Do Residents of Smart Growth Neighborhoods in Los Angeles, California, Travel "Smarter"?

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With the individual trip diary from the recent 2009 National Household Travel Survey, a study was done on the effect of neighborhood-level smart growth patterns and socioeconomic diversity on commute mode choice, daily work travel mode choice, and nonwork travel mode choice for individuals living in neighborhoods in the Los Angeles, California, metropolitan statistical area. Model results consistently showed that nonauto transportation infrastructure diversity and quality were the most important aspects of smart growth patterns that affected the choice of nonauto travel modes. Moreover, housing mix in a neighborhood increased the likelihood of choosing walking and cycling for daily work trips and daily nonwork trips. The socioeconomic diversity of a neighborhood reduced the likelihood of choosing walking and cycling for daily nonwork trips. The remaining two factors—residential density and mixed use—insignificantly affected travel mode choice. Overall, people living in smart growth neighborhoods in Los Angeles do travel smarter, in that they use environmentally more sustainable (bus and train) and healthier (walking and cycling) travel modes.

For half a century, there has been a continuous movement in the United States to view transportation not just as mobility but also as something intimately bound with the quality of life in urban living. In the 1990s when two point–counterpoint articles [see Gordon and Richardson (1) and Ewing (2)] were published in the same issue of the Journal of the American Planning Association (JAPA), the debate on "compact city" and "sprawl" raged. Since then, numerous empirical studies have been conducted to address the effect of the built environment on travel behavior and, subsequently, vehicle miles traveled (VMT) and greenhouse gas emissions (see, e.g., 3–17). These studies incorporated a wide range of empirical techniques with fairly consistent findings. Scholars in the land use and transportation fields have agreed somewhat that land use patterns or the built environment does affect travel, with different aspects having varying degrees of effect. Ewing and Cervero (18) and Salon et al. (19) have provided two of the most recent comprehensive literature reviews. Their findings on the spread for the land use elasticity of travel compare favorably with each other.

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Yet, a recent article published in JAPA, “Growing Cities Sustainably: Does Urban Form Really Matter,” by Echenique et al., triggered a new round of debate on this issue in PLANET, a listserv for academic planners, on July 26, 2012 (20). The article used illustrative simulation models to consider trade-offs between three growth scenarios—compact development, planned expansion, and dispersed development—during a 30-year time frame for three regions in England. The conclusion reached was that compact development is not a better spatial growth strategy than dispersed development or planned expansion because higher costs (e.g., housing price, congestion), induced by increased densities, may wipe out the benefits of reduced VMT. Concerned about the assumptions of the modeling framework and the inappropriateness of its application to U.S. cities, many researchers have publicly criticized this article and pressed for counterpoint articles. There are also others that are supportive of the article, cautioning that more attention should be paid to the costs of compact growth. (For more details about this recent debate, see a series of discussions posted in PLANET since July 26, 2012.)

The major contribution of the present research is to analyze individual travel data from the most recent National Household Travel Survey (NHTS), conducted in the United States during 2008–2009, to provide some new empirical evidence for the effect of neighborhood-level smart growth patterns on travel mode choice. This study focuses on the Los Angeles consolidated metropolitan statistical area (CMSA), an area that is often considered as a synonym for “sprawl.” The investigation included not only the commute mode choice but also the mode choice for daily work travel and daily nonwork travel, based on individual 1-day trip diaries collected by the 2009 NHTS. In addition to neighborhood-level smart growth patterns, socioeconomic diversity measures of the neighborhoods were included in the models.

Literature Review

According to the activity-based approach, travel behavior has been found to be affected by a number of factors, including personal demographics, household socioeconomic status, and place of residence (21–25). In addition, numerous studies have found that a more compact urban form also affects travel behavior and improves transportation outcomes, such as transit ridership and walking and cycling activities (e.g., 26–28). For comprehensive reviews, see Kitamura et al. (29), Messenger and Ewing (30), Ewing and Cervero (18), and, most recently, Salon et al. (19). These empirical works have recognized that there are four “Ds” of the built environment that directly influence travel behavior [e.g., see Cervero and Murakami (28) and Cervero and Kockelman (31)]. The four Ds are density, diversity (or land use mix), destination accessibility, and design (generally expressed in relation to walkability).

