NEIGHBORHOOD ATTRIBUTES AND COMMUTING BEHAVIOR: TRANSIT CHOICE

Final Report

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Abstract

Neighborhood type matters when we try to explain variations in public transit commuting. We found this statistical link over a sample of all census tracts in the four largest California metro areas. In this research, we used statistical cluster analysis to identify twenty generic neighborhood types. The variables used in the analysis included broad indicators of location and population density, street design, transit access and highway access. Once identified, the denser neighborhoods had higher transit use, other things equal. Yet, what distinguishes the research is that we did not use a simple density measure to differentiate neighborhoods. Rather, density was an important ingredient of our neighborhood-type definition -- which surpassed simple density in explanatory power.

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1. INTRODUCTION

Smart Growth planning and New Urbanist designs presume that physical neighborhood characteristics influence commuting decisions. Yet, there have been few tests of this hypothesis. Most research using aggregate commuting data has focused on metro areas as the spatial units of analysis. Crane (2000) summarizes some of the recent work that analyzes the effects of neighborhood types. The research reported here considers data from census tracts across California's major metropolitan areas. We look for the effects of generic neighborhood types defined across all metro areas. This report focuses on the relationship between neighborhood types and transit use. The other research questions, relating to travel time and local jobs-housing balance, were held up by the delays in the release of the 2000 CTPP data. These data have recently been released so that these other research issues can now be explored.

2. NEIGHBORHOODS

One of the underlying concepts in discussions of urban planning is the neighborhood. Neighborhoods are as old as the family system and the kinship network in ancient China (Gordon, 1946). Greek and Roman city planning laid out neighborhoods with specific boundaries, often for social and religious segregation. Roman cities organized *vici* (hence our word vicinity) with their own markets and administration. Medieval cities had their 'quarters' and 'ghettoes' with sometimes distinctive architecture and varying levels of self-government (Mumford, 1961).

In the relatively recent history of urban America, the idea of explicitly using the neighborhood unit to promote health and cultural values was related to acculturating America's large immigrant population to be good citizens and industrial workers (Perry, 1939). Inspired by the experience of living in New York's Forest Hills Gardens, social planner Clarence Perry proposed "neighborhood units" as part of the 1929 Regional Plan for New York. Perry conceived of the neighborhood as the building block of urban growth, a self-contained closed system. These are reflective of common sense approaches that refer to the beginning of the street car suburbs of the late 19th Century, the garden city movement in the United Kingdom, and a reaction against dense immigrant housing in America. Perry's ideas received the backing of the then recently established Federal Housing Administration (FHA) which sent out brochures nationwide describing the concept to developers. However, developers tended to focus on housing construction rather than on neighborhood civic and commercial uses, undercutting one of Perry's goals and reinforcing the segregation of land uses that make automobile travel attractive even for short neighborhood trips (ICMA, 2000).

Perry identified six attributes in his neighborhood model:

1. <u>Size</u> – based on elementary school average attendance (about 400 children) to which children can walk without crossing major streets. The precise area would depend on residential density and the amount of non-residential land uses. An average population would be about 7,000, or about 2,000 housing units. *(This measure implies assumptions regarding the number of children per household, household age distribution, household size, fertility rates of child-bearing age women, and that most children attend public school.)*

2. Boundaries – bounded on all sides by arterial streets sufficiently wide to allow through traffic to bypass rather than penetrating the neighborhood. *(Geographical feature such as railroads and rivers may also form boundaries.)*

3. Open Space – small parks and other local-serving institutions that coincide with the neighborhood area sufficient to meet the needs of the population.

4. Institution Sites – school and institutional sites should be grouped near the center of the neighborhood.

5. Local Shops – one or more shopping districts, adequate for the resident and daytime population, should be laid out near the circumference, preferably at traffic junctions, and adjacent to similar districts for adjoining neighborhoods.

6. Internal Street System – the neighborhood should have an internal street system proportional to its probable traffic load and designed to facilitate internal circulation and to discourage use by through traffic. (Perry, 1939, p. 51)

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.

The neighborhood shopping center is designed to meet the day-to-day demands of a limited trade area of 2,500 to 40,000 people. It is generally located at the entrance to a neighborhood from an arterial. The anchor is typically a grocery store with adjacent drug stores, small retail and service establishments, and restaurants. A typical center would be 50,000 square feet (but could range between 30,000 to 100,000, depending on the trade area population) and require 3 to 10 acres (Porterfield, 1995).

Jane Jacobs questions some aspects of the neighborhood concept in her classic critique of urban planning, *The Death and Life of Great American Cities.* She argues that city residents are mobile and pick and choose from the entire city (and beyond). They are not restricted to the provincialism of a neighborhood (Jacobs, 1961). This critique was written over 40 years ago in the middle of the Baby Boom when most households had one car and when, the suburbs were in their first phase of post-war expansion.

Baer and Banerjee (1984) expanded Perry's definition, adding three aspects:

Context: The neighborhood 'movement' was a turn-of-the-century (1900) outgrowth of the concern over urban lifestyle and its weakening of the traditional links between the individual, the place, and community (White and White, 1962). The erosion of the family and the general moral order was thought to be a function of the lack of dignity and community found in industrial city housing, which were generally described as impersonal and unhealthy. This approach might be seen as "social engineering" and "assimilation of immigrants." It is reflected in today's preference for home ownership and the single family house.

Manifest: Perry (1952) recognized early that the automobile was the chief 'villain' that the neighborhood unit was trying to counterbalance, with an emphasis on a walkable radius focused on the school and surrounding civic and retail functions. This concept was perhaps first realized in Radburn and other garden cities (Stein, 1957).

Tacit: Uniformity of design, scale, and people was an underlying assumption. The emphasis on child-rearing (especially young children) spilled over into economic and racial homogeneity. This policy was explicitly enforced by covenants and FHA lending practices into the 1950s.

The neighborhood has become a prototypical planning element of the American suburban city and a standard 'product' of developers and merchant builders. Today's new neighborhoods typically have entry and image treatments and/or may be gated. The better plans included a neighborhood park near the center, perhaps adjacent to the school. Many are developed with Home Owners Associations, with extensive landscaping and regulations for painting and maintenance, and perhaps a swimming pool and other facilities.

The classic neighborhood unit could not have been intended to capture the majority of the work-related trips internally, as it included only a small amount of non-residential land uses. But, in theory, it would capture trips to elementary schools, neighborhood retail stores, and neighborhood civic uses such as attending church or visiting a park. The question, then, seems to be whether Perry's 'neo-traditional' neighborhood model ever worked (assuming it was developed and tested) or have so many residents changed their reasons and destinations for travel that the classic neighborhood model simply does not capture their destinations as well as it used to, even if it were built according to the classic definition? This research effort attempts to answer that question in California, by defining a range of neighborhoods from Perry's classic model (which may include New Urbanist developments and older suburbs) to new, sprawling suburbs.

