# DO NEIGHBORHOOD ATTRIBUTES AFFECT COMMUTING TIMES?

METRANS Project 04-13

September 1, 2005

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## Abstract

Can generic neighborhood types for California's major metropolitan areas be defined? To what extent do neighborhood differences affect commuting times? Using census data, including TIGER file variables that describe street patterns and transit and highway accessibility, we found that there are identifiable residential as well as workplace neighborhood types observable throughout the four major California metropolitan areas. We also found that many of these had consistent effects on commuting durations across the four areas. In most cases, neighborhood effects helped to explain a longer commute than could be explained by a generalized accessibility index. Many households trade off desirable neighborhood characteristics (at work and/or at home) for a longer commute. All things considered, jobs-housing "balance" is, apparently, not high on most people's agenda.

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## Introduction

Commuting times are related to job accessibility. The standard urban economic model elaborates and tests the idea that site value is a simple function of distance from the one and only job center. Many empirical studies have investigated the nature of this relationship, some based on micro data and others on aggregates. What about the remaining, and often substantial, unexplained variations in commuting times and distances? There is more than job access to account for, and workers may trade off many local opportunities, residential choices and amenities for slightly longer journeys-to-work (Giuliano, 1995). In addition, many employers invest in campus-like office park settings, complete with local eating and shopping facilities, and for good reason. They have to compete for workers who may have alternative job opportunities at intervening locations.

There is also a widespread view among planners that regional land uses can be managed and arranged in ways that improve jobs-housing "balance" and reduce commuting lengths and times. Although descriptions of "balance" tend to be vague, there are many regional plans and proposals to arrange spatial patterns to reduce commute distances.

What neighborhood types contribute to "balance" and offer a model for planners? What types, on the other hand, have the opposite effect, facilitating more residential choice, perhaps at a cost of a longer journey to work? The latter might be residential areas or workplace zones. There are now enough data available to enable us to evaluate the nature and direction of neighborhood effects on commuting. We were able to test the importance of generalized job accessibility relative to the importance of various neighborhood types (both residential and workplace). We included neighborhood attributes that might contribute to variations in the journey to work. We found that neighborhood types make a difference, in many cases resulting in a longer commute. This paper describes how the tests were carried out and what conclusions the results suggest.

## 1. Literature: neighborhood attributes and travel behavior

Planners are promoting regional jobs-housing "balance" and transit-oriented neighborhood designs. Their goals are to limit commuting lengths, reduce highway congestion, and cut automobile emissions. However, there are good reasons to be skeptical. First, the ability of planners to fine-tune land use arrangements is open to doubt. Matching a huge variety of worker skills and preferences with an equally huge number of employment opportunities is an impossible task. Second, even if planners had all of the necessary data, they would be overwhelmed by the scale of the task. Third, even if the task was feasible, its impact would be marginal. Most households and most employers do not often relocate frequently enough to substantiate the "rational relocator" model.

Pre-1960s neighborhood planning was based largely on a hierarchy of simple grids (regional, arterial, collector, and neighborhood streets). Beginning in the 1960s, subdivisions began using more looping and branching designs with cul de sacs, T-intersections, and limited entry points (Porterfield, 1995, p.76). While the intent was to slow traffic, eliminate through traffic, and increase pedestrian safety, the unintended effect was to reduce connectivity with other areas and increase automobile trips and lengths. This pattern is now associated with sprawl while the grid-based system is considered compatible with neo-traditional and Smart Growth.

Ten years ago, Crane (1995) wrote that, "… the traffic impacts of new plans are generally indeterminate, and it is unclear that designers understand the reasons well enough to avoid indeterminate results." Indeed, case studies by Cervero (1991) show that New Urbanist communities can only be expected to cut auto travel for very short shopping trips. Minor changes in on-site travel behavior have no impact on off-site driving. Even in one of America's most touted Transit-Oriented Development, Orenco Station in suburban Portland, where the primary rationale for the existence of this New Urbanist community was its access to MAX (the light rail system), less than 20 percent use rail because even for commuters to downtown it is twice as fast and much more convenient to use the freeway (Bae, 2002). Furthermore, using a different data base than the more common NHTS/NPTS sources, i.e. the American Housing Survey, Crane and Chatman (2004) found that suburbanization was associated with shorter rather than longer commutes, although their analysis never descended to the neighborhood level. Levine (1998) found the opposite result, especially for low-income households. Clearly, the evidence is very mixed.

## 2. Research approach

***Data and study areas***

The purpose of the investigation is to test whether and how neighborhood characteristics of residential areas and workplace areas in major California cities influence workers' commuting times. The study areas include all of the neighborhoods of the four largest metropolitan areas in California: Los Angeles, San Francisco, San Diego, and Sacramento, using the 1999 Metropolitan Statistical Area (MSA) definitions from the U.S. Office of Management and Budget. The Los Angeles, San Francisco, and Sacramento Consolidated Metropolitan Statistical Areas (CMSAs) include five, ten, and four counties, respectively, while San Diego is a single county metropolitan statistical area (MSA). The analyses in this research are conducted at the census tract level for the four MSAs. A neighborhood, whether referring to homes or workplaces, is defined as a census tract or a spatial cluster of census tracts.

We relied on journey-to-work data from the U.S. decennial Census; the Census Transportation Planning Package 2000 (CTPP, 2000) was a key data source. It provides information on commuting and commuters, which is summarized by place of residence, by place of work, and by commuting flows between residence and workplace census tracts. Neighborhood attributes data were drawn from more diverse sources. The 2000 Census Summary File 3 (SF3) is a rich source of census tract-level housing data that complements the CTPP.

We omitted using many of the census socio-economic variables because the physical characteristics of neighborhoods are the most important, given our research questions. We derived most of the variables representing neighborhood level physical attributes using Geographical Information Systems (GIS) technology. We used the 2000

TIGER® (Topologically Integrated Geographic Encoding and Referencing system) street networks files to measure street design factors, often suggested as associated with local and regional accessibility, and hence affecting commuting behavior. GIS map files of rail transit lines were also obtained from the metropolitan planning organization of the four metropolitan areas and were used to measure transit access. All these GIS tasks were done using ArcView GIS 3.3 software, often utilizing avenue scripts.

### *Methodology*

The strategy adopted to test how neighborhood attributes influence commuting times involved two major steps. The first step involved classifying all census tracts in the four metropolitan areas into meaningful prototypes of residence and workplace neighborhoods utilizing a statistical cluster analysis. In the second step, we tested the significance of neighborhood characteristics on commuting time, controlling for the effects of traditional explanatory variables such as job/worker accessibility and household income.

Most previous research has attempted to measure travel impacts of individual variables measuring local area characteristics in a multivariate analysis fashion (Cervero and Kockelman, 1997; Boarnet and Crane, 2001). Some literature involves tests of whether residents in different types of neighborhoods vary in their travel behavior. These tend to be case studies (Cervero and Gorham, 1995; Handy, 1996) that typically compare auto-oriented postwar suburban neighborhoods with what are known as New Urbanist or more transit-oriented communities. The selection of study areas necessarily depends on prior knowledge regarding the development of those communities.

In contrast, we investigated whether all census tracts in the four metropolitan areas cluster into meaningful neighborhood units and then examined the neighborhood effects on commuting behavior. Smith and Saito's (2001) findings suggested that meaningful spatial aggregates can be identified via this approach. Further, we studied neighborhood effects not only at place of residence but also at a place of work. This approach required two separate cluster analyses with different input variables to obtain the two sets of neighborhood prototypes.

We pooled data from the four regions for the cluster analyses to identify generic neighborhood types in California's major metropolitan areas. Ten variables were used in residence neighborhood clustering. These included measures of the contextual position, street design factors, and transit and highway access of each census tract (Table A1). Population density, distance from the core central business district (CBD) of each metropolitan area, and the age of housing stock are basic descriptors of a neighborhood's spatial location. It is claimed that street design factors (such as street density, intersection density, and cul-de-sac ratios) are associated with pedestrian access, intra-neighborhood connectivity, and ultimately automobile dependence. These factors are considered especially important in New Urbanist community designs. Access to major transportation infrastructure such as rail transit systems, park and ride stations, and highways is also expected to affect commuting behavior. Bus transit access, however, is not taken into account here on the ground that it is more likely to be endogenous than to be exogenous because bus routes are ubiquitous and flexible.

We used eleven descriptor variables in the workplace cluster analysis (Table A2). Job density and the distance from metropolitan center are general descriptors of the workplace neighborhood. Average job density of neighbor census tracts within one mile distance could also present a spatial context, expected to be associated with local congestion levels. Access to transportation infrastructures such as rail stations, highway interchanges, and airports are important descriptors of the workplace neighborhood.

Industrial composition is another important descriptor of workplace. We conducted a standard common factor analysis to extract four industrial concentration indices from 13 industrial sectors' share of census tract employment. Four factors were retained according to the Scree test and the extracted factors were rotated by a variance maximizing (Varimax) principle. As shown in the rotated factor pattern (Table A3), each factor presents a concentration of industrial sectors with similar characteristics: manufacturing, wholesale, and transportation and warehousing are loaded on Factor1; FIRE, professional services, and information sectors on Factor2; retail and arts, entertainment, recreation, accommodation and food services on Factor3; and public administration on Factor3. These four factor scores as well as six other workplace attributes were used in the cluster analysis.

