies encouraging such rational decisions are needed. A recent study by Levinson and Wu (2005), however, finds that while drive alone commuting times were stable for metropolitan Washington, DC, commuting times rose for an intra-metropolitan area, the Twin Cities. Average commuting time for an entire metropolitan area may indeed conceal intra-metropolitan variations in commuting time. A study using 1990 data at the census block group level for the 20 largest US metropolitan areas shows considerable spatial variations in commuting time (Shen, 2000). The study subsequently conducts regression analysis for the Boston metropolitan area and finds significant associations between urban spatial structure and average commuting time.

A number of studies examine the relationships between urban spatial structure and commuting durations, and some recent studies take a step to examine their temporal changes (Horner, 2006; Vandersmissen *et al.*, 2003; Yang, forthcoming). Only a limited number, however, differentiate between car and public transit in their analyses. Using metropolitan-area level data for 82 US metropolitan areas in 2000, Gordon *et al.* (1989) examine the effects of densities, urban size, and some other urban structure variables on average commuting times by car and public transit, and obtain similar results for the two travel modes. Levinson (1998) uses a 1987–1988 household travel survey in metropolitan Washington, DC, and analyzes the effect of job accessibility and housing accessibility at traffic zones at home and work destinations on commuting times for car and public transit. The result indicates that while residences with higher job accessibility are associated with shorter commuting time for car as well as for public transit, workplaces with higher job accessibility are associated with longer commuting time for car but with shorter commuting time for public transit. Little is known, however, about the temporal changes in the association between urban spatial structure and commuting time for car vis-à-vis public transit.

## 3 The Study Area

The study area is the San Francisco Bay Area which covers the nine counties of Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma. Basic descriptive statistics on population and transportation characteristics for the US nationally (presented as reference) and the San Francisco Bay Area from Censuses 1990 and 2000 are shown in Table 1. In the following, statistics for the San Francisco Bay Area discussed are otherwise noted.

**Table 1.** National and regional characteristics in 1990 and 2000

| | United States | | San Francisco Bay Area | |
|---|---|---|---|---|
| | 1990 | 2000 | 1990 | 2000 |
| Total population (000) | 248,711 | 281,422 | 6,024 | 6,784 |
| Persons 16 years+ in labor force (000) | 125,182 | 138,821 | 3,322 | 3,535 |
| Total households (000) | 91,994 | 105,539 | 2,246 | 2,466 |
| % Households with 1+ vehicles | 88.5% | 89.7% | 89.5% | 90.0% |
| % Households with 2+ vehicles | 54.7% | 55.5% | 57.0% | 57.0% |
| Means of transportation to work | | | | |
| % Drove alone | 73.2% | 75.7% | 68.2% | 68.0% |
| % Carpooled | 13.4% | 12.2% | 13.0% | 12.9% |
| % Public transportation | 5.3% | 4.7% | 9.5% | 9.7% |
| % Other means | 5.2% | 4.1% | 5.9% | 5.4% |
| % Worked at home | 3.0% | 3.3% | 3.4% | 4.0% |
| Mean travel time to work (min.) | | | | |
| All modes | 22.4 | 25.5 | 25.6 | 29.4 |
| Drive alone | | 24.1* | 23.6** | 27.3** |
| Public transportation | | 47.7* | 41.2** | 46.3** |

Note: Public transportation for mean travel time includes taxicab for the US nation but excludes taxicab for the San Francisco Bay Area. Unmarked data are from 1990 and 2000 Decennial Censuses. *Census Transportation Planning Package (CTPP) 2000 Profile Sheets (AASHTO, 2002). **Authors' calculations from CTPPs 1990 and 2000.

The population grew between 1990 and 2000. The study area added about 760,000 people to the base of 6 million residents (a 13% increase), 213,000 workers to the base of 3.3 million workers (a 6% increase), and 220,000 households to the base of 2.2 million households (a 10% increase).

The transportation statistics indicate a high degree of automobile dependence. Approximately nine out of ten households have one or more cars, and more than half of households own two or more cars. A great majority use cars to commute to work. The proportions of commuters who drive alone and carpool are about 68% and 13%, respectively. The proportion of commuters who use public transit, on the other hand, is considerably lower, about 10%, but this figure is twice as high as the US average of 5%.

According to past decennial census data (not shown in Table 1), between 1960 and 1990 the proportion of workers who use cars to commute to work rose from 69.9% to 81.2% and the proportion of workers who use public transit fell from 15.4% to 9.5% (MTC, 2002b). Between 1990 and 2000, however, this trend reversed. Statistics in Table 1 indicate that the proportions of workers who drive alone and carpool decreased slightly, from 68.2% to 68.0% and from 13.0% to 12.9%, respectively. Combined, the proportion of car commuters *decreased* from 81.2% to 80.9%. The proportion of public transit commuters, on the other hand, *increased* from 9.5% to 9.7%. Indeed, among the 49 largest US metropolitan areas, San Francisco ranked the second in terms of increase in numbers taking public transit to work (McGuckin and Srinivasan, 2003). For the US nationally, on the other hand, the trend of increasing auto usage and decreasing public transit usage continued (but slowed) in the 1990s. During the thirty years between 1960 and 1990, the proportion of car commuters increased from 64.0% to 86.5% and the proportion of public transit commuters decreased from 12.1% to 5.3% (McGuckin and Srinivasan, 2003). During the 1990s the proportion of car commuters increased slightly, from 86.5% (not 86.6% due to rounding) to 87.9%, and the proportion of public transit commuters continued to decrease from 5.3% to 4.7%.

Travel time to work increased during the 1990-2000 period. The average commuting time for the San Francisco Bay Area grew from 25.6 to 29.4 minutes (a 3.8 minute increase). This is a notable increase compared to the increase from 24.3 to 25.6 minutes (a 1.3 minute increase) during the 1980s (MTC, 2002a). The average commuting time by public transit is considerably longer, about 1.7 times that by driving alone (about twice for the US nationally). When the data were analyzed separately by travel mode, the average commuting time increased for both solo drivers and public transit commuters, from 23.6 to 27.3 minutes and from 41.2 to 46.3 minutes, respectively.

# 4 Methodology

Methodology comprises two parts. The first part calculates and visualizes job accessibility and commuting time at the spatial level of RTAZ for car and public transit in 1990 and 2000, and examines their spatial and temporal variations and travel mode disparity. The second part estimates OLS and spatial regression models to examine the associations between urban spatial structure and commuting time in general and between job accessibility and commuting time in particular. Results for driving alone and public transit are then compared. The following three subsections describe in detail the measurements of job accessibility, regression models, and data, respectively.

## *4.1 Measurements of Job Accessibility*

In order to examine the research questions outlined earlier, we calculate job accessibility that takes into account the spatial distributions of not only the supply side (jobs) but also the demand side (workers) as well as the distinction of travel modes (car and public transit). Job accessibility formulae, which utilize accessibility frameworks developed by Weibull (1976) and Shen (1998), are shown by :

$$A_i^{car} = \sum_{j:\, t_{ij}^{car} < t_0} \frac{E_j}{\sum_{k:\, t_{kj}^{car} < t_0} \alpha_k W_k + \sum_{k:\, t_{kj}^{tran} < t_0} (1-\alpha_k) W_k} \,, \qquad (1)$$

$$A_i^{tran} = \sum_{j:\, t_{ij}^{tran} < t_0} \frac{E_j}{\sum_{k:\, t_{kj}^{car} < t_0} \alpha_k W_k + \sum_{k:\, t_{kj}^{tran} < t_0} (1-\alpha_k) W_k} \,, \qquad (2)$$

where $A_i^{car}$ and $A_i^{tran}$ are measures of job accessibility in resident zone *i* for car commuters and public transit commuters, respectively; $t^{car}_{ij}$ and $t^{tran}_{ij}$ are the travel times between zone *i* and zone *j* by car and public transit, respectively; $t_0$ indicates a travel time threshold; $E_j$ represents the number of jobs in zone *j*; $W_k$ indicates the number of workers (consisting of both the employed and unemployed) living in zone *k*; $\alpha_k$ is the proportion of households with cars in zone *k*. Note that spatial competition is incorporated directly into job accessibility. A resultant job accessibility value in resident zone *i* represents the number of jobs within reach for a given commuting time by a particular travel mode for a worker living in zone *i*.

We assign approximately the average commuting time, 30 minutes, to the threshold $t_0$. The travel-time threshold approach, rather than the gravity-based approach, is employed to impose the same travel time constraint to car and public transit commuters.