3. RESEARCH APROACH

A. DATA

The purpose of this research is to test how physical neighborhood characteristics influence commuting decisions, especially transportation mode choice, where choice exists and, commuting time. So far, we have examined commuting mode choice.

We relied on journey-to-work data from the U.S. decennial census to analyze commuting behavior at the census tract level for California's four biggest metro areas, Los Angeles, San Francisco, San Diego and Sacramento. Several census tract-level social, economic and housing characteristics data are taken from the 1990 and 2000 Census Summary File 3 (STF3).

One standard problem in using the census data over time is that census geography changes significantly across census years, especially at a small geographic scale. The Census Neighborhood Change Database (NCDB) 1970-2000 Tract Data, provided by GeoLytics and the Urban Institute, enabled us to overcome the geographic comparability problem by remapping earlier census year data to 2000 census tract boundaries. Therefore, all census variables for any census year in this report are presented for 2000 census geography.

Measures of physical neighborhood characteristics that are critical in testing our research questions were not readily available. However, we derived many of the required variables using geographical information systems (GIS). The 2000 TIGER® (Topologically Integrated Geographic Encoding and Referencing system) street networks files were used to measure street design, which has often been suggested as associated with local and regional accessibility, and hence affect commuting behavior. In addition to the TIGER files, GIS map data of rail transit lines were obtained from each metropolitan planning organization (MPO) of our study areas and are used to measure rail transit access.

B. STATISTICAL CLUSTER ANALYSIS

The strategy we adopted to test physical neighborhood characteristics' influence on commuting decisions involved two steps. First, we classified all census tracts in our study areas into twenty prototypical neighborhood categories using a statistical cluster analysis. Smith and Saito's (2001) results suggested that meaningful spatial aggregates can be identified via this approach. In an analysis of local area characteristics and their effects on mode choice, Srinivasan (2002) gathered data on these variables for Boston area TAZs. In contrast, we first investigated which census tracts cluster into meaningful neighborhood units.

In the next step, we tested influences on commuting decisions of these neighborhood types as well as those of traditional explanatory variables; as an example, for mode choice it is logical to test the influence of household income.

We used ten physical descriptor variables in the cluster analysis. These included measures of the contextual position, street design, and transit and highway access of each census tract (Table A1). Population density, distance from the core-CBD of each metropolitan area, and the age of housing stock are basic variables for a census tract. Street design variables, such as street density, intersection density, and the cul-de-sac ratio, are expected to be associated with pedestrian access, intra-neighborhood connectivity, and ultimately automobile dependence. These factors are considered especially important in New Urbanist neighborhood design. Access to such major transportation infrastructure as rail transit systems, park and ride stations, and highways would also affect commuting behavior. Bus transit access, however, is not taken into account in classifying neighborhood types on the ground that bus routes are highly ubiquitous and very flexible. Hence, they are endogenous to transit demand rather than being exogenous.

All these variables, except population density and the median age of the housing stock that are directly available from the Census STF3 file, are derived from TIGER street networks files and GIS map files of each metropolitan area's rail transit system. We pooled all 5,727 census tracts data in the four study areas, excluding ones on islands and ones without commuters. We then performed cluster analysis to seek generic California neighborhood prototypes across the four metropolitan areas.

Whereas a variety of techniques are available for cluster analysis, we have chosen perhaps the most commonly used methods in this field[1]: Euclidean distance is used as a similarity measure, and Ward's minimum-variance method is used as a hierarchical clustering technique. We standardized the distributions of all variables to normal distributions before conducting the cluster analysis. Twenty clusters or neighborhood types were determined by evaluating the statistical clusters *ex post*. Reasonable size distributions of clusters and their spatial distribution, and how many clusters were manageable were considered in making the decision. Some arbitrariness is inevitable given that such statistics such as the Cubic Clustering Criterion (CCC), the Pseudo F-statistic (PSF), and the Pseudo-t^2 statistic do not clearly indicate an optimal number of clusters. All data analyses used procedures provided by the SAS software package. The

[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).

resulting distribution of twenty clusters is presented in Table A2, along with cluster mean values for each variable.

Neighborhood Types 16-20 are largely unpopulated and have no significance for this study. Types 11-15 are the outer suburbs (for example, for the case of the Los Angeles area, including Victorville, Barstow and the Moreno Valley area [Type 13]; areas near the cities of Ventura, Lancaster, San Bernardino, Riverside and Redlands; see Figures A2-a and A2-b). Types 5-10 are more central; 5 and 9 tend to be near rail lines and in the inner city; 6, 7, 8 and 10 describe the more typical inner city small-lot suburbs. For the Los Angeles metro area, Type 6 describes western areas of Los Angeles county, while 7 describes parts of Orange county; Type 8 areas are to be found in the San Fernando, San Gabriel and Torrance areas. Again, referencing Los Angeles, neighborhood Type 1 describes the downtowns of Los Angeles and Long Beach; Type 2 areas cluster around these whereas Type 4 areas cluster around both; Type 3 appears to describe the "beach cities" of Venice Beach, Marina Del Rey, Manhattan Beach, Hermosa Beach and Long Beach.

C. MULTIPLE REGRESSIONS

Multiple regression analyses were done to test neighborhood type effects on commuting mode choices. The dependent variable of our regression models, the number of transit users in each census tract, is a *count* variable, which takes on nonnegative integer value or zero in many incidences. Hence, the Poisson or negative binomial regression model is more appropriate for our data, because linear models by ordinary least square (OLS) estimation may predict negative counts.

The Poisson regression model assumes that the count variable of interest, the number of transit users in our case, follows a Poisson distribution:

$$prob(Y = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, y = 0,1,..., where \ln\lambda_i = \beta' x_i$$

The maximum likelihood estimator of the coefficients is the semielasticity of E(y|x) with respect to a covariate (Wooldridge, 2002). That is, the percentage change in E(y|x) can be approximated by $100\beta_j{*}\Delta x_j$, for a small change Δx_j. Cameron and Windmeijer (1996)'s measure based on the deviances is often used to evaluate the goodness of fit:

$$R_d^2 = 1 - \frac{\sum_{i=1}^{n} y_i \ln(\frac{y_i}{\hat{\lambda}_i})}{\sum_{i=1}^{n} y_i \ln(\frac{y_i}{\bar{y}})}$$

However, the Poisson regression model's strong assumption that the conditional variance equals the mean is very often violated. Transit user counts in our data are also overdispersed. As shown in Figure A1, the variance is over 250 times larger than the mean. A common alternative in overdispersion cases is the negative binomial regression model, which allows the variance to differ from the mean,

$\ln \lambda_i = \beta' x_i + \varepsilon$, where exp(ε) follows a gamma distribution with mean 1 and variance α.