Of the four Ds, density is the one that attracts most attention and debate, especially in regard to its effect on VMT. Some studies [e.g., Ewing et al. (17) and Ewing and Nelson (26)] found that density “soaks up” the influences of the three other Ds. For example, Holtzclaw concluded that doubling urban density results in a 25% to 30% decrease in VMT (32). Once other variables are controlled for, the reduction in VMT becomes even smaller. However, others have also cautioned that the land use variable that often proves significant to travel is regional accessibility, not local density (2). Boarnet and Sarmiento explicitly modeled a set of joint choice—where to live and then how to travel—and found that overall land use variables do not influence travel in their southern California sample (4). Salon et al. also noted that density is a weak proxy for land use patterns when the effect on VMT is studied and that other measures of land use, especially measures of employment accessibility, have a larger effect (19). However, density is easy to measure and commonly used in many studies.

In regard to the effect of the built environment on travel mode choice, previous research found that the four Ds do play important roles (33–40). These studies generally concluded that people are more likely to use transit and walk and bike in neighborhoods where development is more intense, commercial uses and convenience services are closer, land use is more mixed, and population and employment densities are higher. In a recent meta-analysis, Ewing and Cervero found that transit (bus and train) use is strongly related to destination accessibility (proximity to transit stations) and design (street intersection density), with diversity (of land use) a less important factor (18). Walking is most strongly related to diversity, destination accessibility, and design. They found that density (both population and job density) is only weakly related to travel mode choice after other variables, such as measures of destination accessibility and street network design, are controlled for. In this paper, these different measures of the four Ds will be included at the neighborhood level.

In recent years, debates on smart growth have moved beyond considering it solely as an urban form; now concerns about transportation and environmental issues as well as socioeconomic dimensions are included. In the travel behavior literature, although individual socioeconomic factors are often used as control variables in many of these empirical studies, few have simultaneously addressed the travel impact of physical smart growth patterns and neighborhood socioeconomic diversity. [The literature on spatial mismatch provides another set of research addressing the effect of socioeconomic diversity (e.g., race, income) on travel behavior. Yet, the models usually do not take into account land use patterns and the built environment.] Therefore, another contribution of this paper is to investigate the effect of neighborhood socioeconomic diversity on travel mode choice.

Research Method

Measuring Smart Growth at the Neighborhood Level

A number of variables are selected to represent four key aspects of smart growth patterns in Los Angeles neighborhoods: residential density, mixed use, mixed housing, and the quality and diversity of the nonauto transportation infrastructure. Socioeconomic diversity is measured separately with a different set of variables. Since the unit of analysis for this study is the neighborhood, land use patterns that are appropriate only at the regional level, such as centrality and nuclearity, are not used. Table 1 explains the indexes developed to measure and compare smart growth neighborhoods in the Los Angeles CMSA.

TABLE 1 Measurement of Smart Growth Patterns and Socioeconomic Diversity with Explanation and Data Source

Measurement	Explanation	Data Source
Net residential density	Total housing units over acres of residential land (unit/acre)	SCAG and ACS 2006–2010
Mixed use		
Land use type diversity	Land use diversity of four land use types: SFH, MFH, commercial, and open space	SCAG
Mix of service and residence	Mix of personal service employee and household	SCAG and ACS 2006–2010
Job-home balance	Mix between job and household	SCAG
Mixed housing		
Housing tenure diversity	Mix of owner-occupied and renter-occupied houses	ACS 2006–2010
Housing structure diversity	Mix of 4 housing structure types by number of housing units in structure: 1 unit, 2 units, 3 units, and 4+ units	ACS 2006–2010
Housing size diversity	Mix of houses of four sizes by number of bedrooms: 0 or 1 bedroom, 2 bedrooms, 3 bedrooms, and 4+ bedrooms	ACS 2006–2010
Housing value–rent diversity	Mix of houses of 3 value–rent levels: low, medium, and high	ACS 2006–2010
Nonauto transportation		
Transit availability	Percentage of residential land within ¼ mi of bus or ½ mi of rail transit stops	SCAG
Quality bike lane availability	Percentage of land within ¼ mi of high-quality bicycle lanes	SCAG
Street density	Length of local streets per acre of land (miles per acre)	Census TIGER
Street intersection density	Number of intersections per acre of land	Census TIGER
Socioeconomic diversity		
Household income diversity	Mix of households of 4 income levels: low, medium-low, medium-high, and high	ACS 2006–2010
Racial–ethnic diversity	Mix of 6 racial ethnic types: non-Hispanic white; Hispanics; black or African-American; Asian; non-Hispanic American Indian, Alaska Native, Native Hawaiian and other Pacific Islanders; and non-Hispanic multiraces or other races	ACS 2006–2010
Household type diversity	Mix of 4 household types: married couple family, single-householder family, nonfamily household with householder living alone, and nonfamily household with householder not living alone	ACS 2006–2010