### *4.2 Regression Analysis*

We estimate a set of regression models of average commuting times by driving alone and public transit. Our specific questions of interest are: whether the association between job accessibility and commuting time by public transit is stronger than the association by driving alone; and whether the association between job accessibility and commuting time changed from 1990 to 2000. The models are estimated separately for 1990 and 2000. All models use essentially the same set of explanatory variables, which makes it easier to compare results. In the models for driving alone, job accessibility for car commuters is incorporated as an explanatory variable, and in the models for public transit, job accessibility for public transit is included as an explanatory variable. The other explanatory variables are neighborhood employment and population densities and socioeconomic characteristics such as income, gender, race, and occupation compositions (shown later in Table 2), which previous studies suggest are likely to be associated with commuting time.

Some may question the inclusion of commuting time on the left hand side and a travel time variable as part of job accessibility measure on the right hand side of the regression models. Commuting time on the left hand side of the models is the average commuting time for residents of each zone. The travel time incorporated in job accessibility on the right hand side of the models, on the other hand, is the average time to travel from each origin to each destination. This travel time indicates the proximity between each pair of zones. Using the 30-minute threshold time, a resultant job accessibility value for a resident zone represents the number of jobs accessible within 30 minutes for a worker residing in that zone, and not commuting time itself.

We start the regression analysis by estimating OLS models that can be expressed, as usual, by:

$$y = X\beta + \varepsilon , \tag{3}$$

where $y$ is a vector (n×1) of observations of the dependent variable; $X$ is a matrix (n×k) of observations of the independent variables; $\beta$ is a vector (k×1) of regression coefficients; and $\varepsilon$ is a vector (n×1) of error terms.

Regression diagnostics, however, suggested the presence of considerable spatial autocorrelation. We therefore estimated two basic spatial regression models, spatial lag and spatial error models, which take into account spatial autocorrelation as described below.

The spatial lag model incorporates a spatially lagged dependent variable on the right hand side of the regression model as follows:

$$y = \rho W_y + X\beta + \varepsilon \quad , \tag{4}$$

where $W$ is a spatial weights matrix (n×n); $W_y$ is the corresponding spatially lagged dependent variable; and $\rho$ is the spatial autoregressive parameter. The spatial weights matrix, $W$, is a positive and symmetric matrix which specifies neighborhood sets for each observation; $w_{ij} = 1$ when $i$ and $j$ are neighbors, and $w_{ij} = 0$ otherwise. An observation is conventionally assumed not to be a neighbor to itself, so the diagonal elements of the weight matrix are set to zero ($w_{ii} = 0$). In order to make estimated parameters between alternative models more comparable, the spatial weights matrix is row-standardized so that the sum of elements in each row is one. Since the dependent variable $y$ at $i$ in a spatial lag model is correlated with the error terms at all locations in the system, an OLS estimator will be biased and inconsistent. The spatial lag model, therefore, is generally estimated by the maximum likelihood or instrumental variable estimation (see Anselin, 1988; Kelejian and Prucha, 1999; Kelejian and Robinson, 1993; Ord, 1975).

The spatial error model, on the other hand, takes into account spatial autocorrelation by incorporating a spatial autoregressive process in the error terms as follows:

$$y = X\beta + \varepsilon \,, \tag{5}$$

$$\varepsilon = \lambda W_\varepsilon + \xi \,, \tag{6}$$

where $\lambda$ is the spatial autoregressive coefficient for the error lag $W_\varepsilon$; and $\xi$ is an uncorrelated and homoskedastic error term. The error covariance is nonspherical, and OLS estimates are unbiased but inefficient. Estimation of the spatial error model is generally carried out by the maximum likelihood or generalized moments estimation (Kelejian and Prucha, 1999). In this study, the maximum likelihood estimation is used for both the spatial lag and spatial error models. The regression models are estimated using GeoDa, freestanding geodata analysis software (Spatial Analysis Lab, 2005). More detailed descriptions of the spatial regression models are provided by Anselin (1988) and Anselin and Bera (1998).

There are a number of ways to specify spatial weights (Anselin, 1988, 2002; Anselin and Bera, 1998; Cliff and Ord, 1973, 1981). Typical specifications are: the *rook*-

(common boundaries), *bishop*- (common vertices) and *queen*- (common boundaries as well as vertices) based contiguity spatial weights; and distance-based spatial weights where two observations at $i$ and $j$ are considered neighbors if the distance between $i$ and $j$ is less than a given cutoff value. In practice, a spatial weights matrix is rather arbitrarily selected, especially when there is no formal theoretical foundation for the extent of spatial interaction. After testing the first-order rook-based spatial weights, queen-based contiguity spatial weights, and distance-based spatial weights using various cutoff distance values, we elected to use the first-order queen-based contiguity spatial weights, as they generally yielded better fits and it is reasonable to consider zones having common boundaries and vertices as neighbors.

Anselin (2005) suggests that the choice of the spatial lag or spatial error model can be made based on four Lagrange Multiplier (LM) tests—two LM tests for spatial lag and spatial error dependence (LM-Lag and LM-Error, respectively) and two robust LM tests for spatial lag and spatial error dependence (Robust LM-Lag and Robust LM-Error, respectively). Since both LM-Lag and LM-Error test statistics were highly significant in all the estimated OLS models, we subsequently investigated the Robust LM-Lag and Robust LM-Error test statistics. If one of them is more significant than another, the model for more significant statistics is preferable; if the Robust LM-Lag test statistics is more significant than the Robust LM-Error test statistics, the spatial lag model is preferably estimated, or vice versa. If two of the statistics are highly significant, the model with the largest test statistics is selected, although in this case we have to be cautious about other sources of misspecification.

### *4.3 Data*

The spatial unit of the analysis is the regional travel analysis zone (RTAZ), which is delineated to serve as the smallest geographic basis for travel demand model forecasting systems by the Metropolitan Transportation Commission (MTC), the regional transportation planning agency for the San Francisco Bay Area. In this study, we use the 1099 RTAZ system (a total of 1,099 zones in the San Francisco Bay Area).

The calculations of job accessibility use data on the numbers of jobs and workers, the rates of auto ownership, and OD commuting times by car and public transit. Data on the numbers of jobs and workers and the rates of auto ownership are extracted from the Urban Elements of 1990 and 2000 Census Transportation Planning Packages (CTPPs). CTPPs for San Francisco do not contain data summarized for RTAZs, but they have data summarized for census traffic analysis zones (CTAZs) which are more disaggregated than RTAZs. We created an area-weighted factor table using GIS and used it to aggregate the CTAZ-level data to RTAZ-level data. Data on 1990 and 1998 OD average commuting times by car and public transit are provided by MTC.

Data on the average commuting times for car and public transit at the spatial level of RTAZ are not available, so we created these commuting time data using CTPPs, which contain data on the number of workers by travel mode and average travel time by travel mode at the spatial level of CTAZ, as follows. First, for each commuting mode, multiply the number of workers by average travel time at the CTAZ level and obtain aggregated travel time at the CTAZ level. Second, for each commuting mode, aggregate the travel time aggregated at the CTAZ level to the RTAZ level and get travel time aggregated at the RTAZ level. Third, for each commuting mode, aggregate the number of workers at the CTAZ level to the RTAZ level and obtain the number of workers at the RTAZ level. And finally, for each commuting mode, divide the travel time aggregated at the RTAZ level by the number of workers aggregated at the RTAZ level and obtain average commuting time at the RTAZ level.

Data for the neighborhood socioeconomic variables in the regression models are obtained from 1990 and 2000 CTPPs, 1990 Census Summary Tape File 3A (STF3A), and 2000 Census Summary File 3 (SF3). The CTAZ-level data for CTPPs, census tract-level data for STF3A, and census block group-level data for SF3 are converted to RTAZ-level data. For the income variable, we use mean household income (not median household income) since for the RTAZ level, mean household income can be calculated but median household income cannot be computed with available data.

# 5 Empirical Results

We present results for visualization in the maps (visualized results) and then results for regression analysis (regression results).

## *5.1 Visualized Results*

Figures 1 to 4 show a series of maps that visualize job accessibility and average commuting times which are calculated at the spatial level of RTAZ for car and public transit in 2000 and that visualize their temporal changes from 1990 to 2000.[1] It is apparent that there is considerable inequality in job accessibility and commuting time between car and public transit and among locations within the San Francisco Bay Area. It is also apparent that there are substantial spatial variations in the temporal changes in job accessibility and average commuting time for car as well as for public transit within the metropolitan area.