Data for the year 2000 for our variables of interest were compiled and examined for the 5,727 census tracts in the Los Angeles, San Francisco, San Diego and Sacramento MSAs. Results for both OLS and negative binomial regressions for the pooled data set and for each MSA are reported below. The two sets of results are very similar and in what follows, only the OLS findings are discussed

OLS regression results are shown in Table 1 (corresponding negative binomial results are shown in Table 2). At the census tract level, the number of transit commuters is explained by the total number of commuters and by how many are below the poverty line. Metro area dummy variables add a negative influence if the census tract is not in the San Francisco area. All the signs are as expected with very large t-values. Forty percent of the variation of the dependent variable is explained. The model for pooled metro areas explains more than the individual area models, with the exception of Los Angeles.

The explanatory power of these models is improved, as expected, if census tract population densities are added (Table 1b). Higher density tracts account for more transit commuting. Models using the pooled data as well as models for Los Angeles and San Diego explain more than fifty percent of the variation of the dependent variable.

The results in Table 1c show that neighborhood type matters. Replacing the density variable with all the neighborhood type variables boosts the explanatory power of the models. Also, all the neighborhood type dummy variables have large t-values except for Type 3 (neighborhood Type 8 is the reference type). The neighborhood types are listed in the order of their average population density (which, reasonably, correlates with street densities). As expected, almost all of the dense types have positive signs while all of the less dense types have negative signs. This model is superior to the models in Table 1b, not only because more variance of the dependent variable is explained but also because neighborhood type includes much more information than population density alone.

Yet, the neighborhoods identified vary along various other interesting dimensions. Whereas Types 1 and 2 were the densest, Type 1 is limited to downtown areas of Los Angeles and Long Beach; Type 2 describes areas nearby these centers but also found in central parts of Glendale and Santa Ana.

It is also noteworthy that the improvement in statistical fit for the four other metro areas improves to the point where all are almost equally able to explain transit commuting. With rare exceptions, neighborhood types have similar effects across metro areas.

Trying to explain the ten-year change in transit use (1990-2000) at the small-area level is less successful. Table 3a shows tests that mirror those reported in Table 1a with the dependent variable being the 1990-2000 *change* in transit commuting. Independent variables include the change in the number of commuters and the change in the number of people in poverty. This is where the GeoLytics software described earlier was useful. The number of census tracts studied was slightly fewer (5680) reflecting the fact that a few 1990 tracts had no commuters. The signs of all three independent variables (and the three dummy variable coefficients) are as expected with high t-values. Yet, only 11 percent of the cross-section's variation of transit commuting is explained for the pooled sample. Individual metro area models provide similar results.

Adding 1990 census tract population densities (Table 3b) yields mixed results. For the pooled sample and for the Los Angeles area, higher densities have a negative effect on transit use once the effects of other variables are accounted for.

Results in Table 3c show what happens when 1990 densities are replaced with the ten-year change in densities. This time as densities increase, so does transit use. This effect was also found for all areas but Sacramento.

Table 3d results show the density variables replaced by the neighborhood type dummy variables for 2000; these are again ranked (labeled) by average population density. Only some of these are significant and there is no apparent pattern in terms of their density variation.

4. DISCUSSION

Our results support the idea that neighborhood type matters when it comes to transit commuting. This does not imply that neighborhood change as a policy is cost-effective or worth pursuing. Such a strategy, even if feasible, would take too long. It suggests, however, that at the margin, transit commuting impacts and neighborhood type are interdependent. Nevertheless, the politicized placement of many of the recently installed rail transit stations in California (Altshuler and Leberoff, 2003, Ch.6) suggests that it is reasonable to test one-way causation.

5. FURTHER WORK

We plan to extend our research along similar lines to the study of the variations in commuting time. We will use the same neighborhood types. We will also investigate the impacts of destination neighborhood types The (default) competing variable will be each census tract's conventionally calculated regional job accessibility index. This variable will be computable by using the CTPP data for the four metro areas.

Given the finding that our neighborhood types can explain variations in transit commuting, even when the impacts of poverty levels are held fixed, can they also explain variations in commuting times, when the impacts of job accessibility are held fixed?

We also intend to examine whether the identified neighborhoods lend any credence to the concept of local jobs-housing balance. Still another direction for further work would be an investigation of alternate definitions neighborhood types and their consequences.

Table 1. OLS regression results of transit use models, 2000

1-a) Base models

Dependent variable: Log of # transit users	Pooled (4 MSAs) Obs. 5727		Los Angeles Obs. 3307		San Francisco Obs. 1430		San Diego Obs. 593		Sacramento Obs. 397	
	Beta	t	Beta	t	Beta	t	Beta	t	Beta	t
Intercept	-2.0487	-8.99	-3.5134	-12.15	-1.7987	-3.99	-3.1968	-4.63	-4.575	-5.49
Log of # commuters	0.3389	11.02	0.2670	6.79	0.5236	8.27	0.2841	2.95	0.704	5.96
Log of # persons in poverty	0.7383	47.11	0.8510	43.9	0.4436	12.13	0.7895	16.67	0.458	8.09
D Los Angeles	-1.3075	-33.94								
D San Diego	-1.2588	-21.94								
D Sacramento	-1.4284	-21.44								
R-square	0.397		0.408		0.192		0.377		0.280	
Adj. R-square	0.397		0.408		0.191		0.375		0.276	

1-b) Models with population density

Dependent variable:	Pooled (4 MSAs)		Los Angeles		San Francisco		San Diego		Sacramento	
Log of # transit users	Beta	t	Beta	t	Beta	t	Beta	t	Beta	t
Intercept	-0.8690	-4.22	-2.0859	-7.94	-1.0679	-2.67	-2.4557	-4.07	-2.7094	-3.38
Log of # commuters	0.2343	8.49	0.1383	3.91	0.4755	8.50	0.2542	3.03	0.5282	4.75
Log of # persons in poverty	0.5239	34.75	0.6290	33.26	0.2308	6.80	0.5593	12.57	0.3006	5.41
Log of pop density	0.4093	38.16	0.4178	29.06	0.4133	20.21	0.4531	13.76	0.3059	8.32
D Los Angeles	-1.2692	-36.88								
D San Diego	-1.1447	-22.31								
D Sacramento	-1.0692	-17.76								
R-square	0.520		0.528		0.372		0.529		0.388	
Adj. R-square	0.519		0.528		0.371		0.526		0.383	

1) Shaded cells are significant at 10% level. 2) San Francisco is the reference for MSA dummy variables.