NOTE: SCAG = Southern California Association of Government; ACS = American Community Survey; SFH = single-family home; MFH = multifamily home; TIGER = Topographically Integrated Geographic Encoding and Referencing.

Net residential density is the only density index counted toward the calculation of the density factor. The entropy index, which has been widely used in the literature [e.g., see Song (41) and Iceland (42)], is adopted to measure the mixed use, mixed housing, and quality and diversity of nonauto transportation infrastructure, as well as socioeconomic diversity in each residential neighborhood. It can be expressed as follows:

$$E_i = \sum_{1}^{r} \left(\frac{\Pi_r \ln\left[\frac{1}{\Pi_r}\right]}{\ln(r)} \right)$$

Where

Πr = proportion of each group,

r = number of groups in a neighborhood, and

Ei = diversity index measuring evenness of groups in neighborhood i; Ei ranges from 0 to 1, and a higher score in Ei indicates a higher level of diversity in that neighborhood.

Unlike residential density, the other four factors are all measured by multiple inter-correlated indexes. To combine sub-indexes under each factor into one comprehensive index, information from multi-indexes is extracted through principal components analysis [see for example, Song (41), Miles and Song (43), and Ewing et al. (44)].

Ultimately, the four smart growth indexes (SGIs) that measure the built environment of a neighborhood are the standardized scores of the four physical urban form factors: residential density ($density_{res}$), mixed use (mix_{use}), mixed housing ($housing_{mix}$), and nonauto transportation infrastructure diversity and quality ($transport_{qua}$). The socioeconomic diversity index (SDI) is the standardized score of the socioeconomic diversity factor (soc_{div}).

Model Specification and Variables

First, the individual worker's commute mode choice is studied. The empirical model assumes that individuals choose to travel to work from among three alternatives—driving a privately owned vehicle (POV), taking public transit, and walking or biking. To determine how neighborhood smart growth patterns (smart growth indexes), neighborhood socioeconomic diversity, and individual socioeconomic characteristics affect their commute mode choice, a multinomial logit model is used as follows:

$$\Pr(Y_i = j) = \frac{\exp(\beta_{jS}\mathrm{SGI}_i + \beta_{jD}\mathrm{SDI}_i + \beta_{jP}P_i + \beta_{jH}H_i)}{\sum_{l=1}^{3}\exp(\beta_{lS}\mathrm{SGI}_i + \beta_{lD}\mathrm{SDI}_i + \beta_{lP}P_i + \beta_{lH}H_i)}.$$

In the model, i identifies worker i, and j represents three travel mode choices: driving a POV, taking public transit, and walking or biking. Driving a POV is used as the base category, against which all estimates are compared. Y_i refers to the ith worker's travel mode.

This study is particularly interested in whether residents in smart growth neighborhoods are more inclined to choose a specific type of commuting mode. For that purpose, four SGIs are constructed at the neighborhood level (block group) by using methods discussed before and are included in the model, as represented by SGI. To test the effect of neighborhood socioeconomic diversity on individual commute mode choice, the socioeconomic diversity index was included in the model, as noted by SDI. Individual demographics and household socioeconomic status are also important factors in travel mode choice models (45, 46). Thus, they are included as control variables. In the model, *P* stands for personal demographics, including age, gender, medical condition that makes travel difficult, education, and occupation. *H* represents household socioeconomic status and locational attributes, including number of vehicles per driver in the household, household income, children in the household, and household located in urbanized area.