[1] As reference, we present maps that visualize job accessibility and average commuting time for all travel modes in 2000 and that visualize their temporal changes from 1990 to 2000 in Figures a1 and a2 in Appendix. General job accessibility in resident zone $i$ ($A_i^G$) is calculated as follows:

$$A_i^G = \alpha_i A_i^{auto} + (1-\alpha_i) A_i^{tran} \cdot \qquad (7)$$

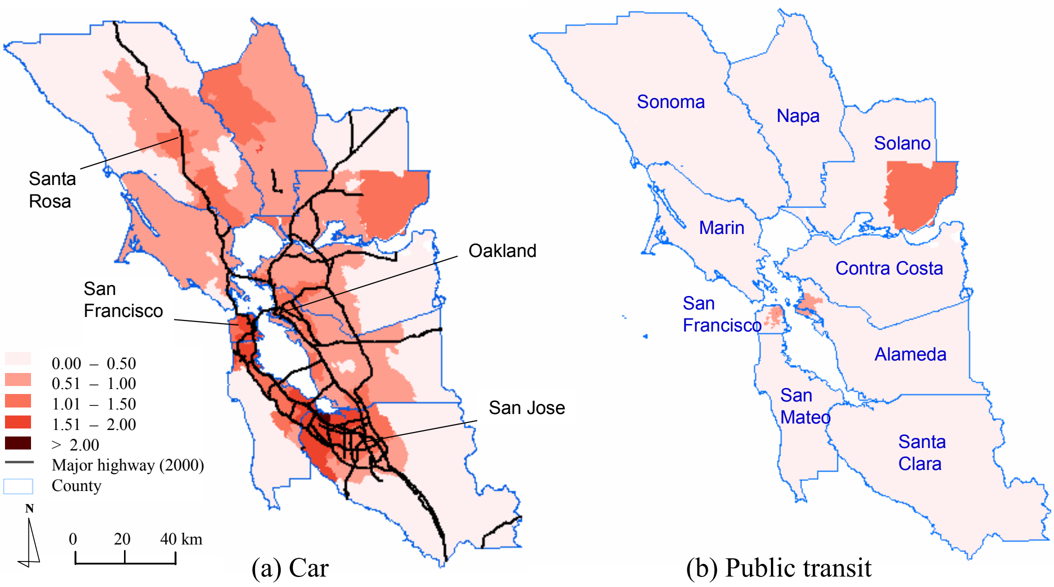



**Figure 1.** Job accessibility in the San Francisco Bay Area in 2000

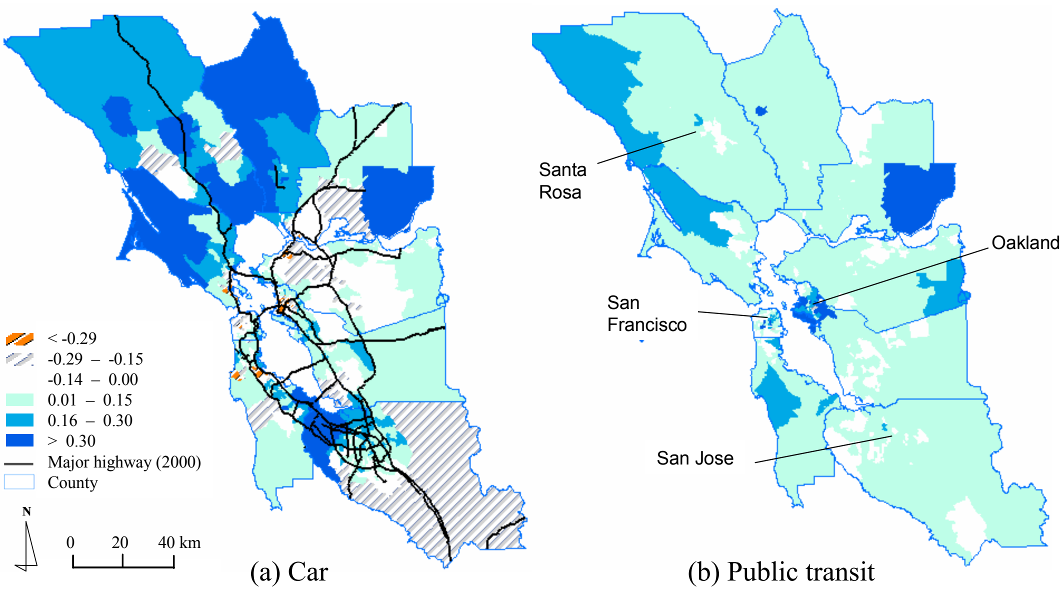
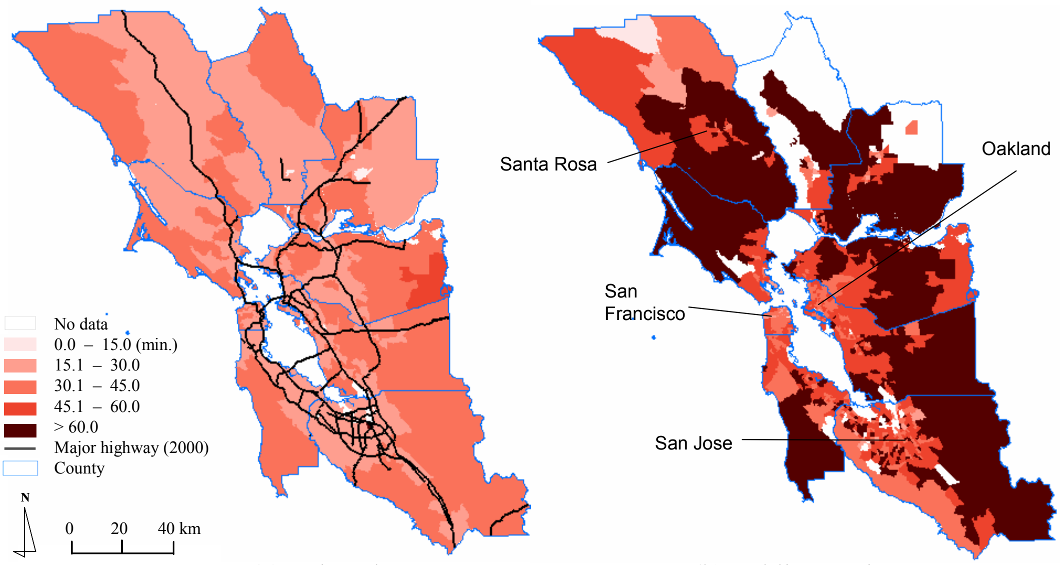
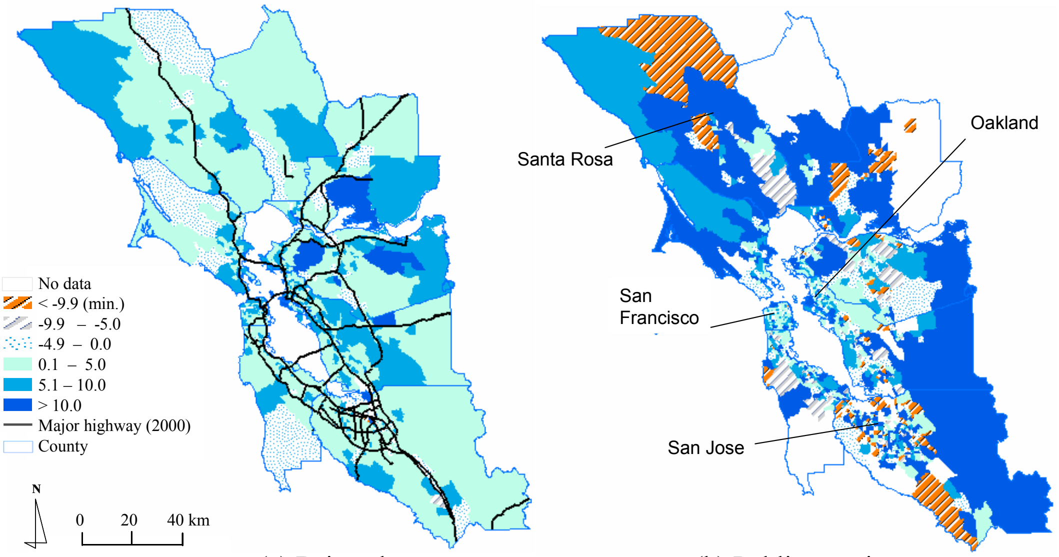



**Figure 2.** Changes in job accessibility in the San Francisco Bay Area from 1990 to 2000




(a) Drive alone (b) Public transit

**Figure 3.** Average travel time to work in the San Francisco Bay Area in 2000




(a) Drive alone (b) Public transit

**Figure 4.** Changes in average travel time to work in the San Francisco Bay Area from 1990 to 2000

Figure 1 indicates that job accessibility for public transit users is considerably lower than that for car users, and that job accessibility varies among locations within the metropolitan area. Since the weighted average of job accessibility is 0.97 (which represents the ratio of the total number of jobs to the total number of potential workers looking for jobs in the whole metropolitan area), a job accessibility value above one (which approximates the overall weighted average) can be considered relatively high job accessibility, and a value below one can be considered relatively low job accessibility. For people who commute by public transit, job accessibility is very low (a value below 0.5) in most zones, whereas it is relatively high in only a limited number of zones around the northeastern area of San Francisco City and the southeastern area of Solano County.[2] For people who commute by car, on the other hand, job accessibility is relatively high in many zones, especially locations surrounding the San Francisco Bay.