Whereas a variety of techniques are available in cluster analysis, we have chosen perhaps the most commonly used methods in this field[1]: Euclidean distance was used as a similarity measure, and Ward's minimum-variance method was used as a hierarchical clustering technique. We standardized all variables before running the cluster analyses. Twenty clusters of residence tracts and fourteen clusters of workplaces were determined by evaluating resulting clusters *ex post*. The reasonableness of the size distribution of clusters, their spatial distribution, and the ease of interpreting and evaluating results were taken into account in settling on the number of clusters. Some arbitrariness was inevitable given that common statistics such as the Cubic Clustering Criterion, the Pseudo F-statistic and the Pseudo-$t^2$ statistic do not clearly indicate a statistically optimal number of clusters.

The effects of residence and workplace neighborhoods defined in this way on commuting durations (privately operated vehicles only) were tested via multiple regression analyses. Three sets of regression models explaining average commute time by residence tract, workplace tract, and by O-D flows were run for each metropolitan area as well as for the pooled data. Each set of regressions controlled for job/worker accessibility and commuters' median household income, the conventional explanatory variables. The three models can be summarized as follows:

- Commute time by residence tract (origin) = f (job accessibility, median household income of workers, 20 residence neighborhood-type dummies)

- Commute time by workplace tract (destination) = f (worker accessibility, median household income of workers, 14 workplace-type dummies)

- Commute time by flow (origin and destination pairs) = f (origin tract's job accessibility, destination tract's worker accessibility, median household income of commuters, origin tract's residence neighborhood-type dummies, destination tract's workplace-type dummies)

[1] A study attempting to classify 343 planning districts in Utah's Wasatch Front region to 35 land-use distribution scenarios found after applying a series of cluster analysis options that a combination of the Ward's linkage method and the Squared Euclidean distance measure produced the most reasonable outcome (Smith and Saito, 2001).

The median household income variable is readily available only by place of residence. Workers' distribution by income group, instead, is reported by all three types (origin, destination, and flow) in the CTPP 2000 data. Thus, the median household income variable is derived by interpolation. Following the Census Bureau's guide, we used linear interpolation for the lowest income group and Pareto interpolation for other intervals. For the top open-ended intervals (e.g. $150,000 or more), we set the upper bound at the level of twice the lower bound.

Both job and worker accessibilities in each census tract were estimated using Shen's (1999) version of the gravity measure. A traditional gravity-type accessibility index discounts opportunities (number of jobs for employees and number of workers for employers) by distance via some impedance function. However, this measure cannot take into account competition for opportunities at intervening locations. For instance, a worker in a particular zone may have to commute further when there is a large labor force competing for the same job opportunities. Similarly, an employer may have to draw workers from more distant residences if there are more firms competing for the same labor force. The gravity accessibility measure employed in this research considers the demand potentials for opportunities as well as distance. An inverse power function was adopted as an impedance function and parameters for the function were estimated for each metropolitan area (Table A4) using 2000 CTPP Part 3 commuting flow data.

$$JA_i = \sum_{j=1}^{n} \frac{E_j d_{ij}^{-\beta}}{JD_j}, \quad JD_j = \sum_{k=1}^{m} W_k d_{jk}^{-\beta}$$

$$WA_i = \sum_{j=1}^{n} \frac{W_j d_{ij}^{-\beta}}{WD_j}, \quad WD_j = \sum_{k=1}^{m} E_k d_{jk}^{-\beta}$$

where $JA_i$ = Job accessibility of zone i;
$WA_i$ = Worker accessibility of zone i;
$JD_j$ = Demand for jobs located in zone j;
$WD_j$ = Demand for workers located in zone j;
$E_j$ = Number of jobs in zone j;
$W_j$ = Number of workers in zone j;
$d_{ij}$ = Euclidean distance between zone i and j; and

$\beta$ = Inverse power function parameter.

## 3. Neighborhood typologies

Twenty residential and fourteen workplace neighborhood prototypes from the cluster analyses results are described in Tables 1 and 2, with cluster mean attribute values for the various descriptor variables. For convenience, the two sets of clusters are numbered by population or job densities in descending order. These statistical clusters of census tracts also show up as strong spatial clusters as shown in Figure 1 – Figure 4; thus, census tracts with similar attributes tend to cluster in similar locations. Each of the neighborhood type's characteristics and locations are briefly described in the rest of this section.

### *Residence neighborhood typology*

The spatial distribution of the twenty residential neighborhood types approximately fits the broad categories of the general urban spatial model, consisting of downtown – inner city – inner suburbs – outer suburbs – exurban. Los Angeles is best known to the authors and the following interpretation of residence neighborhood types heavily reflects Los Angeles references.

Rtype 1 consists of very dense apartment and commercial mixed use communities adjacent to Los Angeles and San Francisco downtowns. Parts of Los Angeles Koreatown and San Francisco Chinatown belong to this category. The older apartment buildings are two-story while the newer ones tend to 3-4 stories. These areas have densely laid out street structures and usually have relatively good rail transit and highway access.

Rtype 2, 3, and 5 are inner city communities for the most part, accounting for about 14 percent of total population. Rtype 2 and 3 are small clusters of high density census tracts in core central cities and in secondary cities such as Long Beach, Glendale, and Pasadena in Los Angeles, and Oakland and Berkeley in San Francisco. Rtype 2 and 3 communities exhibit similar attributes except that Rtype 3 consists of somewhat older communities and has denser and more irregular street patterns. Most of the Rtype 2 communities are found in Los Angeles metro areas. Rtype 5 describes typical small lot inner city neighborhoods mostly found in cities of Los Angeles and San Francisco, and in some old secondary cities such as Long Beach, Pasadena, Burbank, Santa Ana, Berkeley, and Oakland, but not in San Jose. It has the oldest housing stocks, high street densities, and the least cul-de-sacs.

Rtype 4 and 7 are characterized as having very good rail transit access. In particular, 92 percent of people in Rtype 4 neighborhoods are within a half-mile distance from any rail transit station. Core CBD areas of all four metropolitan areas and downtowns of some secondary cities with a good transit access belong to this type. Rtype 7, consisting of less dense census tracts with good transit access, is lined up along rail transit lines. Both Rtype 4 and 7 also have good highway access because most transit lines are built along major highways.

Rtype 6 areas are typical inner-ring suburbs surrounding inner cities, which account for 13 percent of regions' population. Tracts in this category in Southern California comprise large clusters in relatively older suburbs in the San Fernando and San Gabriel Valleys and the South Bay areas in the Los Angeles metro area. Neighborhoods of this type are characterized as having about average density, but with fewer cul-de-sacs than outer ring suburbs. They also have good highway access. Rtype 10 is another category of inner ring suburbs, but with older homes, lower densities and many more cul-de-sacs. Both inner ring suburbs have good highway access.

Rtype 8, accounting for the largest proportion of population (13.1 percent), has attributes closest to the regional average. Compared to Rtype 6 neighborhoods, Rtype 8 neighborhoods are relatively new and are located farther away from regional centers with much higher cul-de-sac ratios. The majority of census tracts in Orange and Santa Clara Counties belong to this group. They include many prototype cases of post-war auto-oriented suburban developments introduced in previous studies (Cervero and Gorham, 1995; Handy, 1996; Southworth, 1997).

Rtype 13 describes low density and large lot residence neighborhoods often in hilltop or hillside areas such as the ones along Mulholland Drive in Los Angeles and the cities of San Rafael and Lafayette near San Francisco. The names of cities of this neighborhood type often end with "Heights".

Rtypes 11 and 15 are typical outer-ring suburbs filling the remaining areas of core urbanized areas. They comprise more than 15 percent of the regions' population. These neighborhoods are fairly new, developed in the 1980s or later periods, and are characterized as low density and cul-de-sac neighborhoods.

Rtype 9 and 12 found in the outer urbanized areas far beyond the cores. These include Riverside, San Bernardino, Ventura, Oxnard, and Temecula in Los Angeles and Santa Rosa, Napa, Fairfield, Petaluma, and Santa Cruz in San Francisco. Rtype 9 is central areas of these cities while Rtype 12 describes the rest. Thus, Rtype 9 neighborhoods share attributes of inner ring surburbs in terms of their moderate density and grid street patterns in spite of their outermost location.

Rtype 14 tracts are found only in Palm Springs area, which is more than 100 miles away from Los Angeles CBD. Neighborhood types 16, 18, and 20 are largely unpopulated mountain and desert areas, accounting for only about 1.5 percent of regional population. Thus, they have little significance for this study.

Rtypes 17 and 19 are exurban communities. Neighborhoods in Rtype 17 are clustered around cities more than 50 miles away (often much further) from the metropolitan center such as Barstow, Victorville, Hemet, and Temecula in the Los Angeles area and Santa Rosa in San Francisco area. Whereas Rtype 17 neighborhoods are clustered in a few locations, Rtype 19 census tracts comprise a complete outer ring, surrounding core urbanized areas in the four metropolitan areas. They were developed mostly in the 1970s and 1980s as spillovers from the urbanized areas. Thus, they are characterized as typical auto-oriented neighborhoods with low street densities and very high cul-de-sac ratios. These exurban communities comprise a significant and growing proportion (8.5 percent) of regional populations.