1-c) Models with neighborhood type dummies

Dependent variable:	Pooled (4 MSAs)		Los Angeles		San Francisco		San Diego		Sacramento	
Log of # transit users	Beta	t	Beta	t	Beta	t	Beta	t	Beta	t
Intercept	-1.7089	-8.63	-2.4179	-9.5	-2.4960	-7.13	-3.4481	-5.49	-4.0123	-5.07
Log of # commuters	0.4574	16.67	0.2850	7.93	0.7530	14.97	0.5079	5.58	0.8964	8.01
Log of # persons in poverty	0.5476	36.80	0.6892	35.37	0.2788	9.49	0.5837	12.09	0.2134	3.86
Type1	1.5028	11.17	1.3569	8.43	1.6221	7.19				
Type2	1.2316	14.10	0.8708	7.22	1.5172	11.97	0.7554	1.10		
Type3	-0.1555	-0.66	-0.1167	-0.48	-0.2360	-0.27				
Type4	0.6618	11.42	0.5111	7.92	0.9431	5.44	0.6270	2.73		
Type5	0.7519	9.87	0.6711	5.99	0.7863	6.12	0.7413	3.69	0.9653	3.34
Type6	0.4377	7.93	0.3116	4.22	0.7604	7.89	0.2955	1.59	0.1739	0.69
Type7	-0.3821	-8.37	-0.3118	-5.48	-0.5539	-6.30	-0.1567	-1.02	-0.0086	-0.03
Type9	0.2691	4.09	0.3009	3.04	0.1790	1.72	0.3711	1.97	0.5052	1.58
Type10	-0.2518	-3.79	-0.1243	-1.18	-0.4384	-3.04	0.0188	0.11	-0.5899	-3.50
Type11	-1.0748	-15.44	-1.1083	-13.19	-1.0546	-8.64	-1.1290	-1.65	-2.1070	-2.06
Type12	-0.5442	-11.70	-0.4596	-7.53	-0.5899	-6.27	-0.4637	-3.69	-1.0584	-5.40
Type13	-1.4886	-20.46	-1.4868	-18.13	-1.4175	-9.28	-2.0364	-2.12	-3.3576	-4.60
Type14	-1.3051	-10.86	-1.3634	-11.3						
Type15	-0.2238	-3.17	-0.3624	-3.94	0.2775	2.11	-0.5177	-2.61	-0.5156	-1.55
Type16	-2.1977	-16.72	-2.4215	-16.28	-2.6979	-5.28	-3.1561	-4.61	-1.2466	-3.15
Type17	-1.0765	-4.14	-2.4564	-6.3					-0.2626	-0.68
Type18	-1.9945	-7.35	-2.1785	-8.03						
Type19	-0.8117	-10.74	-0.6333	-5.08	-0.5565	-3.96	-1.0986	-6.24	-1.2487	-5.88
Type20	-1.8683	-21.92	-1.6776	-12.6	-1.9071	-14.46	-2.4166	-8.57	-1.9642	-7.20
D Los Angeles	-1.1443	-34.65								
D San Diego	-1.1375	-23.32								
D Sacramento	-1.1664	-19.83								
R-square	0.593		0.599		0.559		0.539		0.488	
Adj. R-square	0.591		0.596		0.553		0.526		0.468	

1) Shaded cells are significant at 10% level.
2) San Francisco is the reference for MSA dummy variables and type 8 is the reference type for neighborhood type dummies.

Table 2. Negative binomial regression results of transit use models, 2000

2-a) Base models

Dependent variable: Log of # transit users	Pooled (4 MSAs) Obs. 5727		Los Angeles Obs. 3307		San Francisco Obs. 1430		San Diego Obs. 593		Sacramento Obs. 397	
	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.
Intercept	-5.4680	6020.9	-7.5969	6031.6	-3.8611	618.7	-6.2651	1089.2	-5.4836	477.6
Log of # commuters	fixed		fixed		fixed		fixed		fixed	
Log of # persons in poverty	0.5511	2114.4	0.7048	2132.1	0.2618	94.4	0.4744	238.0	0.3158	57.8
D Los Angeles	-1.1495	1112.7								
D San Diego	-1.2534	610.6								
D Sacramento	-1.3790	546.8								
R-square	0.574		0.552		0.304		0.537		0.416	
Log-likelihood	-31601		-17504		-8990.9		-3041.4		-1936.0	
Deviance	6909.6		4041.9		1666.6		722.9		485.4	

1) Shaded cells are significant at 10% level.
2) San Francisco is the reference for MSA dummy variables.
3) R-square in negative binomial regression models are measured based on the deviances.

2-b) Models with population density

Dependent variable: Log of # transit users	Pooled (4 MSAs) Obs. 5727		Los Angeles Obs. 3307		San Francisco Obs. 1430		San Diego Obs. 593		Sacramento Obs. 397	
	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.
Intercept	-5.1310	5499.5	-7.1347	5599.5	-3.3258	521.1	-6.2210	1070.7	-5.1298	414.6
Log of # commuters	fixed		fixed		fixed		fixed		fixed	
Log of # persons in poverty	0.3520	715.7	0.4930	860.9	0.0193	0.5	0.3549	112.8	0.1994	20.2
Log of pop density	0.3346	1215.8	0.3481	698.9	0.3546	460.2	0.3166	100.8	0.2279	47.3
D Los Angeles	-1.0743	1115.9								
D San Diego	-1.1046	546.6								
D Sacramento	-1.0055	323.8								
R-square	0.673		0.635		0.461		0.652		0.503	
Log-likelihood	-31124		-17229		-8818.3		-3002.0		-1916.2	
Deviance	6932.0		4069.7		1648.9		737.6		485.1	

1) Shaded cells are significant at 10% level.
2) San Francisco is the reference for MSA dummy variables.
3) R-square in negative binomial regression models are measured based on the deviances.