Figure 2 illustrates temporal changes in job accessibility from 1990 to 2000 substantially differing among locations within the metropolitan area for car as well as for public transit. For car users, job accessibility increased markedly in some zones, while it decreased noticeably in other zones. For public transit users, on the other hand, job accessibility increased in most metropolitan zones. This latter result suggests improved public transit systems for the San Francisco Bay Area, which may be related to the fact that transit usage did increase during the 1990s for the first time over the past four decades as noted earlier.

Figure 3 shows that commuting time by public transit is considerably longer than commuting time by driving alone and that commuting times for both travel modes differ considerably by location within the metropolitan area. Commuting times tend to be shorter in zones around the San Francisco Bay than in zones around the outer suburbs. Commuting times by public transit in the outer suburbs are especially long, often exceeding 60 minutes. When the results in Figures 1 and 3 are compared to each other, the zones showing higher job accessibility appear to overlap with the zones showing shorter commuting times for car as well as for public transit.

Figure 4 illustrates that there are substantial spatial variations in temporal changes in average commuting times for both driving alone and public transit during the period between 1990 and 2000. The principal finding is that average commuting time by driving alone increased in most zones in the metropolitan area, while average commuting time by public transit decreased in a relatively large number of zones, especially locations around the San Francisco Bay.

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[2] The relatively high job accessibility zone in the eastern Solano County appears aberrant. With a 30-minute threshold, the zone has an accessibility value of 1.01, which is the same as the ratio of jobs to workers in that zone (Figure 1). In other words, with a 30-minute threshold, this zone is beyond the reach of other zones. When the threshold time lengthens, however, the accessibility value for this zone becomes smaller (for example, 0.03 for the 45-minute threshold) because jobs in this zone are now accessible for workers residing in some of the neighboring zones.

## *5.2 Regression Results*

Table 2 shows variables and their descriptive statistics, and Tables 3 and 4 present regression results estimated from the models of average commuting times by driving alone and public transit, respectively.[3] Likewise, the results estimated from the three models (OLS, spatial lag, and spatial error models) are presented so that the estimate variables can be compared to each other. In addition to $R^2$ and adjusted $R^2$ values for OLS, the tables report the Log-Likelihood, Akaike information criterion (AIC), and Schwarz criterion (SC) values which can be used to compare goodness-of-fit across the three models mentioned above. A higher log-likelihood value indicates a better fit, and a lower AIC or SC value, which takes into account the number of parameters, suggests a better fit.

**Table 2.** Variable descriptions and descriptive statistics

| | 1990 | | 2000 | |
|---|---|---|---|---|
| Variable | Mean | Std. dev. | Mean | Std. dev. |
| *Dependent variables* | | | | |
| Average travel time by driving alone | 23.4 | 4.2 | 27.2 | 4.8 |
| Average travel time by public transportation | 47.6 | 13.2 | 53.0 | 16.3 |
| Average travel time by all modes* | 25.4 | 4.7 | 29.1 | 5.2 |
| | | | | |
| *Explanatory variables* | | | | |
| Accessibility for car users (30 min.) | 1.03 | 0.43 | 1.08 | 0.45 |
| Accessibility for public transit users (30 min.) | 0.09 | 0.16 | 0.14 | 0.20 |
| General accessibility (30 minutes)* | 0.91 | 0.37 | 0.96 | 0.41 |
| % Public transit commuters (excluding taxicab) | 9.6 | 11.4 | 10.1 | 10.4 |
| Employment density (jobs per $km^2$) | 2,166 | 8,909 | 2,243 | 9,840 |
| Population density (persons per $km^2$) | 3,040 | 3,963 | 3,316 | 4,207 |
| % Female civilian labor force | 45.0 | 6.6 | 45.6 | 5.6 |
| % Female-headed households | 16.2 | 9.7 | 16.4 | 9.2 |
| Mean household income ($) | 52,722 | 23,732 | 84,582 | 38,739 |
| % Persons without high school diplomas | 17.7 | 12.8 | 16.0 | 13.0 |
| % Foreign-born | 19.3 | 11.9 | 26.1 | 14.2 |
| % Non-Hispanic white** | 62.3 | 23.7 | 52.0 | 24.5 |
| % Non-Hispanic black | 8.8 | 15.4 | 7.4 | 12.2 |
| % Non-Hispanic Asian | 13.9 | 12.6 | 17.7 | 15.9 |
| % Hispanic | 14.4 | 13.3 | 18.0 | 15.9 |
| % Other races | 0.7 | 0.6 | 4.8 | 2.8 |
| % Management, business, and financial operations occupations | 16.2 | 8.1 | 18.1 | 8.5 |
| % Professional and related occupations | 21.2 | 10.0 | 25.6 | 11.3 |
| % Service occupations | 12.0 | 7.5 | 12.8 | 6.9 |
| % Sales and office occupations | 28.5 | 6.2 | 25.4 | 5.7 |
| % Farming, fishing, and forestry occupations | 1.7 | 3.3 | 0.5 | 2.7 |
| % Construction, extraction, and maintenance occupations | 10.1 | 5.7 | 7.4 | 4.7 |
| % Production, transportation, and material moving occupations** | 10.3 | 6.4 | 10.1 | 7.3 |

Note: Means are unweighted zonal averages and hence are not consistent with those in Table 1. Observations with no data are excluded. Public transportation includes bus or trolley bus, streetcar or trolley car, subway or elevated, railroad, and excludes ferryboat, taxicab, and motorcycle. *Variables used in the models for all travel modes presented in Appendix. **Variables not included in the models.

[3] As reference, regression results estimated from the models of average commuting time by all travel modes are presented in Table a1 in Appendix.