### *Workplace neighborhood typology*

Workplace generic neighborhood types can also be described. Wptypes 1, 2, and 3 workplace neighborhoods are traditional CBD-type office districts with a very high job density and job/worker ratio. They account for about 11.5 percent of the regions' total employment. Wptype 1 is the financial district in San Francisco with an extremely high job density. Wptype 2 consists of the regional CBDs of the four metropolitan areas plus strictly defined office districts in West Los Angeles and Oakland. Wptype 3 is made up of the more broadly defined downtowns of these cities surrounding Wptype 2 districts. Office and commercial districts along Wilshire corridor and downtowns of San Jose, Long Beach, Pasadena, Glendale, Burbank, Santa Monica, and Irvine also belong to this group. Workplaces of these types are specialized in business services.

Wptype 4 consists of less centralized business services or office centers with much lower job densities, often in suburban locations. Most edge cities listed in Lang (2003) such as North San Jose, Walnut Creek, Pleasanton, and San Ramon in San Francisco, and Irvine/Costa Mesa, Sherman Oaks, and Woodland Hills belong to this group. Wptype 4's job share (10.8 percent) is almost as big as that of downtown employment centers.

Wptypes 5, 6, and 7 are medium job density areas with good transportation access. They are mostly located within core urbanized areas, accounting for about 18 percent of the regions' employment. Wptypes 5 and 7 have typical economic structures except that Wptype 5 is moderately specialized in personal services and Wptype 7 is strongly specialized in educational services (LQ = 2.39). Workplaces in Wptype 6 describe the civic centers of small cities showing a very strong concentration of public administration employment (LQ = 9.13).

Wptype 8 describes industrial job centers with a high concentration of jobs in the manufacturing, wholesale trade, and transportation, warehousing, and utilities sectors. This type of workplaces comprises the largest fraction of total employment (26.2 percent) and about 56 percent of regional employment in the three industrial sectors. They tend to cluster along major freeways.

Wptypes 9, 10, and 11 describe workplaces where residences dominate. The number of workers is about twice the number of jobs in these areas. Thus, Wptype 9 is specialized in population-supporting sectors such as retail and entertainment, food, and accommodation services. These workplaces with moderate densities are mostly found within major urbanized areas. The majority of residential areas in Orange County and San Jose belong to this group. Wptype 10 consists of more suburban residential areas with even lower job densities, more often found outside the core urbanized areas. Most

Census Tracts in the Riverside-San Bernardino, Oxnard, and Mission Viejo urbanized areas belong to this group. Wptype 11 is characterized by very low densities with moderate to strong specialization in business and other services.

Wptype 12 consists of exurban workplaces with extremely low job density. Lancaster, Temecula, and Victorville in Los Angeles, and Santa Rosa and Santa Cruz in San Francisco, belong to this group. The shares of agriculture, construction, and manufacturing sectors are above average. Wptypes 13 and 14 are marginally urbanized areas in fringe locations with little significance for the study.

## 4. Neighborhood attributes and commuting times

Tables 1 and 2 present mean values of descriptive data for both residential and workplace neighborhood types (a glossary of variable definitions is in Table A1). They show that these neighborhoods (encompassing 5,814 census tracts and more than 28 million people) are very diverse, in terms of population size, population density, street layout and similar characteristics, and even commuting time. Note that with the exception of income, the neighborhoods are not stratified by socio-economic characteristics; the reason is that the research in its neighborhood analysis focuses on physicical characteristics. The variation in commuting time is between 22.7 minutes (Rtype 14) and 32.9 minutes (Rtype 17), except for the extreme outlier (Rtype 18 with 15.9 minutes); also, it should be remembered that these are census tract averages not individual commuting times. These differences are as wide as those found in intermetropolitan comparisons across the country, and certainly far from the hypothesis of a constant national average commuting time. When we look at workplace-based commuting times (over 12.24 million jobs), the range is somewhat wider (from 20.6 minutes to 39.65 minutes), with significant variation by neighborhood type. However, another notable feature of Table 2 is the extreme skewness in job densities; after the first three ranked workplaces (with 436, 104 and 35 jobs per acre), densities fall off to 7 jobs per acre or less.

Greater commuting times may create problems for regional planners, but they often reflect opportunities taken by commuters. In a world of trade-offs, employers and workers optimize the consumption of location and neighborhood (accessibility) along with many other goods. They are unlikely to minimize or maximize any single good or service.

For reference purposes, Table 3 shows regression results without neighborhood effects considered. In each case, the dependent variable is commuting times reported in 2000 for the drive alone mode only. Panel (a) shows results for travel times reported by residential census tracts for the pooled sample as well as for each of the metropolitan areas. The job access variable is, as expected, negatively significant: The greater the generalized access, the shorter the average commuting duration. Interestingly, the income effect is mixed, positive as expected only in the San Diego and Sacramento areas. The reference area is San Francisco: Los Angeles commutes are slightly longer while those of the other two areas tend to be shorter.

Similar results are seen in panel (b) where the dependent variable is average trip times as recorded at destinations. The generalized access variables are, again, negatively significant, as expected. The income effects are more pronounced in this case. The effects of the metro area dummy variables are consistent with the results in panel (a).

Panel (c) shows results for commuting flows that were available for origin-destination pairs. Generalized job access at the place of residence explains more than generalized workplace access: The latter is not significant in Los Angeles and has the wrong sign in Sacramento. Median income is now significant everywhere. The dummy variable effects show that the three metro areas all have average commutes shorter than San Francisco. Adding neighborhood types to any of these three models enhances their explanatory powers considerably.

We focus on neighborhood types that show consistent effects across metropolitan areas and across estimated models (Table 4).

Residential neighborhoods labeled Rtype 6 are one of the few to have significantly *shorter* commutes in the flow (O-D) model for the pooled sample as well as for three of the four metropolitan areas. These are inner suburbs with both better than average highway and transit access. Transit access only matters indirectly in our analysis because we are studying private vehicle access only; however, as more local residents use transit there may be an improvement in road traffic conditions. They have average street density and average intersection densities. Model results suggest similar advantages for Rtypes 14 and 18, but these locations are too peripheral to for the results to be meaningful.

Seven residential neighborhood types consistently are associated with significantly *longer* time commutes. Rtype 1 and Rtype 2 are centrally located commercial districts with good access to both highways and transit. However, the high levels of access in these locations are accounted for by the generalized job access variable. Beyond this, centrality, as a result of the higher densities, may mean worse road traffic conditions. *Ceteris paribus*, these older areas are relatively affordable and attractive. Rtypes 11 and 15 also account for longer commutes, but these are suburban and low-density areas. Many of them are attractive high-amenity areas. Rtypes 16, 17 ad 19 are outlying but apparently attractive enough for commuters to trade off distance for local neighborhood benefits.

Turning to employment areas, Wtype 9 areas account for shorter commute times. There are many retail strip-commercial jobs in these areas catering to secondary workers in multi-worker households. Wtype 9 and 10 may also be "edge city-type" areas, typically mainly residential with low jobs-workers ratios.

Employment areas Wtypes 2, 3 4 and 8 each consistently account for longer worktrips. The first two are relatively centrally located. Wptype 1 is only found in San Francisco; Wptype 2 is the Los Angeles CBD. These job-rich areas tend to draw workers from far, rather than near, locations. In Southern California, the Wptype 4 surrounds the John Wayne Airport in Orange county. It includes new relatively high-amenity campus-like office parks that are attractive job locations. Similarly, the Wptype 8 districts surround LAX (Los Angeles International Airport) and the Ports of Long Beach and Los Angeles. Specialized industrial job opportunities at these places, indicated by the high industrial factor score in Table 2, help to explain these locations' draw over longer distances.

## 5. Discussion

Our main finding is that many neighborhood types have a significant effect on commuting. In particular, controlling for accessibility to both workers and jobs, neighborhood types and their identified characteristics explain much of the variance in workers' choice of commutes. Many of these commutes are considerably longer than can be explained by generalized accessibility. Many of the identifiable neighborhood types that matter have consistent effects across the four California metropolitan areas studied (Los Angeles, San Francisco, San Diego and Sacramento).

This result may not be so surprising. In a world of trade-offs it is not difficult to imagine that many commuters find attributes of their home (or work) neighborhoods that they deem attractive enough to pay for by accepting a longer commute. Our findings may surprise urban economists who have given residents' interests in worktrips predominance in theoretical explanations of urban form. What is interesting is that the original trade-off model of residential location has a long lifespan, even in a clearly policycentric world of multiple neighborhood types and complex lifestyle choices that involve trade-offs and travel for a variety of purposes.

Our results may also be unsettling to urban transportation planners and policy makers, many of whom have embraced New Urbanist hypotheses. They have devoted most of their policy discussions to methods of reducing commuting, with special attention given to neighborhood attributes that might have this effect.