2-c) Models with neighborhood type dummies

Dependent variable: Log of # transit users	Pooled (4 MSAs) Obs. 5727		Los Angeles Obs. 3307		San Francisco Obs. 1430		San Diego Obs. 593		Sacramento Obs. 397	
	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.	Beta	Chi-Sq.
Intercept	-4.5039	3823.1	-6.1608	3467.4	-3.3768	632.6	-5.4333	631.4	-4.7544	267.1
Log of # commuters	fixed		fixed		fixed		fixed		fixed	
Log of # persons in poverty	0.3536	934.2	0.4701	876.4	0.1476	43.5	0.3366	109.3	0.2283	31.2
Type1	1.5747	187.6	1.5665	128.7	1.4618	57.7				
Type2	1.2144	264.1	1.1106	115.6	1.3059	145.7	0.9803	2.9		
Type3	0.3984	3.9	0.3424	2.7	-0.3438	0.2				
Type4	0.7597	235.1	0.6701	146.3	0.8886	36.0	0.7048	13.5		
Type5	0.9521	213.5	0.9497	98.4	0.8148	55.3	1.0673	40.3	1.0577	19.8
Type6	0.5347	125.3	0.4331	45.3	0.7316	78.2	0.3446	4.8	0.2305	1.3
Type7	-0.3629	84.6	-0.3325	44.9	-0.4906	41.7	-0.0794	0.4	-0.0298	0.0
Type9	0.3319	34.3	0.4247	24.3	0.1958	4.8	0.5120	10.4	0.5456	4.4
Type10	-0.3865	44.7	-0.3965	17.7	-0.3611	8.5	-0.0293	0.0	-0.4357	10.6
Type11	-0.8439	191.9	-0.7777	109.9	-0.9749	84.5	-1.5213	5.9	-2.2701	6.6
Type12	-0.6032	224.1	-0.6003	122.4	-0.5290	44.0	-0.4696	20.2	-0.6470	17.5
Type13	-1.2453	368.2	-1.1686	247.3	-1.3573	106.3	-2.1440	6.3	-3.4705	22.1
Type14	-0.8904	69.9	-0.9055	70.4						
Type15	-0.0204	0.1	-0.1949	5.7	0.2911	6.6	-0.3552	4.4	-0.2327	0.7
Type16	-1.3601	124.8	-1.6530	139.2	-2.1804	23.2	-3.2583	16.1	-0.2870	0.8
Type17	-0.6083	7.0	-2.3248	42.2					-0.0646	0.0
Type18	-1.7631	33.3	-1.7098	30.9						
Type19	-0.6656	95.7	-0.4927	17.3	-0.4964	16.9	-0.7971	24.9	-0.8591	23.3
Type20	-1.4118	323.9	-1.3461	107.8	-1.3812	142.2	-2.0017	60.0	-1.3026	30.2
D Los Angeles	-0.9329	1039.8								
D San Diego	-0.9605	507.8								
D Sacramento	-0.9680	350.7								
R-square	0.820		0.795		0.738		0.699		0.577	
Log-likelihood	-30376		-16865		-8522.3		-2939.3		-1869.5	
Deviance	6854.2		4033.9		1612.7		721.0		489.0	

1) Shaded cells are significant at 10% level.

2) San Francisco is the reference for MSA dummy variables and type 8 is the reference type for neighborhood type dummies.

3) R-square in negative binomial regression models are measured based on the deviances.

Table 3. OLS Regression results of transit use change models, 1990-2000

3-a) Base models

Dependent variable: Change in # transit users	Pooled (4 MSAs) Obs. 5680[1)]		Los Angeles Obs. 3284		San Francisco Obs. 1428		San Diego Obs. 583		Sacramento Obs. 385	
	Beta	t	Beta	t	Beta	T	Beta	t	Beta	t
Intercept	9.067	5.34	-7.501	-6.34	2.542	1.07	-2.572	-1.24	4.482	1.79
Change in # Commuters	0.030	19.30	0.024	13.21	0.058	13.26	0.014	4.24	0.018	5.56
Change in # persons in poverty	0.044	14.59	0.044	13.71	0.041	3.61	0.050	6.50	0.024	2.89
DLos Angeles	-16.760	-8.16								
DSan Diego	-13.797	-4.49								
DSacramento	-10.718	-2.98								
R-square	0.110		0.104		0.130		0.104		0.092	
Adj. R-square	0.109		0.103		0.129		0.101		0.087	

1) All transit use change models exclude census tracts with no commuters in 1990.
2) Shaded cells are significant at 10% level.
3) San Francisco is the reference for MSA dummy variables.

3-b) Models with population density

Dependent variable:	Pooled (4 MSAs)		Los Angeles		San Francisco		San Diego		Sacramento	
Change in # transit users	Beta	t	Beta	t	Beta	T	Beta	t	Beta	t
Intercept	17.390	8.99	6.696	4.32	3.161	1.01	-4.722	-1.51	-4.634	-1.15
Change in # Commuters	0.026	16.87	0.017	8.88	0.057	13.21	0.015	4.30	0.022	6.30
Change in # persons in poverty	0.046	15.45	0.050	16.00	0.040	3.53	0.047	5.78	0.021	2.47
1990 Pop density	-0.580	-8.76	-1.084	-13.71	-0.043	-0.31	0.230	0.92	1.377	2.87
DLos Angeles	-17.337	-8.49								
DSan Diego	-16.149	-5.26								
DSacramento	-14.950	-4.15								
R-square	0.121		0.152		0.130		0.105		0.111	
Adj. R-square	0.121		0.152		0.128		0.100		0.104	

3-c) Models with population density change

Dependent variable:	Pooled (4 MSAs)		Los Angeles		San Francisco		San Diego		Sacramento	
Change in # transit users	Beta	t	Beta	t	Beta	T	Beta	t	Beta	t
Intercept	6.513	3.82	-9.086	-7.64	-1.012	-0.41	-2.964	-1.42	4.435	1.77
Change in # Commuters	0.025	16.04	0.021	10.88	0.052	11.83	0.011	2.93	0.019	4.82
Change in # persons in poverty	0.032	10.00	0.033	9.38	0.027	2.31	0.042	4.63	0.026	2.80
Change in Pop density	3.532	9.29	3.431	7.98	4.698	4.93	2.029	1.71	-0.759	-0.46
DLos Angeles	-15.853	-7.77								
DSan Diego	-12.409	-4.06								
DSacramento	-7.730	-2.16								
R-square	0.123		0.121		0.144		0.108		0.092	
Adj. R-square	0.122		0.120		0.143		0.104		0.085	

1) Shaded cells are significant at 10% level.
2) San Francisco is the reference for MSA dummy variables.