**Table 3.** Estimation results for average commuting time by driving alone

| | OLS | | Lag-ML | | Err-ML | |
|---|---|---|---|---|---|---|
| Variable | 1990 | 2000 | 1990 | 2000 | 1990 | 2000 |
| Constant | **17.273** | **42.141** | 2.115 | **24.917** | **22.035** | **45.112** |
| | (5.26) | (13.91) | (0.76) | (8.79) | (8.20) | (16.47) |
| Job accessibility for car users | **-5.290** | **-6.135** | **-2.417** | **-3.228** | **-4.061** | **-5.021** |
| (30 min) | (-14.96) | (-17.59) | (-7.82) | (-9.44) | (-7.74) | (-9.63) |
| Employment density | 0.00001 | 0.00001 | -0.00002 | -0.00002 | **-0.00006** | -0.00002 |
| (jobs per km$^2$) | (0.44) | (0.97) | (-1.21) | (-1.43) | (-3.57) | (-0.90) |
| Population density | **0.00013** | **0.00037** | *0.00005* | **0.00020** | -0.00004 | **0.00019** |
| (persons per km$^2$) | (4.09) | (9.73) | (1.86) | (5.98) | (-1.09) | (4.13) |
| % Female civilian labor force | **-0.157** | **-0.197** | **-0.146** | **-0.179** | **-0.151** | **-0.225** |
| | (-7.01) | (-7.02) | (-8.05) | (-7.39) | (-7.38) | (-8.79) |
| % Female-headed households | *0.032* | *-0.041* | **0.044** | -0.025 | **0.047** | -0.020 |
| | (1.71) | (-1.91) | (2.91) | (-1.39) | (3.03) | (-1.07) |
| Mean household income ($) | **0.00002** | **-0.00001** | 0.00001 | **-0.00002** | 0.00000 | **-0.00002** |
| | (2.09) | (-2.65) | (1.10) | (-3.64) | (-0.09) | (-4.32) |
| % Persons without high | **-0.041** | **-0.058** | *-0.031* | *-0.042* | **-0.044** | **-0.051** |
| school diplomas | (-1.96) | (-2.30) | (-1.84) | (-1.95) | (-2.45) | (-2.26) |
| % Foreign-born | 0.017 | *-0.046* | *0.040* | 0.006 | *0.047* | 0.020 |
| | (0.58) | (-1.76) | (1.74) | (0.25) | (1.78) | (0.82) |
| % Non-Hispanic black | **0.045** | **0.094** | **0.028** | **0.064** | **0.027** | **0.067** |
| | (3.98) | (6.65) | (3.04) | (5.28) | (2.37) | (4.14) |
| % Non-Hispanic Asian | **0.094** | **0.084** | **0.042** | *0.031* | **0.053** | 0.023 |
| | (4.14) | (4.22) | (2.31) | (1.84) | (2.46) | (1.12) |
| % Hispanic | 0.009 | 0.006 | -0.010 | -0.016 | -0.014 | *-0.035* |
| | (0.48) | (0.31) | (-0.68) | (-0.99) | (-0.75) | (-1.80) |
| % Other races | **-0.440** | 0.044 | **-0.362** | 0.019 | **-0.373** | -0.015 |
| | (-2.31) | (0.92) | (-2.36) | (0.47) | (-2.49) | (-0.35) |
| % Management, business, and | **0.142** | **0.181** | **0.101** | **0.145** | **0.068** | **0.174** |
| financial operations occupations | (3.59) | (4.92) | (3.14) | (4.58) | (2.13) | (5.27) |
| % Professional and related | **0.099** | **-0.103** | **0.119** | **-0.080** | **0.093** | **-0.114** |
| occupations | (2.99) | (-3.30) | (4.44) | (-3.01) | (3.42) | (-4.04) |
| % Service occupations | **0.107** | 0.009 | **0.086** | -0.013 | 0.044 | -0.037 |
| | (2.61) | (0.24) | (2.60) | (-0.39) | (1.33) | (-1.06) |
| % Sales and office occupations | **0.248** | -0.008 | **0.206** | -0.024 | **0.176** | -0.019 |
| | (6.67) | (-0.21) | (6.82) | (-0.77) | (5.94) | (-0.60) |
| % Farming, fishing, and | **0.226** | **-0.143** | **0.236** | **-0.111** | **0.179** | **-0.149** |
| forestry occupations | (3.70) | (-2.81) | (4.76) | (-2.54) | (3.35) | (-3.43) |
| % Construction, extraction, and | **0.261** | 0.040 | **0.236** | 0.019 | **0.218** | 0.013 |
| maintenance occupations | (4.95) | (0.81) | (5.54) | (0.46) | (5.14) | (0.31) |
| $\rho$ | | | **0.626** | **0.546** | | |
| $\lambda$ | | | (21.87) | (17.50) | **0.694** | **0.624** |
| | | | | | (25.28) | (19.91) |
| N | 1,068 | 1,075 | 1,068 | 1,075 | 1,068 | 1,075 |
| $R^2$ | 0.33 | 0.38 | | | | |
| Adjusted $R^2$ | 0.32 | 0.37 | | | | |
| Log likelihood | -2798.8 | -2942.7 | -2628.0 | -2817.1 | -2619.47 | -2809.5 |
| AIC | 5635.7 | 5923.5 | 5295.9 | 5674.2 | 5276.9 | 5657.0 |
| SC | 5730.1 | 6018.1 | 5395.4 | 5773.8 | 5371.4 | 5751.7 |
| LM (lag) | **442.63** | **326.11** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| Robust LM (lag) | **40.61** | **17.23** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| LM (error) | **407.48** | **331.92** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| Robust LM (error) | **5.46** | **23.05** | | | | |
| *P-value* | 0.02 | 0.00 | | | | |

Note: *t* statistics (OLS) and *z* statistics (Lag-ML and Err-ML) are in parentheses. **Bold** indicates significant at $p<0.05$, and *italic* denotes significant at $p<0.10$.

**Table 4.** Estimation results for average commuting time by public transit

| | OLS | | Lag-ML | | Err-ML | |
|---|---|---|---|---|---|---|
| | 1990 | 2000 | 1990 | 2000 | 1990 | 2000 |
| | Coef. | Coef. | Coef. | Coef. | Coef. | Coef. |
| Constant | **77.358** | **64.999** | **51.098** | **34.812** | **69.819** | **55.743** |
| | (5.63) | (4.76) | (3.91) | (2.66) | (5.25) | (4.03) |
| Job accessibility for public | **-20.677** | **-15.106** | **-11.332** | **-9.107** | **-20.493** | **-12.637** |
| transit users (30 min) | (-5.91) | (-4.86) | (-3.32) | (-3.06) | (-4.91) | (-3.46) |
| Employment density | -0.00004 | -0.00008 | -0.00004 | -0.00006 | -0.00005 | *-0.00011* |
| (jobs per km$^2$) | (-0.87) | (-1.39) | (-0.78) | (-1.08) | (-0.85) | (-1.65) |
| Population density | **-0.00036** | **-0.00050** | **-0.00030** | *-0.00028* | **-0.00040** | **-0.00045** |
| (persons per km$^2$) | (-3.04) | (-3.13) | (-2.73) | (-1.85) | (-3.24) | (-2.52) |
| % Female civilian labor force | **-0.256** | -0.190 | **-0.213** | -0.142 | **-0.227** | -0.127 |
| | (-2.99) | (-1.57) | (-2.65) | (-1.24) | (-2.61) | (-1.03) |
| % Female-headed households | **-0.178** | **-0.238** | *-0.122* | **-0.178** | *-0.120* | *-0.163* |
| | (-2.57) | (-2.77) | (-1.88) | (-2.21) | (-1.77) | (-1.96) |
| Mean household income ($) | 0.00004 | 0.00000 | 0.00004 | 0.00000 | *0.00005* | -0.00001 |
| | (1.52) | (-0.10) | (1.53) | (-0.01) | (1.81) | (-0.23) |
| % Persons without high | **-0.203** | -0.159 | *-0.139* | -0.131 | -0.113 | -0.161 |
| school diplomas | (-2.47) | (-1.51) | (-1.80) | (-1.32) | (-1.39) | (-1.53) |
| % Foreign-born | -0.140 | **-0.229** | -0.092 | *-0.175* | -0.108 | *-0.181* |
| | (-1.44) | (-2.21) | (-1.00) | (-1.79) | (-1.06) | (-1.67) |
| % Non-Hispanic black | 0.006 | *0.096* | 0.010 | *0.096* | -0.025 | 0.096 |
| | (0.16) | (1.76) | (0.26) | (1.86) | (-0.58) | (1.58) |
| % Non-Hispanic Asian | 0.076 | *0.141* | 0.069 | *0.131* | 0.057 | 0.134 |
| | (0.98) | (1.73) | (0.95) | (1.72) | (0.71) | (1.54) |
| % Hispanic | *-0.108* | -0.069 | -0.072 | -0.022 | -0.093 | -0.038 |
| | (-1.69) | (-0.94) | (-1.20) | (-0.31) | (-1.35) | (-0.47) |
| % Other races | -1.010 | -0.108 | -0.974 | -0.014 | -0.669 | 0.016 |
| | (-1.58) | (-0.56) | (-1.63) | (-0.08) | (-1.10) | (0.08) |
| % Management, business, and | -0.172 | 0.022 | -0.168 | 0.119 | -0.172 | 0.144 |
| financial operations occupations | (-1.09) | (0.14) | (-1.14) | (0.83) | (-1.13) | (0.92) |
| % Professional and related | **-0.279** | -0.059 | -0.178 | 0.016 | -0.169 | -0.021 |
| occupations | (-2.02) | (-0.43) | (-1.38) | (0.12) | (-1.25) | (-0.15) |
| % Service occupations | 0.050 | 0.171 | -0.004 | 0.185 | -0.007 | 0.172 |
| | (0.31) | (1.08) | (-0.03) | (1.25) | (-0.04) | (1.08) |
| % Sales and office occupations | -0.010 | 0.124 | 0.021 | 0.126 | 0.059 | 0.129 |
| | (-0.06) | (0.75) | (0.14) | (0.81) | (0.39) | (0.79) |
| % Farming, fishing, and | **0.771** | *0.740* | **0.612** | *0.672* | **0.633** | *0.792* |
| forestry occupations | (3.35) | (1.77) | (2.83) | (1.71) | (2.74) | (1.80) |
| % Construction, extraction, and | 0.044 | **1.000** | -0.018 | **0.817** | -0.012 | **0.893** |
| maintenance occupations | (0.22) | (4.71) | (-0.10) | (4.08) | (-0.06) | (4.29) |
| $\rho$ | | | **0.384** | **0.369** | | |
| | | | (9.75) | (9.53) | | |
| $\lambda$ | | | | | **0.382** | **0.378** |
| | | | | | (9.21) | (9.10) |
| N | 1,033 | 1,044 | 1,033 | 1,044 | 1,033 | 1,044 |
| $R^2$ | 0.31 | 0.26 | | | | |
| Adjusted $R^2$ | 0.30 | 0.24 | | | | |
| Log likelihood | -3940.9 | -4216.1 | -3896.30 | -4173.7 | -3904.8 | -4182.3 |
| AIC | 7919.8 | 8470.1 | | 8387.3 | | 8402.5 |
| SC | 8013.7 | 8564.2 | | 8486.3 | | 8496.6 |
| LM (lag) | **110.37** | **100.38** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| Robust LM (lag) | **29.99** | **26.46** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| LM (error) | **84.21** | **74.87** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| Robust LM (error) | **3.83** | 0.95 | | | | |
| *P-value* | 0.05 | 0.33 | | | | |