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## Tables and Figures

**Table 1**. Mean attribute values by residential neighborhood type

| Residence type[1] | Number of tracts | Population | (%) | Commute Time[2] | CoTime by drive alone | PopDen | Median Yr Built | CBD Distance | Street Density | Intsersection Density | Cul De Sac | RswPrDist | Bprst | PPopRsBf | Hwy Distance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rtype1 | 30 | 142981 | 0.5 | 29.95 | 29.85 | 125.34 | 1955 | 2.38 | 28.93 | 7.91 | 0.10 | 5.86 | 4.98 | 0.56 | 0.96 |
| Rtype2 | 159 | 804708 | 2.9 | 30.79 | 27.14 | 44.63 | 1962 | 8.08 | 20.91 | 4.98 | 0.05 | 3.28 | 2.79 | 0.03 | 0.97 |
| Rtype3 | 208 | 977933 | 3.5 | 30.08 | 27.84 | 41.10 | 1953 | 8.16 | 27.85 | 8.08 | 0.07 | 4.47 | 3.83 | 0.05 | 1.07 |
| Rtype4 | 186 | 715868 | 2.6 | 28.81 | 26.20 | 31.65 | 1956 | 7.55 | 25.31 | 7.14 | 0.05 | 3.36 | 3.89 | 0.92 | 0.56 |
| Rtype5 | 510 | 2276211 | 8.1 | 28.76 | 26.41 | 20.36 | 1950 | 9.98 | 24.07 | 6.42 | 0.06 | 4.05 | 2.74 | 0.01 | 1.04 |
| Rtype6 | 753 | 3601447 | 12.9 | 27.39 | 26.02 | 16.82 | 1961 | 13.55 | 18.98 | 5.62 | 0.11 | 3.46 | 2.47 | 0.01 | 0.94 |
| Rtype7 | 345 | 1623558 | 5.8 | 27.60 | 25.31 | 15.25 | 1961 | 15.95 | 19.40 | 6.01 | 0.16 | 2.30 | 2.79 | 0.50 | 0.69 |
| Rtype8 | 701 | 3681504 | 13.1 | 27.49 | 26.35 | 15.24 | 1970 | 27.69 | 19.25 | 6.86 | 0.26 | 4.97 | 2.14 | 0.00 | 1.26 |
| Rtype9 | 168 | 829294 | 3.0 | 26.07 | 24.84 | 12.08 | 1962 | 50.01 | 19.76 | 6.55 | 0.14 | 20.77 | 3.78 | 0.00 | 1.17 |
| Rtype10 | 346 | 1619758 | 5.8 | 27.63 | 26.31 | 11.87 | 1957 | 16.37 | 18.76 | 6.16 | 0.25 | 4.23 | 2.06 | 0.00 | 0.89 |
| Rtype11 | 542 | 2717341 | 9.7 | 28.86 | 27.66 | 8.20 | 1977 | 23.97 | 14.71 | 6.25 | 0.32 | 6.36 | 2.48 | 0.00 | 1.84 |
| Rtype12 | 344 | 1838877 | 6.6 | 28.67 | 27.31 | 6.60 | 1975 | 52.18 | 12.89 | 5.41 | 0.27 | 23.28 | 3.44 | 0.00 | 1.22 |
| Rtype13 | 539 | 2430840 | 8.7 | 27.43 | 26.14 | 5.96 | 1969 | 18.02 | 11.45 | 4.58 | 0.28 | 4.82 | 2.26 | 0.02 | 0.99 |
| Rtype14 | 69 | 300866 | 1.1 | 22.74 | 21.89 | 4.52 | 1979 | 108.81 | 12.72 | 5.23 | 0.20 | 77.76 | 44.85 | 0.00 | 3.28 |
| Rtype15 | 301 | 1649368 | 5.9 | 30.81 | 29.51 | 4.32 | 1985 | 31.40 | 9.68 | 5.24 | 0.37 | 9.12 | 2.42 | 0.00 | 1.73 |
| Rtype16 | 67 | 264651 | 0.9 | 33.45 | 33.07 | 2.77 | 1975 | 58.94 | 8.28 | 3.74 | 0.30 | 36.76 | 15.09 | 0.00 | 12.16 |
| Rtype17 | 123 | 665231 | 2.4 | 32.87 | 31.55 | 1.18 | 1980 | 63.81 | 6.50 | 3.40 | 0.27 | 41.75 | 6.86 | 0.00 | 3.62 |
| Rtype18 | 13 | 33139 | 0.1 | 15.93 | 16.95 | 1.02 | 1974 | 209.12 | 4.42 | 2.80 | 0.27 | 181.54 | 145.18 | 0.00 | 8.06 |
| Rtype19 | 371 | 1649699 | 5.9 | 31.21 | 30.51 | 0.92 | 1977 | 33.21 | 4.19 | 2.97 | 0.37 | 13.34 | 3.97 | 0.00 | 2.86 |
| Rtype20 | 39 | 176844 | 0.6 | 24.45 | 23.84 | 0.66 | 1974 | 96.98 | 4.84 | 3.51 | 0.26 | 74.30 | 41.59 | 0.00 | 24.98 |
| All | 5814 | 28000118 | 100 | 28.48 | 26.98 | 14.22 | 1967 | 25.28 | 16.65 | 5.72 | 0.21 | 9.65 | 4.06 | 0.07 | 1.63 |

1) Residence types are sorted and numbered according to (unweighted) average population density.
2) Cotime: commuting time averaged by commuters' origin (residence) tract.
3) Variables only in third panel (from popden to hwydist) are used in the cluster analysis.

**Table 2**. Mean attribute values by workplace neighborhood type

| Work-place type[1)] | Number of tracts | Civilian jobs | (%) | WCotTme[2)] | WCotTme by drive alone | JobDen | CbdDist | RsDist | IntchDist | AirDist | NbrJDen | Industrial[4)] | Business Services[4)] | Retail[4)] | Public[4)] | Job/ Worker ratio[3)] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WPtype1 | 4 | 170452 | 1.4 | 39.65 | 37.25 | 436.02 | 0.26 | 0.28 | 1.80 | 11.52 | 141.16 | -0.68 | 3.41 | -0.23 | 0.36 | 88.3 |
| WPtype2 | 32 | 430841 | 3.5 | 36.79 | 34.98 | 104.03 | 1.41 | 0.64 | 1.44 | 10.86 | 100.91 | -0.23 | 1.10 | 0.40 | 0.99 | 7.1 |
| WPtype3 | 113 | 824827 | 6.7 | 33.38 | 31.58 | 35.05 | 6.73 | 2.10 | 1.82 | 8.54 | 33.66 | -0.33 | 1.44 | -0.12 | 0.74 | 3.6 |
| WPtype4 | 282 | 1321425 | 10.8 | 29.77 | 29.00 | 7.14 | 21.00 | 3.56 | 2.71 | 10.41 | 5.68 | -0.12 | 2.04 | -0.17 | 0.45 | 2.1 |
| WPtype5 | 686 | 1057010 | 8.6 | 26.88 | 25.94 | 5.58 | 10.32 | 2.40 | 2.48 | 9.68 | 7.48 | -0.34 | -0.14 | 0.26 | -0.14 | 0.7 |
| WPtype6 | 172 | 340052 | 2.8 | 27.66 | 26.97 | 5.18 | 17.34 | 4.03 | 2.84 | 12.63 | 4.23 | -0.35 | 0.06 | -0.48 | 2.67 | 1.2 |
| WPtype7 | 594 | 852357 | 7.0 | 25.82 | 24.78 | 5.12 | 14.75 | 2.54 | 2.54 | 9.96 | 4.89 | -1.03 | -1.08 | -1.06 | 0.18 | 0.8 |
| WPtype8 | 986 | 3206324 | 26.2 | 28.85 | 27.75 | 4.71 | 18.05 | 3.40 | 2.59 | 9.77 | 4.48 | 1.47 | -0.31 | -0.11 | 0.08 | 1.7 |
| WPtype9 | 862 | 1096060 | 9.0 | 24.87 | 23.74 | 3.18 | 19.72 | 3.48 | 3.18 | 10.20 | 3.44 | -0.35 | -0.06 | 1.33 | -0.16 | 0.6 |
| WPtype10 | 781 | 1072006 | 8.8 | 23.85 | 23.03 | 2.07 | 42.06 | 13.24 | 4.64 | 21.62 | 2.33 | -0.34 | -0.20 | -0.04 | -0.03 | 0.6 |
| WPtype11 | 680 | 734173 | 6.0 | 28.00 | 26.42 | 1.70 | 18.79 | 4.09 | 3.53 | 12.53 | 2.75 | -0.17 | 0.80 | -0.61 | -0.80 | 0.5 |
| WPtype12 | 515 | 944356 | 7.7 | 23.94 | 23.73 | 1.18 | 52.41 | 26.32 | 17.27 | 38.74 | 1.26 | 0.39 | -0.17 | -0.11 | -0.18 | 0.9 |
| WPtype13 | 113 | 181397 | 1.5 | 23.13 | 22.34 | 1.01 | 105.61 | 76.73 | 23.46 | 76.25 | 1.01 | 0.05 | 0.03 | 0.46 | -0.01 | 1.0 |
| WPtype14 | 11 | 8256 | 0.1 | 20.64 | 19.70 | 0.43 | 212.91 | 180.99 | 101.77 | 176.16 | 0.43 | 0.56 | -0.45 | 0.28 | 1.05 | 1.1 |
| All | 5831 | 12239536 | 100 | 26.54 | 25.53 | 5.09 | 25.25 | 8.37 | 4.92 | 16.01 | 5.11 | 0.00 | 0.00 | 0.00 | 0.00 | 1.0 |

1) Workplace types are sorted and numbered according to (unweighted) average job density.
2) Wcotime: commuting time averaged by commuters' destination (workplace) tract.
3) Job/worker ratio is a weighted mean value while all other values by workplace type are weighted means.
4) Four variables of industrial concentration are standardized factor scores.
5) Variables only in third panel (from jobden to public) are used in the cluster analysis.