3-d) Models with neighborhood type dummies

Dependent variable:	Pooled (4 MSAs)		Los Angeles		San Francisco		San Diego		Sacramento	
Change in # transit users	Beta	t	Beta	t	Beta	T	Beta	t	Beta	t
Intercept	9.694	3.81	-5.542	-2.54	-5.095	-0.83	-2.293	-0.52	2.483	0.45
Change in # Commuters	0.029	17.84	0.020	10.47	0.059	12.93	0.013	3.88	0.019	5.66
Change in # persons in poverty	0.045	14.86	0.047	15.07	0.042	3.70	0.045	5.37	0.023	2.67
Type1	-59.181	-6.91	-109.718	-11.92	48.451	2.39				
Type2	-23.597	-4.25	-39.076	-5.70	-7.596	-0.67	42.482	1.31		
Type3	-22.831	-1.51	-26.702	-1.92	28.267	0.36				
Type4	-4.638	-1.28	-9.811	-2.72	8.152	0.53	15.200	1.43		
Type5	-1.458	-0.30	-38.210	-6.03	41.815	3.63	-6.582	-0.73	37.381	3.30
Type6	-15.662	-4.43	-25.501	-5.98	0.226	0.03	-19.487	-2.29	3.311	0.33
Type7	7.560	2.58	11.602	3.54	8.794	1.11	-2.415	-0.34	10.427	0.93
Type9	14.278	3.39	-1.688	-0.30	31.679	3.35	7.665	0.89	8.108	0.64
Type10	8.591	1.99	16.333	2.61	12.192	0.94	13.904	1.73	0.544	0.08
Type11	3.135	0.70	9.115	1.89	-6.753	-0.61	-44.432	-1.42	0.523	0.01
Type12	6.378	2.14	9.407	2.69	11.333	1.33	3.050	0.53	-1.009	-0.13
Type13	-5.984	-1.26	-1.068	-0.22	-28.945	-2.06	-27.791	-0.63	-10.087	-0.35
Type14	-8.315	-1.08	-7.727	-1.10						
Type15	2.298	0.51	3.323	0.63	5.676	0.48	-3.621	-0.40	4.603	0.35
Type16	-7.711	-0.91	-7.457	-0.87	-13.574	-0.29	-8.437	-0.27	-6.083	-0.40
Type17	-19.877	-1.19	-6.716	-0.30					-33.420	-2.21
Type18	6.012	0.35	4.725	0.31						
Type19	0.683	0.14	5.639	0.78	1.520	0.12	-1.535	-0.19	0.805	0.10
Type20	-9.440	-1.72	-5.221	-0.67	-8.893	-0.75	-8.345	-0.64	-2.847	-0.27
DLos Angeles	-16.759	-7.99								
DSan Diego	-17.004	-5.48								
DSacramento	-13.379	-3.56								
R-square	0.133		0.186		0.159		0.136		0.141	
Adj. R-square	0.130		0.180		0.148		0.112		0.106	

1) Shaded cells are significant at 10% level.
2) San Francisco is the reference for MSA dummy variables and type 8 is the reference type for neighborhood type dummies.

REFERENCES

Altshuler, Alan and Luberoff, David (2003) *Mega-Projects: The Changing Politics of Urban Public Investment.* Washington, DC: The Brookings Institution.

Baer, W. and Banerjee, T. (1984) *Beyond the Neighborhood Unit: Residential Environments and Public Policy.* New York: Plenum Press, p. 20-24.

Cameron, C. and Windmeijer, F. (1996) R-Squared measures for count data regression models with applications to health-care utilization, *Journal of Business and Economic Statistics* 14: 209-220.

Crane, Randall (2000) "The Influence of Urban Form on Travel: An Interpretive Review" Journal of Planning Literature. 15:1.

Gordon, N.J. (1946) "China and the Neighborhood Unit." *The American City* 61: 112-113.

ICMA. (2000) *The Practice of Local Government Planning*. ICMA: Washington, DC , p. 269-270.

Jacobs, J. (1961) *The Death and Life of Great American Cities.* New York, Vintage Books, (1961), p. 116.

Mumford, L. (1961) New York: Harcourt, Brace and World, 1961. *The City in History: Its Origins, Its Transformations, and Its Prospects.*

Perry, C. A. (1939) *Housing for the Machine Age.* New York: Russell Sage Foundation

Porterfield, G. and Hall, K. (1995) *A Concise Guide to Community Planning.* New York: McGraw-Hill, p. 126.

Smith, J. and Saito, M. (2001) "Creating land-use scenarios by cluster analysis for regional land-use and transportation sketch planning." *Journal of Transportation and Statistics* 4: 39-49.

Srinivasan, S. (2002) "Quantifying spatial characteristics of cities." *Urban Studies* 39: 2005-2028.

Stein, C.S. (1957) *Toward New Towns for America.* Cambrdge: MIT Press.

White M. and White, L. (1962) *The Intellectual verses the City*. New York: Mentor Books.

Wooldridge, J. (2002) *Econometric Analysis of Cross Section and Panel Data*. Cambridge: MIT Press.

APPENDIX

Table A1. Neighborhood attributes measures used in the cluster analysis

	Variable	Description	Data Source
Density and Context	POPDEN	Pop density (per land acre)	SF3
	MEDYR	Age of housing stock (median year housing built)	SF3
	CBDIST	Distance from the CBD (miles)	Tiger
Street Design	STDEN[1)]	Street density (mile per square mile)	Tiger
	INTSCTDEN[1)]	Intersection density (number intersection / street mile)	Tiger
	CULDESAC[2)]	Cul-de-sac ratio: # Cul-de-sac / (# Cul-de-sac + # 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 these locations, we estimated distances from all census blocks within the census tract to the closest locations and computed weighted average distances with the weight given to the population of each census block.

Table A2. Mean values by each neighborhood type (sorted by population density)