Note: *t* statistics (OLS) and *z* statistics (Lag-ML and Err-ML) are in parentheses. **Bold** indicates significant at $p<0.05$, and *italic* denotes significant at $p<0.10$.

In the models estimated for both driving alone and public transit, the spatial lag and spatial error models generate better fits than do the OLS models (as suggested by the Log-likelihood, AIC, and SC values), and the spatial autoregressive coefficients are highly significant. In the models estimated for driving alone, LM test statistics suggest the spatial lag model as the preferable one for 1990 but the spatial error model as the preferable one for 2000. For both 1990 and 2000, the spatial error models generate the best fit among the three models, but the results for spatial lag and spatial error models are largely consistent with one another. In the models estimated for public transit, in both 1990 and 2000 LM test statistics suggest the spatial lag model as the preferable one, and the spatial lag model indeed offers the best fit. Below, we discuss the results for 2000 first and temporal changes that occurred from 1990 to 2000 subsequently.

First, we discuss the results for 2000. The estimate variables indicate that job accessibility, the variable of particular interest, is inversely and significantly associated with commuting time for driving alone as well as for public transit, after controlling for the other variables related to urban spatial structure. The degree (represented by coefficients) and significance (represented by *t* statistics) of the job accessibility variables are smaller for the spatial regression models (with consideration of spatial autocorrelation) than for the OLS models (without consideration of spatial autocorrelation). This result suggests that an OLS model that does not take into account spatial autocorrelation is likely to inflate the association between job accessibility and commuting time. Still, job accessibility estimated from the spatial regression models exhibit strong associations with commuting time. The degree of the inverse association between job accessibility and commuting time is considerably greater for public transit than for driving alone. For example, the estimated spatial lag models indicate that an increase of 0.41 in job accessibility (one standard deviation of general job accessibility which combines job accessibility for car and public transit) is associated with a decrease of 1.3 minutes for driving alone but is associated with a larger decrease of 3.7 minutes for public transit.

Some of the other urban spatial structure variables also show significant associations with commuting time. We discuss notable results from the best-fitting models; the spatial error model for driving alone and the spatial lag model for public transit. In the model estimated for driving alone, the association between population density and commuting time is positive and significant, which suggests that greater congestion eventually slows travel speed for solo driver commuters. In the model estimated for public transit, on the other hand, the association between population density and commuting time is negative and significant. This result is understandable by considering that public transportation service is usually rather frequent in high density locations and that transit commuting time is rather unaffected by congestion.

An increase in the proportion of female workers is significantly associated with a decrease in commuting time by driving alone, as is the association between the proportion of female-headed households and commuting time by public transit. These results are consistent with observations in a number of studies which suggest that women often work near home because they tend to shoulder domestic burdens and must balance home and work responsibilities (e.g., Blumenberg, 2004; Hanson and Pratt, 1995; Rosenbloom, 1994; Schwanen *et al.*, 2004; Shen, 2000). Mean household income is inversely and significantly associated with commuting time by driving alone, which may suggest that more working families with modest incomes endure long commutes in order to afford housing. The proportion of residents without a high school diploma is inversely and significantly associated with commuting time by driving alone, which suggests that less educated people tend to work in a more localized labor market.

An increase in the proportion of black residents is significantly associated with an increase in commuting time by driving alone as well as by public transit, as is the association between the proportion of Asian residents and commuting time by public transit. These results may result from racial segregation and/or racial minorities residing in relatively congested areas. An increase in the proportion of Hispanic residents, on the other hand, is significantly associated with a decrease in commuting time by driving alone, which may suggest that the areas sought by Hispanic workers looking for work in San Francisco are relatively localized.

Some neighborhood occupation compositions show significant associations with commuting time, when we use the percentage of residents who work in production, transportation, and material moving occupations as the base case. In the model estimated for driving alone, the percentage of residents who work in management, business, and financial operations occupations is significantly and positively associated with commuting time, and the percentages of residents who work in professional and related occupations and farming, fishing, and forestry occupations are significantly and inversely associated with commuting time. The shorter commuting time associated with workers in farming, fishing, and forestry occupations is reasonable since these workers tend to live where they work and hence to have short commutes. The other associations are difficult to explain without further investigation. In the model estimated for public transit, the percentage of residents who work in farming, fishing, and forestry occupations and the percentage of residents who work in construction, extraction, and maintenance occupations are positively and significantly associated with commuting time. The positive association for the percentage of workers in farming, fishing, and forestry is unexpected, and additional research is required before a satisfactory explanation can be given. The positive association for the percentage of workers in construction, extraction, and maintenance occupations is understandable, considering that these workers do not often have fixed workplaces and therefore cannot readily optimize their commutes.

Next, we discuss temporal changes that occurred between 1990 and 2000, based mainly on the best-fitting models: the spatial error models for driving alone and the spatial lag models for public transit.

Between 1990 and 2000, the degree and significance of the inverse association between job accessibility and commuting time increased for driving alone but decreased for public transit. Several factors may account for these changes. During this ten year interval, commuting time increased noticeably, whereas commuting time had been almost unchanged or increased at a modest rate until 1990. Indeed, between 1990 and 2000 the noticeable increases in commuting time occurred for car as well as for public transit as noted earlier. The increase in commuting time for car may be largely due to exacerbated congestion, which presumably makes job accessibility to be a rather important factor associated with commuting time. The increase in commuting time for public transit, on the other hand, may be substantially influenced by changes in socioeconomic structure and people's lifestyles in downtown and its surrounding areas. In fact, the period between 1990 and 2000 experienced increases in the proportion of workers who obtained higher educational degrees and also the proportion of workers who chose to use public transit despite their car ownership.[4] It can be supposed that some of these people prefer and afford to live in the suburbs while taking public transit to work, which might confound the inverse association between job accessibility and commuting time. The in-depth examination of factors behind these changes may be a topic for future research.

Some of the other urban spatial structure variables show noticeable changes. In the models estimated for driving alone, the inverse association between employment density and commuting time is not significant in 2000 but is significant in 1990 (though the association is insignificant in the OLS and spatial lag models). The degree and significance of the association between population density and commuting time are greater in 2000 than in 1990 (not only in the spatial error model but also in the OLS and spatial lag models), which suggests that population density plays an increasing role in the explanation of variation in commuting time by driving alone. It should be noted that in both 1990 and 2000, the association between job accessibility and commuting time are more significant than the association between employment/population density and commuting time by driving alone as well as by public transit. This result suggests that in the explanation of variation in commuting time by travel mode, job accessibility (which takes into account the spatial distributions of jobs and workers in addition to travel mode) is a more important factor than employment and population densities.

The association between the proportion of female-headed households and commuting time by driving alone shows an inverse and insignificant trend in 2000, whereas it shows a positive and significant trend in 1990. This result is unexpected and warrants further investigation to explain why this temporal change took place. By contrast, the association between mean household income and commuting time by driving alone shows an inverse and significant trend in 2000, whereas it shows a positive but insignificant trend in 1990. This temporal change may suggest that during the 1990s, the high price of housing in San Francisco forced many working families to live in outskirts of the city.

While the estimate variables for racial composition are almost consistent in 1990 and 2000 (a few variables are inconsistent for the OLS and spatial lag models though), the significance of some racial estimate variables exhibit notable changes. In the models estimated for driving alone, the associations between the proportions of Asian residents and commuting time and between other races and commuting time are insignificant in 2000 but are significant in 1990. In the models estimated for public transit, the associations between the proportions of black residents and commuting time and between Asian residents and commuting time are significant in 2000 but are insignificant in 1990.