**Table 3**. Commute time regression models without neighborhood dummies

a) Commute time by residence tract (origin)

| | Four MSA | | Los Angeles | | San Francisco | | San Diego | | Sacramento | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Beta | t | Beta | t | Beta | t | Beta | t | Beta | t |
| Intercept | 33.47 | 93.87 | 33.84 | 75.84 | 32.20 | 54.00 | 34.35 | 53.03 | 29.47 | 22.49 |
| jobaccess | -6.36 | -28.35 | -6.30 | -19.25 | -4.42 | -10.85 | -11.50 | -21.73 | -7.45 | -9.74 |
| medinc | 0.03 | 1.43 | 0.03 | 0.99 | -0.06 | -1.39 | 0.21 | 4.02 | 0.44 | 3.39 |
| dla | 0.43 | 2.91 | | | | | | | | |
| dsd | -3.09 | -13.94 | | | | | | | | |
| dsa | -2.58 | -10.04 | | | | | | | | |
| R-Square | 0.182 | | 0.113 | | 0.075 | | 0.452 | | 0.265 | |
| Adj R-Sq | 0.181 | | 0.112 | | 0.074 | | 0.451 | | 0.261 | |

b) Commute time by workplace tract (destination)

| | Four MSA | | Los Angeles | | San Francisco | | San Diego | | Sacramento | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Beta | t | Beta | t | Beta | t | Beta | t | Beta | t |
| Intercept | 28.40 | 39.87 | 29.60 | 33.33 | 28.38 | 21.36 | 26.78 | 15.99 | 20.08 | 10.08 |
| workeracc | -3.63 | -8.14 | -2.60 | -4.28 | -6.91 | -7.63 | -6.32 | -4.81 | -2.30 | -1.86 |
| medinc | 0.16 | 2.79 | -0.14 | -1.74 | 0.59 | 5.76 | 0.36 | 2.17 | 0.92 | 3.59 |
| dla | 0.41 | 2.05 | | | | | | | | |
| dsd | -3.13 | -10.78 | | | | | | | | |
| dsa | -2.46 | -7.38 | | | | | | | | |
| R-Square | 0.059 | | 0.006 | | 0.074 | | 0.044 | | 0.040 | |
| Adj R-Sq | 0.059 | | 0.005 | | 0.073 | | 0.041 | | 0.035 | |

c) Commute time by flow (origin-destination)

| | Four MSA | | Los Angeles | | San Francisco | | San Diego | | Sacramento | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Beta | t | Beta | t | Beta | t | Beta | t | Beta | t |
| Intercept | 35.42 | 88.13 | 25.87 | 45.87 | 46.00 | 62.03 | 38.70 | 35.50 | 26.58 | 24.31 |
| jobaccess | -5.81 | -30.36 | -1.84 | -6.11 | -9.37 | -28.98 | -9.67 | -19.05 | -9.76 | -18.08 |
| workeracc | -3.06 | -9.44 | 0.29 | 0.64 | -11.17 | -18.71 | -5.43 | -5.49 | 5.89 | 5.71 |
| medinc | 0.20 | 16.35 | 0.16 | 8.97 | 0.31 | 14.15 | 0.14 | 4.02 | 0.24 | 5.49 |
| dla | -2.52 | -22.69 | | | | | | | | |
| dsd | -3.36 | -19.88 | | | | | | | | |
| dsa | -3.62 | -18.33 | | | | | | | | |
| R-Square | 0.019 | | 0.002 | | 0.037 | | 0.030 | | 0.043 | |
| Adj R-Sq | 0.019 | | 0.002 | | 0.036 | | 0.030 | | 0.043 | |

1) Dark shaded cells are significant at 5% level, while light shaded cells are significant at 10% level.
2) Jobaccess is job accessibility index of an origin tract; workeracc is worker accessibility index of a destination tract; medinc is median household income of commuters ($10,000).

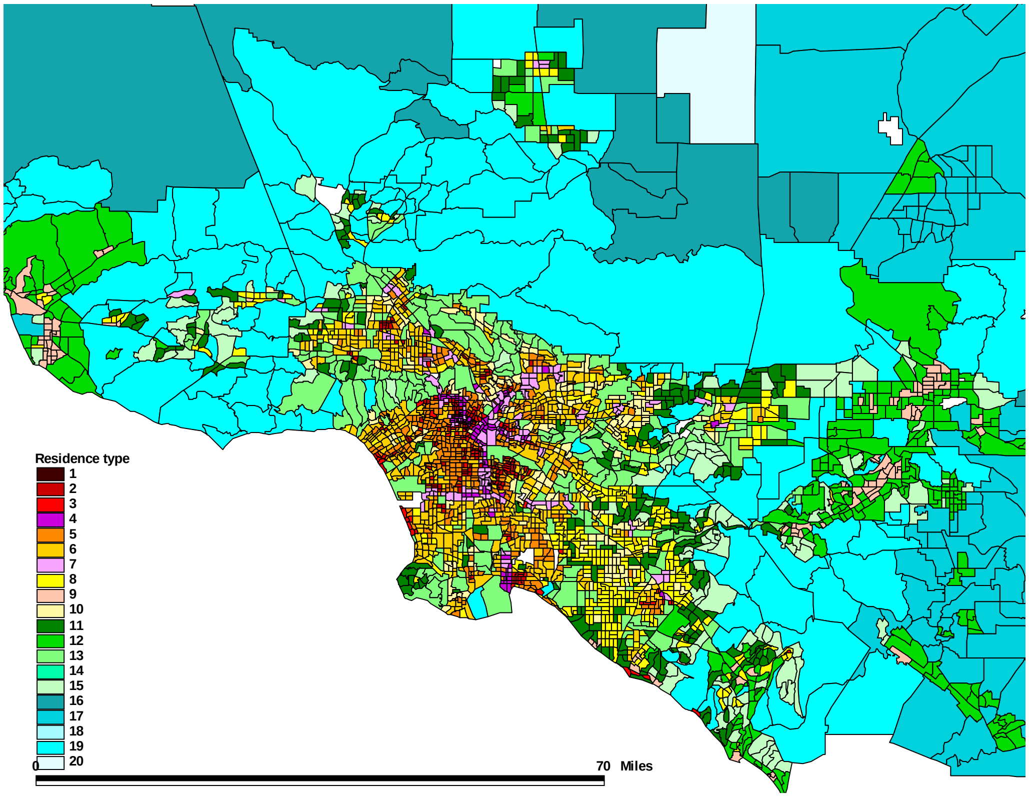
**Table 4.** Commute time regression models with neighborhood dummies