Cluster	No. of Tracts	cotime	transit	popden	medyr	cbdist	stden	intsctden	culdesac	rswprdist	bprdist	ppoprsbf	hwydist
All	5727	28.54	6.0%	13.87	1967	25.47	16.64	5.72	21.6%	9.72	4.06	6.5%	1.64
1	55	32.29	34.7%	79.42	1953	2.99	27.92	7.28	4.3%	4.83	4.77	80.5%	0.78
2	143	30.71	25.0%	51.35	1954	6.86	26.11	7.20	4.9%	4.52	4.09	3.7%	1.05
3	17	29.88	8.5%	32.60	1964	21.97	39.64	13.06	6.5%	4.59	3.80	32.6%	2.03
4	414	29.63	12.4%	31.64	1958	9.14	22.24	5.43	4.3%	3.52	2.57	0.4%	1.04
5	199	27.55	15.5%	19.72	1959	9.94	21.52	6.33	10.9%	2.55	3.36	85.6%	0.58
6	447	28.31	10.8%	19.62	1952	10.64	24.60	7.21	8.3%	4.35	2.87	3.9%	0.93
7	814	27.50	3.7%	14.37	1968	27.54	18.20	6.25	26.9%	5.31	1.94	0.4%	1.04
8	1008	27.33	4.8%	13.34	1959	14.64	18.63	5.72	16.3%	3.62	2.41	0.4%	1.03
9	279	27.69	8.6%	13.02	1962	18.19	19.07	6.16	16.9%	2.32	2.64	41.9%	0.69
10	298	28.14	2.9%	11.67	1980	21.75	17.60	7.45	29.3%	7.53	2.61	0.2%	1.55
11	241	26.75	2.6%	6.40	1964	53.30	13.64	5.42	20.0%	22.05	5.05	0.0%	1.05
12	859	29.81	2.3%	5.66	1980	31.21	11.54	5.39	33.6%	8.16	2.33	0.2%	1.76
13	213	31.63	1.4%	4.91	1981	59.83	11.12	4.85	28.1%	35.27	3.87	0.0%	1.83
14	69	22.73	1.7%	4.52	1979	108.81	12.72	5.23	20.5%	77.76	44.85	0.0%	3.28
15	232	27.78	4.6%	4.04	1962	14.16	9.98	4.28	29.0%	5.27	2.25	0.6%	1.14
16	57	27.68	1.0%	3.19	1976	84.03	9.27	4.47	28.1%	58.05	26.97	0.0%	15.49
17	14	18.49	2.1%	1.40	1971	104.02	7.51	4.34	18.9%	82.09	49.15	0.0%	34.32
18	13	15.93	0.6%	1.02	1974	209.12	4.42	2.80	27.0%	181.54	145.18	0.0%	8.06
19	206	31.69	2.0%	0.71	1981	28.92	3.80	2.90	37.8%	13.30	3.08	0.1%	2.23
20	149	33.32	1.2%	0.35	1971	46.99	3.24	2.26	35.4%	26.12	9.30	0.2%	7.23

* cotime: mean commuting time; transit: percentage transit use in commuting.

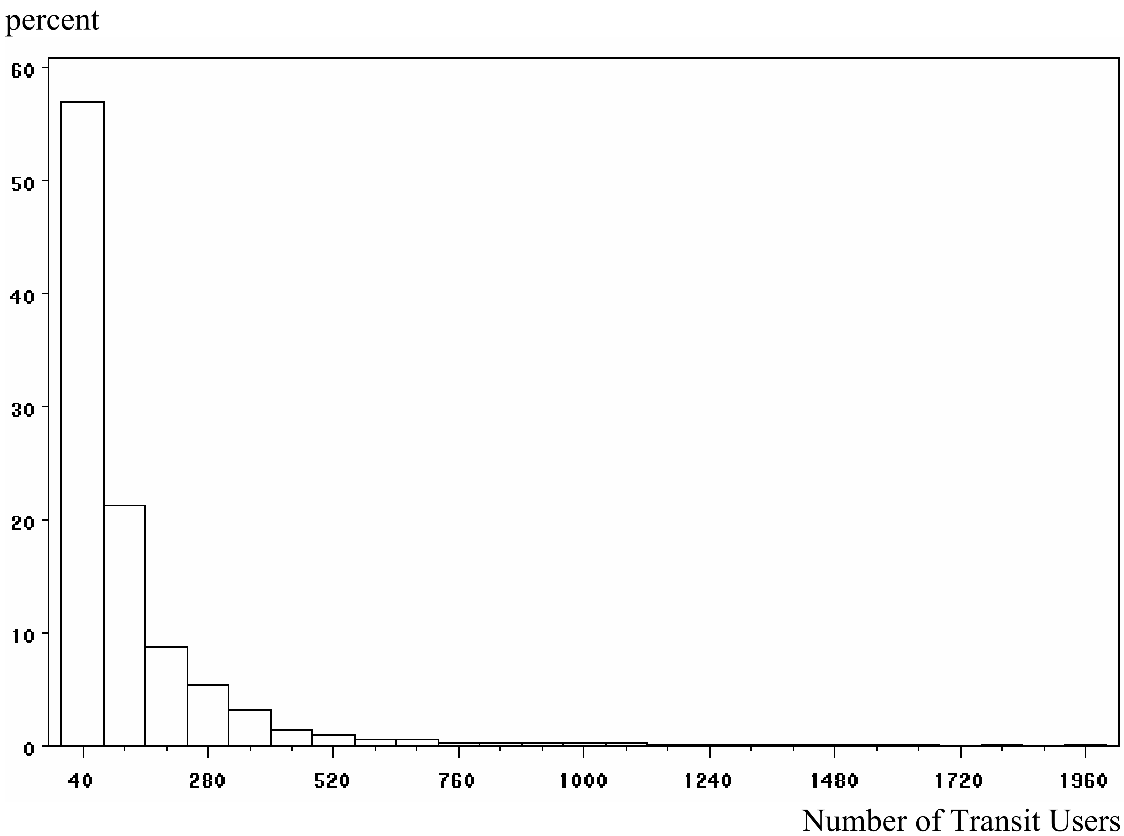
Table A3. Ranks of neighborhood types by each different variable

NAME	FREQ	Popden (densest = 1)		Stden (densest = 1)		Medyr (oldest = 1)		Cbdist (shortest = 1)		Rswprdist (shortest = 1)	
		Average	rank	Average	rank	Average	rank	Average	rank	Average	rank
type1	55	79.42	1	27.92	2	1953	2	2.99	1	4.83	8
type2	143	51.35	2	26.11	3	1954	3	6.86	2	4.52	6
type3	17	32.60	3	39.64	1	1964	9	21.97	10	4.59	7
type4	414	31.64	4	22.24	5	1958	4	9.14	3	3.52	3
type5	199	19.72	5	21.52	6	1959	5	9.94	4	2.55	2
type6	447	19.62	6	24.60	4	1952	1	10.64	5	4.35	5
type7	814	14.37	7	18.20	9	1968	11	27.54	11	5.31	10
type8	1008	13.34	8	18.63	8	1959	6	14.64	7	3.62	4
type9	279	13.02	9	19.07	7	1962	7	18.19	8	2.32	1
type10	298	11.67	10	17.60	10	1980	17	21.75	9	7.53	11
type11	241	6.40	11	13.64	11	1964	10	53.30	15	22.05	14
type12	859	5.66	12	11.54	13	1980	18	31.21	13	8.16	12
type13	213	4.91	13	11.12	14	1981	19	59.83	16	35.27	16
type14	69	4.52	14	12.72	12	1979	16	108.81	19	77.76	18
type15	232	4.04	15	9.98	15	1962	8	14.16	6	5.27	9
type16	57	3.19	16	9.27	16	1976	15	84.03	17	58.05	17
type17	14	1.40	17	7.51	17	1971	12	104.02	18	82.09	19
type18	13	1.02	18	4.42	18	1974	14	209.12	20	181.54	20
type19	206	0.71	19	3.80	19	1981	20	28.92	12	13.30	13
type20	149	0.35	20	3.24	20	1971	13	46.99	14	26.12	15
All	5727	13.87		16.64		1967		25.47		9.72	