[4] For example, the authors' calculations from the 5-Percent Public-Use Microdata Samples (PUMS) of 1990 and 2000 for the San Francisco Bay Area indicate that between those years, the proportion of public transit commuters with bachelor's degrees or higher increased from 42% to 50%, and the proportion of public transit commuters living in households with two or more cars increased from 44% to 46%. Meanwhile, the proportion of drive alone commuters in multiple-car owning households decreased from 80% to 77%.

These temporal changes may have taken place due to the changes in the racial composition between 1990 and 2000 (see Table 2).

Similarly, the estimate variables for occupation composition changed during the 1990s, which may be related to rather complicated temporal changes in the associations between occupation composition variables and commuting time. For example, in the models constructed for driving alone, the association between the proportion of residents who work in professional and related occupations and commuting time shows an inverse and significant trend in 2000, whereas it shows a positive and significant trend in 1990. Also, the association between the proportion of residents who work in farming, fishing, and forestry occupations and commuting time shows an inverse and significant trend in 2000, whereas it shows a positive and significant trend in 1990. In the models estimated for public transit, the association between the proportion of residents who work in construction, extraction, and maintenance occupations and commuting time shows a positive and significant trend in 2000, whereas it shows an inverse and insignificant trend in 1990.

As shown thus far, signs and significance for some variables changed among the three models and between 1990 and 2000. The results for job accessibility, however, are robust in the following two points: (1) job accessibility is inversely and significantly associated with commuting time by driving alone as well as by public transit, and (2) the degree of this inverse association is greater for public transit than for driving alone. Using the OLS models, we investigated sensitivity to alternative specifications of job accessibility at the thresholds of 15, 45, 60, 75, and 90 minutes. We found that the two above-noted points held true except for a few cases: neither job accessibility at the threshold of 90 minutes for driving alone nor job accessibility at the threshold of 15 minutes for public transit showed significant association with commuting time in both 1990 and 2000. However, these exceptions are unlikely to occur because the assumed range in the above cases is quite rare, that is, the threshold of 90 minutes is over three times of the average commuting time for driving alone, and the threshold of 15 minutes is about one-third the average commuting time for public transit (see Table 1).

## 6 Conclusions

Using 1990 and 2000 spatial and temporal data at the spatial level of RTAZ for the San Francisco Bay Area, this empirical study has shown considerable inequality in commuting between car and public transit.

Our results visualized in the maps showed that there was considerable inequality in job accessibility and commuting time between car and public transit and among locations within the metropolitan area. The visualized results also showed that there were substantial spatial variations in the temporal changes in job accessibility and commuting time for car as well as for public transit. Here, it must be noted that job accessibility for car users increased in some zones and decreased in other zones, whereas job accessibility for public transit users increased in most zones. This result may be related to the slight increase in the proportion of public transit commuters that occurred during the 1990s, the first such increase in the San Francisco Bay Area since 1960. Also, noteworthy is the fact that commuting time by driving alone increased in most zones, whereas commuting time by public transit decreased in a relatively large number of zones. These two notable changes may be related to improvements in public transit systems. Still, our visualized results as a whole clearly indicate that job accessibility for public transit is considerably lower than that for car, and commuting time by public transit is markedly longer than that by car.

Subsequently, we estimated the OLS, spatial lag, and spatial error regression models that examine the associations between urban spatial structure and commuting time in general and between job accessibility and commuting time in particular, and compared the results for driving alone with the results for public transit. The main findings are summarized in the following three points. First, in both 1990 and 2000 job accessibility was inversely and significantly associated with commuting time for driving alone as well as for public transit, after adjusting for the other variables related to urban spatial structure. The spatial regression models with consideration of spatial autocorrelation turned out to reduce the degree and significance of the association between job accessibility and commuting time that had been estimated from the OLS models without consideration of spatial autocorrelation. Still, job accessibility estimated from the spatial regression models exhibited strong associations with commuting time. Second, in both 1990 and 2000, the degree of this inverse association was considerably greater for public transit than for driving alone. And third, when the results were compared between 1990 and 2000, the inverse association between job accessibility and commuting time strengthened for driving alone but weakened for public transit. Possible factors behind these temporal changes were discussed.

With the visualization and regression analyses taken together, the empirical results suggest that workers who use public transit are considerably disadvantaged in accessing jobs as compared to those who drive to work, and also suggest that already-built environments and residential locations are more important in commuting to work for public transit users than for car users. The empirical results further suggest that an improvement in job accessibility can shorten commuting time for car users as well as for public transit users, but the resultant reduction in commuting time by increasing the same level of job accessibility is greater for public transit users than for car users.

The considerable commuting inequality between car and public transit calls for more attention to the equity issue, a principal component of sustainability in urban development and transportation. Potentially effective approaches to narrowing the car/public transport disparity include the improvement of public transit mobility and accessibility and the promotion of transit-friendly urban spatial structure. We point out that such efforts are helpful not only for people who do not have private vehicles, as is often the case for disadvantaged people such as low-skilled minority workers and welfare recipients, but also for people who cannot readily use cars for various reasons or who prefer using public transit.[5] For example, a worker in a household where multiple adults

[5] The 5-Percent PUMS of 2000 for the San Francisco Bay Area indicate that 80% of workers who use public transit to work are in households with one or more cars.

share a single car cannot use the car at his/her convenience. As the population ages, there will be more people who rely on public transit for mobility even though they can afford to own cars. There are also growing movements of reducing automobile dependence and increasing public transit usage alternatively. Mobility and accessibility enhancements for public transit are beneficial for all people in a system, not just for those who do not own cars.

This study was conducted for people who live in the San Francisco Bay Area, a metropolitan area with high public transit usage relative to the US average. The spatial and temporal dimensions of commuting inequality between car and public transit may be significantly different in more heavily auto-oriented metropolitan areas, such as Dallas and Detroit, or in metropolitan areas with much higher public transit usage, such as London and Tokyo. Systematic comparison of car/public transit commuting inequality between metropolitan areas with different transport systems and urban spatial structures is a topic for further examination.

## Acknowledgements

This research was supported by research grants from the Asahi Glass Foundation and Nihon-Shoken Scholarship Foundation. The authors wish to thank Chuck Purvis of the Metropolitan Transportation Commission for the San Francisco Bay Area for his assistance in obtaining transportation data used in this research.

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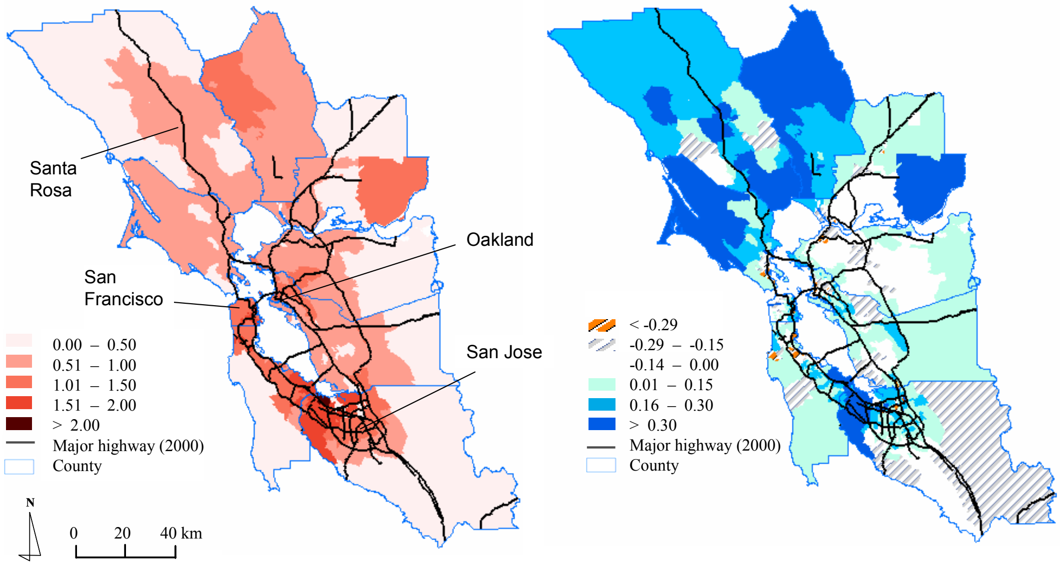
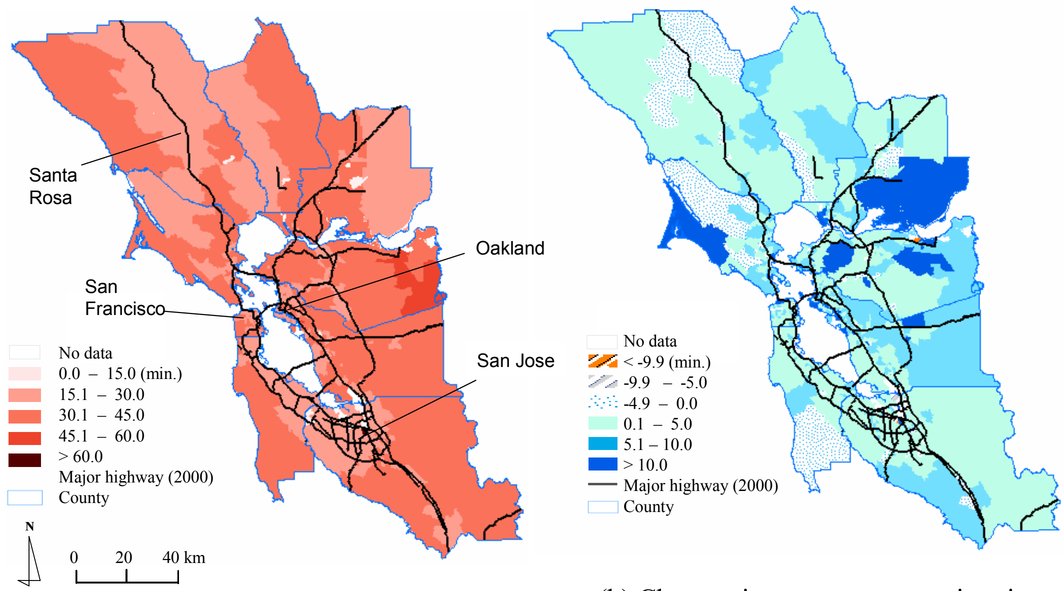
## Appendix