| | **Residence tract (Origin)** | | | | | **Workplace tract (Destination)** | | | | | **Flow (O-D)** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Four** | **LA** | **SF** | **SD** | **SA** | **Four** | **LA** | **SF** | **SD** | **SA** | **Four** | **LA** | **SF** | **SD** | **SA** |
| N obs. | 5808 | 3348 | 1455 | 602 | 403 | 5825 | 3366 | 1453 | 603 | 403 | 130066 | 67564 | 38948 | 14189 | 9365 |
| Intercept | **33.14** | **32.67** | **33.96** | **32.60** | **28.31** | **28.06** | **28.38** | **29.58** | **24.06** | **19.27** | **37.84** | **27.71** | **52.86** | **38.85** | **25.29** |
| jobaccess | **-6.10** | **-5.42** | **-6.12** | **-9.27** | **-5.38** | | | | | | **-10.49** | **-6.52** | **-16.23** | **-11.88** | **-9.50** |
| workeracc | | | | | | **-3.12** | **-1.81** | **-6.22** | **-3.37** | 0 | **-2.75** | 0 | **-10.66** | **-3.13** | **7.00** |
| Medinc | **-0.05** | 0 | **-0.10** | 0 | 0 | 0 | **-0.14** | **0.25** | 0 | 0.47 | 0 | 0 | 0 | 0 | 0 |
| Rtype1 | **6.46** | **3.11** | **11.02** | | | | | | | | **2.51** | **3.72** | **2.70** | | |
| Rtype2 | **1.34** | **1.48** | 0 | **2.75** | | | | | | | **2.85** | **2.22** | 0 | **6.11** | |
| Rtype3 | **2.51** | **1.17** | **3.80** | 0 | | | | | | | 0 | **1.20** | -0.71 | 0 | |
| Rtype4 | **1.79** | **2.84** | **1.27** | 0 | 0 | | | | | | 0 | **2.84** | **-1.87** | 0 | **-2.83** |
| rtype5 | **0.67** | **0.88** | 0 | 0 | 0 | | | | | | **-0.85** | **-0.67** | **-1.72** | **-2.16** | **-3.86** |
| rtype6 | 0 | 0 | 0 | 0 | 0 | | | | | | **-1.18** | **-1.49** | **-1.92** | 0 | -1.14 |
| rtype7 | 0 | **0.88** | **-1.13** | 0 | -2.37 | | | | | | **-0.72** | -0.74 | **-1.21** | 0 | **-3.72** |
| rtype9 | **-2.73** | **-2.45** | **-2.91** | | | | | | | | **1.61** | **0.86** | **4.21** | | |
| rtype10 | 0 | 0 | 0 | 0 | 0 | | | | | | **-1.60** | **-1.19** | **-2.59** | **-1.40** | 0 |
| rtype11 | **1.53** | **1.51** | **1.34** | 1.03 | **1.71** | | | | | | **1.02** | **1.07** | **0.68** | **1.83** | 0 |
| rtype12 | **-0.84** | 0 | **-3.07** | 0 | 0 | | | | | | **2.65** | **2.52** | **5.13** | **4.41** | 0 |
| rtype13 | 0 | **0.70** | 0 | -0.87 | 0 | | | | | | **-0.82** | **-0.64** | **-1.94** | 0 | 0 |
| rtype14 | **-4.82** | **-4.55** | | | | | | | | | 0 | **-3.05** | | | |
| rtype15 | **3.04** | **3.71** | **3.02** | **1.75** | **2.04** | | | | | | **2.97** | **3.56** | **4.00** | **1.67** | 0 |
| rtype16 | **3.59** | **3.94** | 0 | **6.46** | **8.92** | | | | | | **7.48** | **6.78** | **5.02** | **7.22** | **12.76** |
| rtype17 | **2.63** | **4.22** | **-2.57** | | **8.98** | | | | | | **6.06** | **6.16** | **7.38** | | **11.09** |
| rtype18 | **-11.57** | **-11.09** | | | | | | | | | 0 | 0 | | | |
| rtype19 | **2.84** | **3.37** | **1.66** | **2.10** | **3.50** | | | | | | **2.89** | **3.36** | **2.72** | **2.07** | 1.41 |
| rtype20 | **-3.82** | 0 | 0 | 0 | **-9.38** | | | | | | 0 | 0 | **11.38** | **8.73** | **-6.73** |
| wptype1 | | | | | | **11.90** | | **11.47** | | | **22.75** | | **22.47** | | |
| wptype2 | | | | | | **10.07** | **10.90** | **10.48** | 0 | **7.60** | **15.43** | **18.14** | **16.01** | **4.93** | **9.56** |
| wptype3 | | | | | | **6.56** | **6.85** | **6.65** | 3.62 | **5.61** | **9.10** | **11.70** | **7.12** | **4.38** | **5.63** |
| wptype4 | | | | | | **3.85** | **3.40** | **4.17** | **3.28** | **4.72** | **5.02** | **6.35** | **3.30** | **5.51** | **4.49** |
| wptype5 | | | | | | **1.16** | **1.36** | 1.08 | 0 | 0 | **1.43** | **3.56** | **-1.23** | 0 | **-1.27** |
| wptype6 | | | | | | **2.42** | **2.72** | **1.67** | **2.63** | **3.58** | 0 | 0 | **-5.16** | 0 | **2.10** |
| wptype8 | | | | | | **2.69** | **2.33** | **3.65** | 1.21 | **3.64** | **4.66** | **5.46** | **5.54** | **1.34** | **2.79** |
| wptype9 | | | | | | **-1.09** | **-1.33** | -0.87 | 0 | 0 | **-3.05** | **-1.16** | **-4.94** | **-4.46** | **-4.65** |
| wptype10 | | | | | | **-1.89** | **-2.46** | **-1.50** | 0 | 0 | **-6.32** | **-3.76** | **-9.99** | **-7.40** | **-4.03** |
| wptype11 | | | | | | **1.51** | **1.45** | 0.93 | **2.61** | **2.13** | 0 | 0 | **-2.05** | **-1.46** | **2.85** |
| wptype12 | | | | | | **-1.04** | **-1.31** | **-2.72** | **4.47** | **2.64** | **-6.38** | **-3.58** | **-10.57** | **-5.47** | **-5.03** |
| wptype13 | | | | | | **-2.58** | **-2.89** | 0 | | **-3.06** | -1.75 | **3.26** | **-13.49** | | **-7.74** |
| wptype14 | | | | | | **-5.61** | **-6.10** | | | | -8.34 | 0 | | | |
| dla | **0.60** | | | | | 0.35 | | | | | **-1.95** | | | | |
| dsd | **-3.50** | | | | | **-3.07** | | | | | **-2.01** | | | | |
| dsa | **-3.10** | | | | | **-2.55** | | | | | **-3.38** | | | | |
| R-Square | 0.288 | 0.235 | 0.240 | 0.519 | 0.501 | 0.192 | 0.140 | 0.284 | 0.142 | 0.172 | 0.120 | 0.084 | 0.207 | 0.099 | 0.131 |
| Adj R-Sq | 0.285 | 0.231 | 0.230 | 0.506 | 0.481 | 0.190 | 0.137 | 0.277 | 0.125 | 0.144 | 0.119 | 0.084 | 0.207 | 0.097 | 0.129 |

1) Only estimated coefficients are presented, with t-scores compressed.
2) Coefficients in bold are significant at 5% level, while coefficients in a regular font are significant at 10% level. Insignificant coefficients are replaced by zero.
3) To help readers easily read signs of coefficients, positive ones are shaded in dark orange color.
4) Rtype1-rtype20 are residence neighborhood types of origin tract; wptype1-wptype14 are workplace neighborhood 8.5 of destination tract.