Table A3. Ranks of neighborhood types by each different variable (continued)

FOUR20	FREQ	Bprdist (shortest = 1)		Ppoprsbf (highest = 1)		Intsctden (densest = 1)		Culdesac (lowest = 1)		Hwydist (shortest =1)	
		Average	rank	Average	rank	Average	rank	Average	rank	Average	rank
type1	55	4.77	14	80.5%	2	7.28	3	4.3%	1	0.78	3
type2	143	4.09	13	3.7%	6	7.20	5	4.9%	3	1.05	8
type3	17	3.80	11	32.6%	4	13.06	1	6.5%	4	2.03	14
type4	414	2.57	5	0.4%	10	5.43	10	4.3%	2	1.04	6
type5	199	3.36	10	85.6%	1	6.33	6	10.9%	6	0.58	1
type6	447	2.87	8	3.9%	5	7.21	4	8.3%	5	0.93	4
type7	814	1.94	1	0.4%	8	6.25	7	26.9%	12	1.04	7
type8	1008	2.41	4	0.4%	9	5.72	9	16.3%	7	1.03	5
type9	279	2.64	7	41.9%	3	6.16	8	16.9%	8	0.69	2
type10	298	2.61	6	0.2%	12	7.45	2	29.3%	17	1.55	11
type11	241	5.05	15	0.0%	16	5.42	11	20.0%	10	1.05	9
type12	859	2.33	3	0.2%	11	5.39	12	33.6%	18	1.76	12
type13	213	3.87	12	0.0%	15	4.85	14	28.1%	14	1.83	13
type14	69	44.85	18	0.0%	18	5.23	13	20.5%	11	3.28	16
type15	232	2.25	2	0.6%	7	4.28	17	29.0%	16	1.14	10
type16	57	26.97	17	0.0%	17	4.47	15	28.1%	15	15.49	19
type17	14	49.15	19	0.0%	19	4.34	16	18.9%	9	34.32	20
type18	13	145.18	20	0.0%	20	2.80	19	27.0%	13	8.06	18
type19	206	3.08	9	0.1%	14	2.90	18	37.8%	20	2.23	15
type20	149	9.30	16	0.2%	13	2.26	20	35.4%	19	7.23	17
All	5727	4.06		6.5%		5.72		21.6%		1.64	

Figure A1. Histogram of transit user counts



Mean: 119.6
Variance: 30798.3

Figure A2-a. Geographical clustering of neighborhood types in Los Angeles

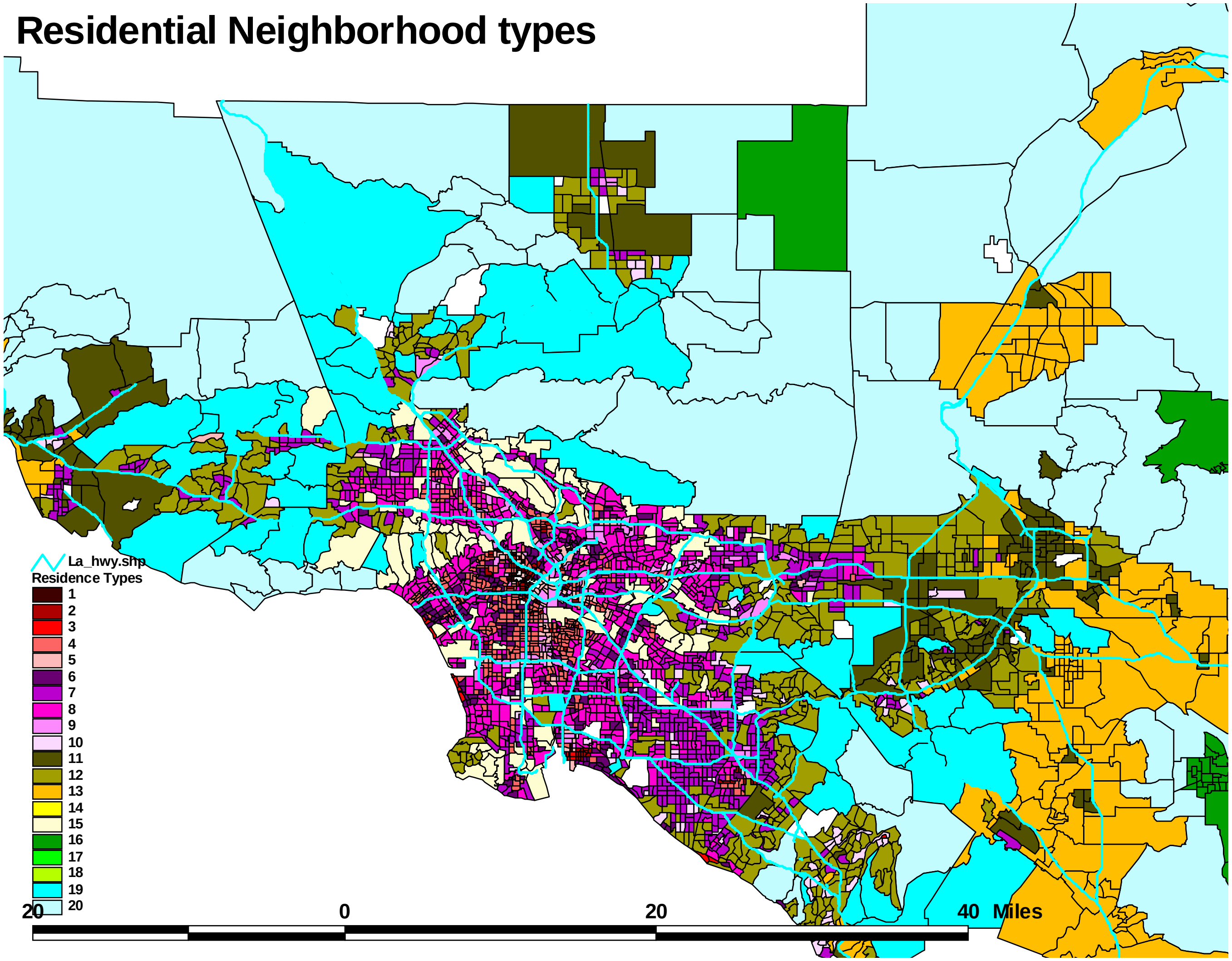


Figure A2-b. Geographical clustering of neighborhood types of more urbanized areas in Los Angeles