(a) Job accessibility in 2000

(b) Changes in job accessibility from 1990 to 2000

**Figure a1.** General job accessibility in the San Francisco Bay Area




(a) Average commuting time in 2000

(b) Changes in average commuting time from 1990 to 2000

**Figure a2.** Average travel time to work by all travel modes in the San Francisco Bay Area

**Table a1.** Estimation results for average commuting time by all travel modes

| | OLS | | Lag-ML | | Err-ML | |
|---|---|---|---|---|---|---|
| Variable | 1990 | 2000 | 1990 | 2000 | 1990 | 2000 |
| Constant | **21.194** | **27.968** | **5.420** | **10.377** | **20.967** | **27.847** |
| | (7.03) | (9.63) | (2.09) | (4.00) | (8.42) | (10.69) |
| General job accessibility | **-7.718** | **-7.123** | **-4.162** | **-3.728** | **-4.970** | **-5.196** |
| (30 min.) | (-21.22) | (-20.34) | (-12.08) | (-10.82) | (-9.15) | (-9.61) |
| % Public transit commuters | **0.255** | **0.205** | **0.142** | **0.097** | **0.200** | **0.106** |
| | (16.76) | (12.93) | (10.27) | (6.91) | (10.16) | (5.23) |
| Employment density | **-0.00008** | **-0.00011** | **-0.00004** | **-0.00007** | **-0.00007** | **-0.00008** |
| (jobs per km$^2$) | (-6.22) | (-8.48) | (-3.83) | (-6.69) | (-4.22) | (-4.99) |
| Population density | **-0.00031** | **-0.00019** | **-0.00023** | **-0.00009** | **-0.00028** | -0.00007 |
| (persons per km$^2$) | (-8.81) | (-4.47) | (-7.75) | (-2.52) | (-8.16) | (-1.44) |
| % Female civilian labor force | **-0.088** | *-0.048* | **-0.090** | **-0.065** | **-0.113** | **-0.106** |
| | (-4.19) | (-1.82) | (-5.24) | (-2.88) | (-6.13) | (-4.39) |
| % Female-headed households | -0.007 | **-0.060** | **0.032** | **-0.040** | **0.035** | *-0.029* |
| | (-0.37) | (-2.94) | (2.06) | (-2.35) | (2.22) | (-1.65) |
| Mean household income ($) | **0.000027** | 0.000002 | **0.000015** | -0.000006 | 0.000003 | *-0.000009* |
| | (3.91) | (0.38) | (2.60) | (-1.33) | (0.42) | (-1.88) |
| % Persons without high | **-0.106** | **-0.100** | **-0.070** | **-0.064** | **-0.085** | **-0.075** |
| school diplomas | (-5.25) | (-4.18) | (-4.17) | (-3.18) | (-4.71) | (-3.52) |
| % Foreign-born | **-0.060** | -0.008 | -0.006 | 0.034 | -0.012 | **0.055** |
| | (-2.13) | (-0.32) | (-0.26) | (1.62) | (-0.44) | (2.38) |
| % Non-Hispanic black | **0.052** | **0.122** | **0.025** | **0.084** | **0.029** | **0.103** |
| | (4.73) | (9.01) | (2.74) | (7.25) | (2.44) | (6.53) |
| % Non-Hispanic Asian | **0.127** | **0.091** | **0.065** | **0.036** | **0.077** | 0.020 |
| | (5.86) | (4.80) | (3.62) | (2.26) | (3.52) | (1.06) |
| % Hispanic | **0.112** | **0.062** | **0.059** | **0.031** | **0.075** | 0.019 |
| | (6.07) | (3.43) | (3.83) | (2.04) | (4.03) | (1.05) |
| % Other races | **-0.469** | 0.044 | **-0.434** | 0.026 | **-0.389** | 0.007 |
| | (-2.51) | (0.95) | (-2.82) | (0.67) | (-2.56) | (0.18) |
| % Management, business, and | **0.110** | **0.199** | **0.084** | **0.199** | **0.106** | **0.263** |
| financial operations occupations | (3.30) | (5.63) | (3.05) | (6.66) | (3.95) | (8.45) |
| % Professional and related | *0.052* | -0.037 | **0.090** | 0.002 | **0.108** | -0.002 |
| occupations | (1.71) | (-1.23) | (3.57) | (0.07) | (4.21) | (-0.08) |
| % Service occupations | **0.116** | **0.121** | **0.109** | **0.112** | **0.110** | **0.119** |
| | (3.38) | (3.23) | (3.85) | (3.55) | (3.92) | (3.59) |
| % Sales and office occupations | **0.192** | **0.096** | **0.153** | **0.081** | **0.168** | **0.108** |
| | (5.59) | (2.78) | (5.40) | (2.77) | (5.98) | (3.66) |
| % Farming, fishing, and | **-0.160** | **-0.225** | **-0.081** | **-0.192** | *-0.071* | **-0.217** |
| forestry occupations | (-3.34) | (-4.64) | (-2.05) | (-4.69) | (-1.72) | (-5.29) |
| % Construction, extraction, and | **0.264** | **0.178** | **0.215** | **0.127** | **0.195** | **0.130** |
| maintenance occupations | (5.53) | (3.78) | (5.45) | (3.20) | (5.01) | (3.28) |
| $\rho$ | | | **0.577** | **0.552** | | |
| | | | (20.72) | (18.81) | | |
| $\lambda$ | | | | | **0.693** | **0.677** |
| | | | | | (250.17) | (23.71) |
| N | 1,074 | 1,075 | 1,074 | 1,075 | 1,074 | 1,075 |
| $R^2$ | 0.48 | 0.52 | | | | |
| Adjusted $R^2$ | 0.47 | 0.51 | | | | |
| Log-likelihood | -2803.6 | -2890.9 | -2643.1 | -2749.1 | -2654.3 | -2758.0 |
| AIC | 5647.3 | 5821.9 | 5328.3 | 5540.2 | 5348.7 | 5556.0 |
| SC | 5746.8 | 5921.5 | 5432.9 | 5644.8 | 5448.3 | 5655.5 |
| LM (lag) | **382.3** | **346.0** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| Robust LM (lag) | **74.2** | **76.1** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| LM (error) | **318.1** | **274.3** | | | | |
| *P-value* | 0.00 | 0.00 | | | | |
| Robust LM (error) | **10.00** | **4.4** | | | | |
| *P-value* | 0.00 | 0.04 | | | | |

Note: *t* statistics (OLS) and *z* statistics (Lag-ML and Err-ML) are in parentheses. **Bold** indicates significant at $p<0.05$, and *italic* denotes significant at $p<0.10$.