**Figure 1**. Spatial clustering of neighborhood types in Los Angeles

a) Residence neighborhood types



b) Workplace neighborhood types

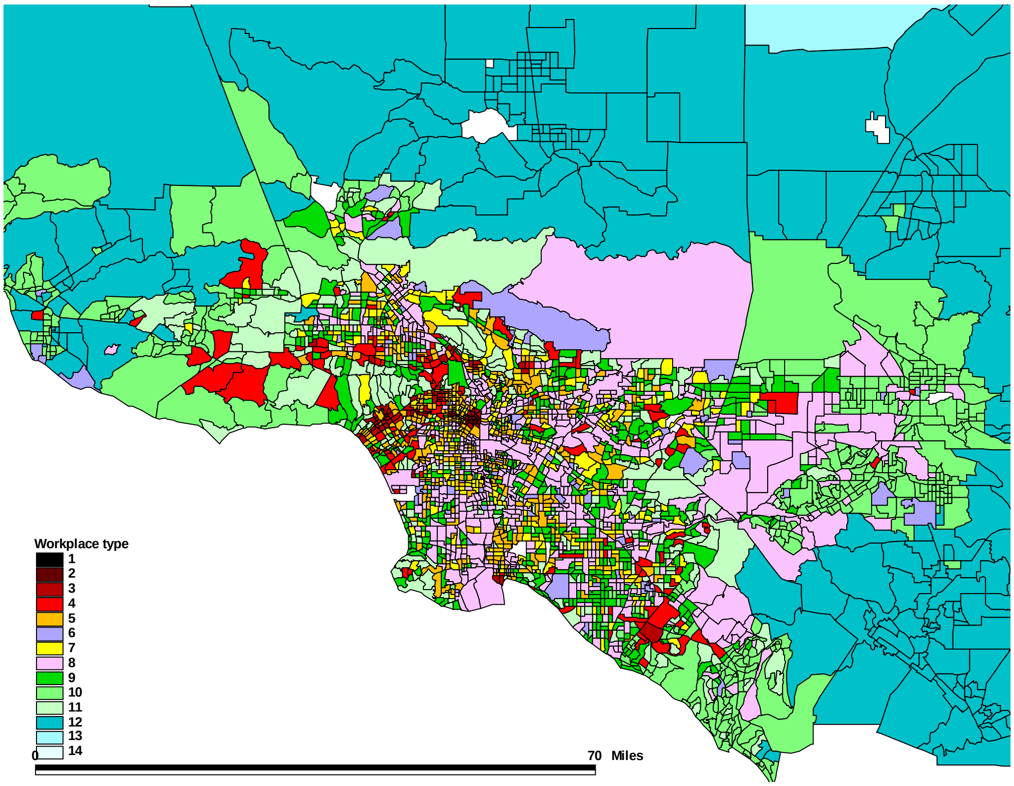


**Figure 2**. Spatial clustering of neighborhood types in San Francisco

a) Residence neighborhood types

b) Workplace neighborhood types

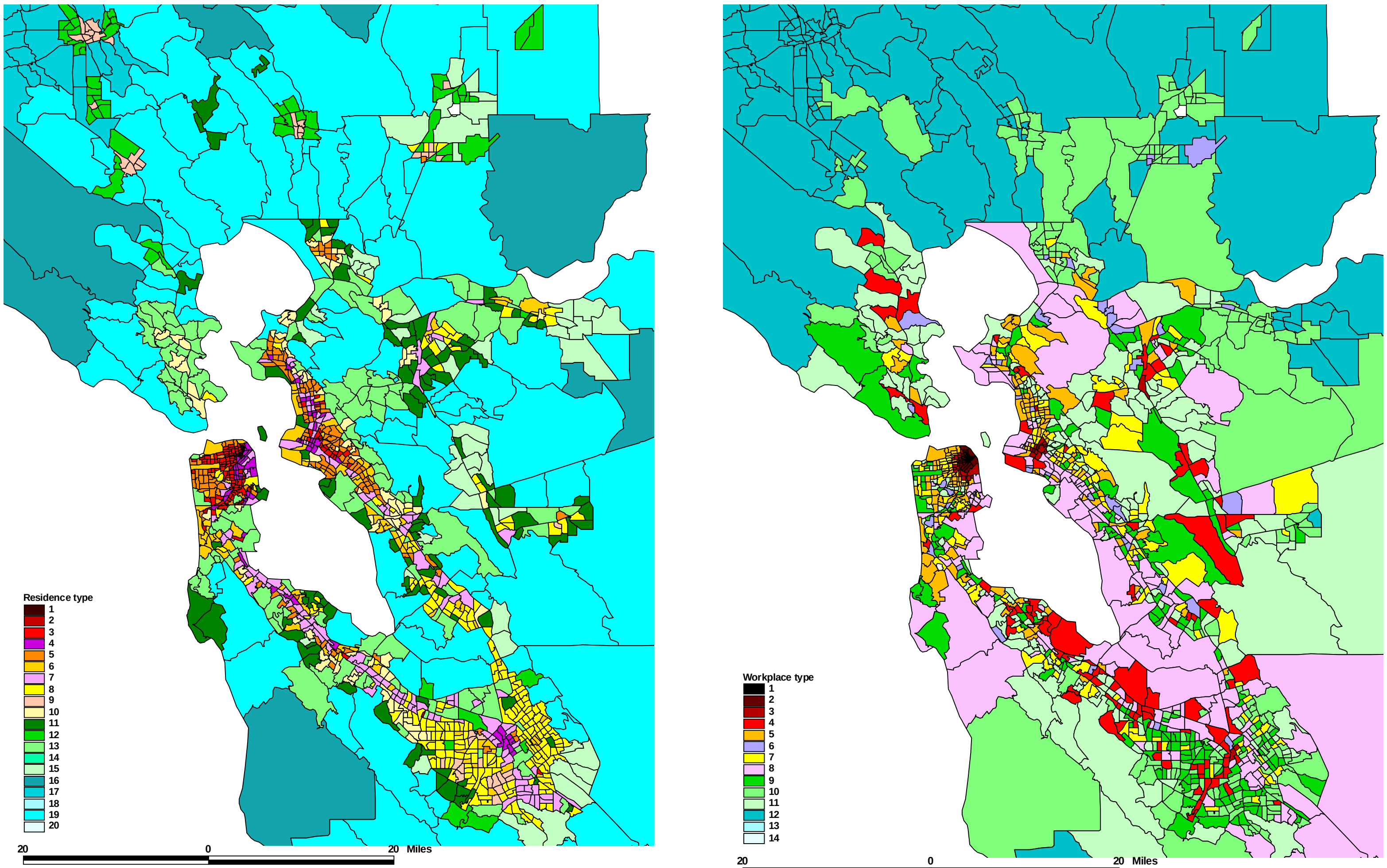
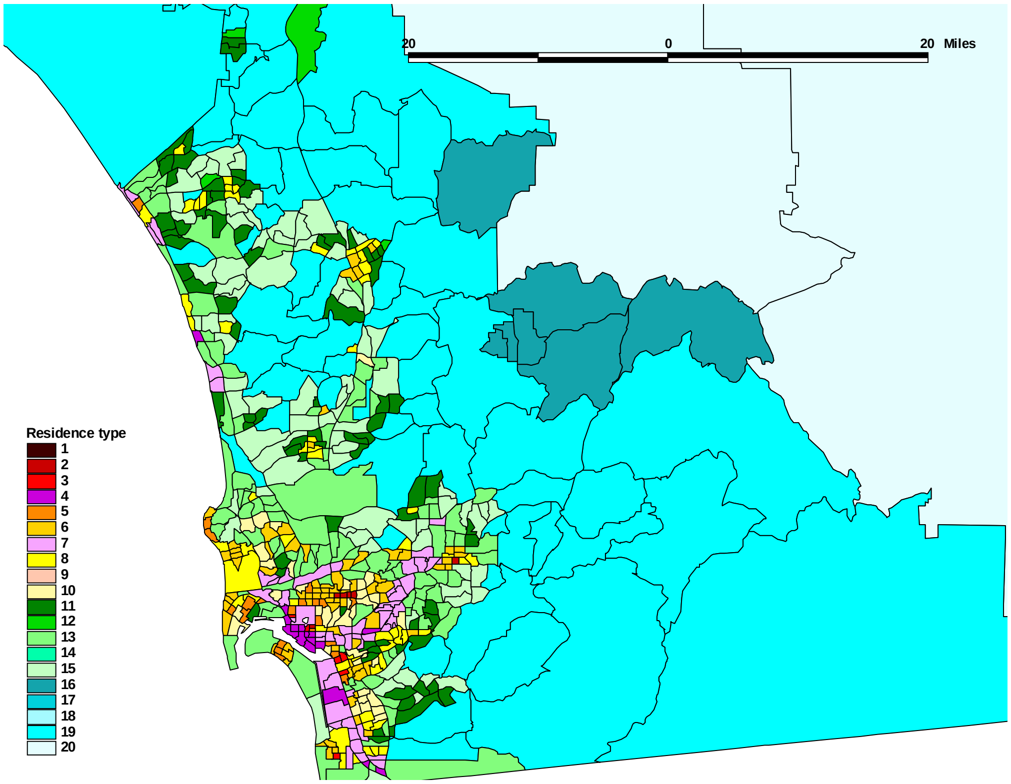


**Figure 3**. Spatial clustering of neighborhood types in San Diego

a) Residence neighborhood types



b) Workplace neighborhood types

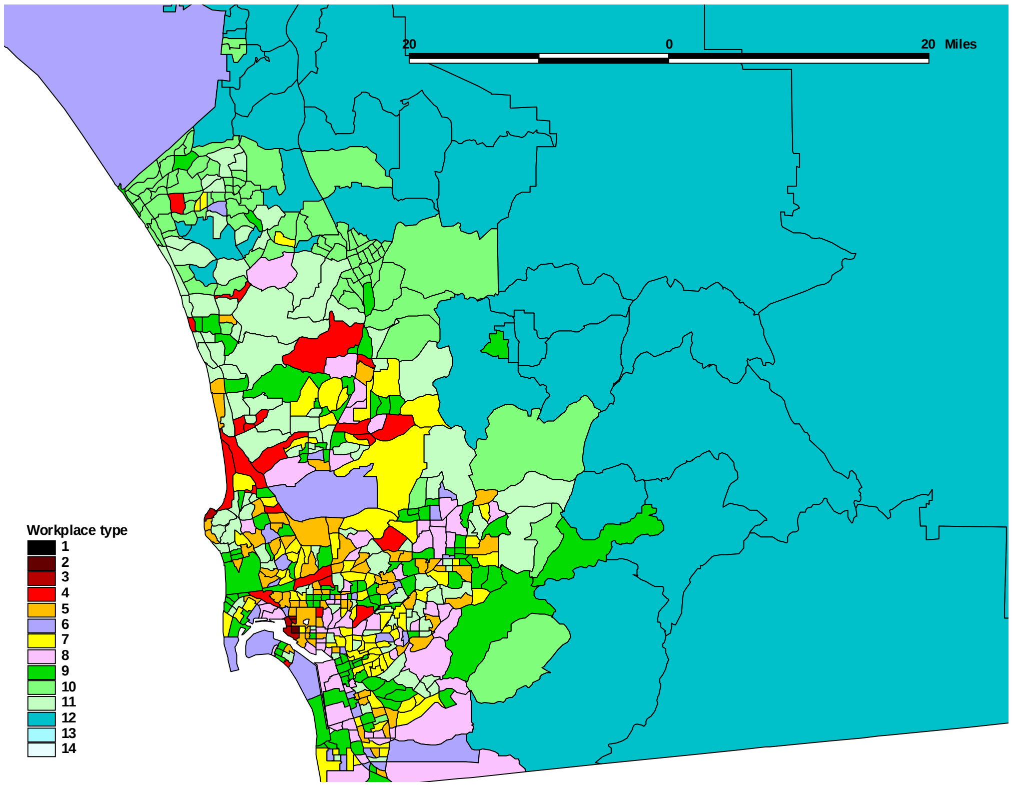
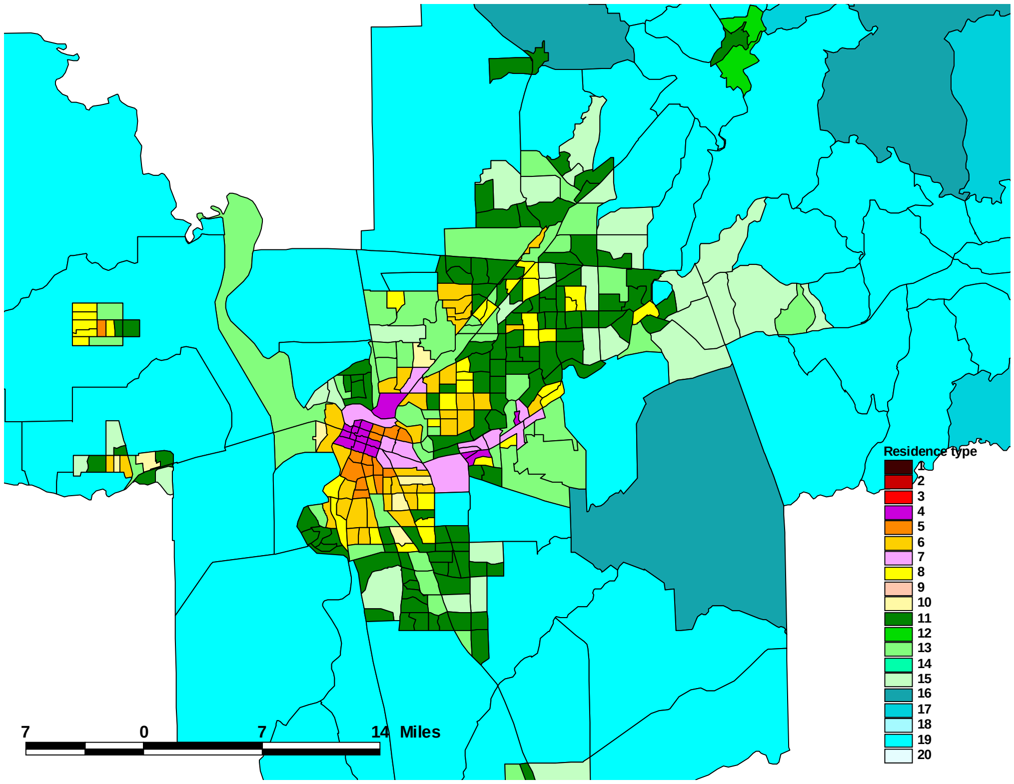
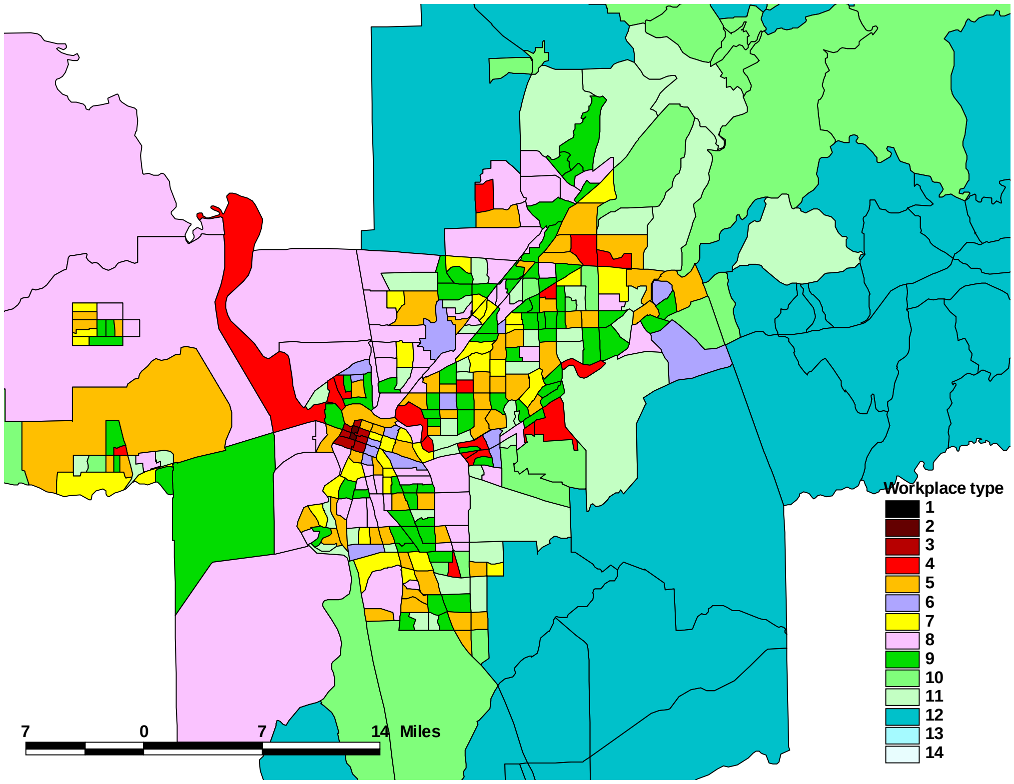


**Figure 4**. Spatial clustering of neighborhood types in Sacramento

a) Residence neighborhood types



b) Workplace neighborhood types



# Appendix

**Table A1**. Residential neighborhood attributes measures used in the cluster analysis

| | Variable | Description | Data Source |
|---|---|---|---|
| Density and Context | POPDEN | Population density (per land acre) | Census SF3 |
| | MEDYR | Age of housing stock (median year housing built) | Census SF3 |
| | CBDIST | Distance from the regional CBD (miles) | TIGER |
| Street Design | STDEN[1)] | Street density (mile per square mile) | TIGER |
| | INTSCTDEN[1)] | Intersection density (No. intersection / street mile) | TIGER |
| | CULDESAC[2)] | Cul-de-sac ratio: No. Cul-de-sac / (No. Cul-de-sac + No. intersections) | TIGER |
| Transit Access | RSWPRDIST | Distance from rail station with park & ride[3)] | MPO |
| | BPRDIST | Distance from bus park & ride[3)] | MPO |
| | PPOPRSBF | Proportion of population within a half mile buffer from a rail station | MPO |
| Highway Access | HWYDIST | Distance from highway ramp[3)] (miles) | TIGER |

1) In calculating street density and intersection density, only A1-A4 type roads are accounted: Primary highway with limited access (A1); Primary road without limited access (A2); Secondary and connecting road (A3); and Local, neighborhood, and rural road (A4).
2) Only local, neighborhood and rural roads (A4) are accounted in computing cul-de-sac ratio.
3) In measuring distances of a census tract to each location, we measured distances from all census blocks within the census tract to the closest location and estimated weighted average distances with the weight given to the population of each census block.

**Table A2**. Workplace neighborhood attributes measures used in the cluster analysis

| | Variable | Description | Data Source |
|---|---|---|---|
| Density and Context | JOBDEN | Job density (per land acre) | CTPP |
| | CBDIST | Distance from the regional CBD (miles) | TIGER |
| | NBRJDEN | Average job density of neighboring census tracts within one mile radius (per land acre) | CTPP |
| Transportation Access | RSDIST | Distance from rail station (miles) | MPO |
| | INCHDIST | Distance from the closest major highway interchange (miles) | TIGER |
| | AIRDIST | Distance from the closest major airport (miles) | TIGER |
| Industrial Composition[1)] | INDUSTRIAL | Concentration of industrial sectors such as manufacturing, wholesale, and TCU | CTPP |
| | BUSINESS SERVICES | Concentration of business service sectors such as FIRE, professional service, and information sectors | |
| | RETAIL | Concentration of retail and arts, entertainment, recreation, accommodation and food services | |
| | PUBLIC | Concentration of public administration sectors | |

1) Four variables in this category are factor scores that are obtained from a factor analysis using 13 industrial sectors' share of total employment in each census tract as input. Each factor is named after the sectors in the corresponding description column that are saliently loaded in the factor.

**Table A3**. Rotated[1)] factor pattern of industrial composition

| | Factor1: Industrial | Factor2: Business Services | Factor3: Retail & Personal Services | Factor4: Public Admini-stration |
|---|---|---|---|---|
| Agriculture, forestry, fishing and hunting, and mining | 0.206 | -0.066 | -0.089 | -0.010 |
| Construction | 0.285 | 0.132 | -0.259 | -0.428 |
| Manufacturing | **0.759** | -0.072 | -0.097 | 0.025 |
| Wholesale trade | **0.638** | -0.001 | -0.051 | -0.083 |
| Retail trade | -0.018 | -0.154 | **0.754** | -0.102 |
| Transportation and warehousing, and utilities | **0.438** | -0.113 | 0.026 | 0.294 |
| Information | 0.004 | **0.460** | -0.034 | 0.211 |
| Finance, insurance, real estate and rental and leasing | -0.275 | **0.552** | 0.186 | -0.042 |
| Professional, scientific, management, administrative, and waste management services | -0.073 | **0.755** | -0.215 | -0.134 |
| Educational, health and social services | -0.609 | -0.545 | -0.501 | 0.058 |
| Arts, entertainment, recreation, accommodation and food services | -0.214 | 0.079 | **0.650** | -0.003 |
| Other services (except public administration) | -0.121 | -0.065 | 0.084 | -0.572 |
| Public administration | -0.038 | 0.048 | -0.081 | **0.673** |

1) Variance maximization (varimax) rotation was utilized.

**Table A4**. Estimated inverse power function parameters for study areas

| | Los Angeles | San Francisco | San Diego | Sacramento |
|---|---|---|---|---|
| Beta | 0.584 | 0.692 | 0.608 | 0.550 |
| Number of obs. | 427,853 | 152,888 | 57,616 | 33,985 |
| R-square | 0.191 | 0.282 | 0.225 | 0.196 |

1) Betas for the inverse power function were estimated from a regression model for each metropolitan area below:

$$\ln \frac{C_{ij}}{W_i E_j} = \ln \alpha - \beta \ln d_{ij}$$

, where $C_{ij}$ = number of commutes from zone i to j; $W_i$ = number of workers in zone i; $E_j$ = number of employments in zone j; $dij$ = distance between zone i and j.

2) For the commutes within a Census Tract, the distance ($d_{ii}$) is defined as half the radius of an area-equivalent circle instead of zero.