Then, daily work travel by workers and daily nonwork travel by all individuals are studied. Daily work travel includes all "to/from work" trips and "work related business" trips on the trip day. It is different from the commute travel discussed in the previous multinomial logit model. More important, commute travel mode is calculated on the basis of the question "how did you usually get to work last week?" Daily work travel mode is calculated on the basis of respondents' actual trips made on that randomly selected trip day. This difference makes it necessary to examine daily work travel in addition to commute travel.

For either daily work trips or daily nonwork trips, because people could use all three alternative travel modes in 1 day, the three alternatives do not necessarily add up to one, which violates the basic assumption of the multinomial logit model. Thus a logit model is used to separately test whether residents in smart growth neighborhoods are (a) more likely to take public transit and (b) more likely to walk or bike. The logit model is shown below:

$$\text{logit}(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_S \text{SGI}_i + \beta_D \text{SDI}_i + \beta_P P_i + \beta_H H_i$$

In the model, p_i is the likelihood of taking public transit or the likelihood of walking or biking in this person's 1-day travel. SGI, SDI, *P*, and *H* represent the same variables as in the previous multinomial logit model.

Data and Sample

The data for this study are drawn from several sources. Land use, public transportation, bike lane, and employment data in 2008 are provided by the Southern California Association of Governments, which is the metropolitan planning organization for Los Angeles. Neighborhood-level (block group) housing and socioeconomic data are from the recently released 2006–2010 American Community Survey data set. Local street networks of the two regions are from Census 2008 TIGER/Line shapefiles. These data are used to construct the smart growth indexes and the SDI.

The individual-level data used for this research are from the 2009 NHTS. The NHTS is a large-sample national survey that collects information on individual and household socioeconomic characteristics, household residential location, and individual commuting patterns, as well as a detailed 1-day trip diary. On the basis of the 1-day trip diary provided by the NHTS, daily travel can be decomposed into work trips and nonwork trips. Daily work trips include all "to/from work" trips and "work related business" trips on the trip day. Daily nonwork trips include shopping trips, other family and personal business trips, school and church trips, medical and dental trips, visiting friends and relatives trips, and other social and recreational trips. The study examined the effect of smart growth patterns and socioeconomic diversity on the transportation mode choice for commute travel, as well as for daily work travel and daily nonwork travel.

Of all workers in the sample, 93% used a POV to commute to work, 4% commute through public transit, and 3% commute by walking or cycling. As shown in Table 2, for daily work trips, 94% of workers used a POV, 4% used public transit, and another 5% walked or biked. For daily nonwork trips, 88% of all respondents used a POV, 4% used public transit, and 26% walked or biked. For daily work or nonwork trips, each respondent could use all three alternative travel modes in 1 day. Therefore, the sum of the percentages of three alternative travel modes may exceed one. The summary statistics of all explanatory variables are listed in Table 2.

TABLE 2 Summary Statistics

Variable	Obs.	Mean	SD	Min.	Max.
Commute mode	5,365	1.09	0.37	1	3
Using POV for any daily work trips	3,670	0.94	0.23	0	1
Taking transit for any daily work trips	3,670	0.04	0.19	0	1
Walking–cycling for any daily work trips	3,670	0.05	0.21	0	1
Using POV for any daily nonwork trips	11,013	0.88	0.32	0	1
Taking transit for any daily nonwork trips	11,013	0.04	0.19	0	1
Walking–cycling for any daily nonwork trips	11,013	0.26	0.44	0	1
Transportation infrastructure index	14,161	−0.35	0.97	−2.21	6.37
Residential density index	14,161	−0.06	0.67	−0.18	47.82
Mixed land use index	14,261	0.01	0.97	−2.36	2.05
Mixed housing index	14,237	−0.15	1.03	−3.13	1.86
Socioeconomic diversity index	14,237	−0.02	1.00	−5.73	2.06
Vehicles per driver	14,392	1.10	0.50	0	7.5
Household income	13,513	69,892	40,097	2,500	120,000
Age	14,392	46.75	22.52	5	92
Male	14,392	0.47	0.50	0	1
Presence of child	14,392	0.39	0.49	0	1
Medical condition	12,420	0.12	0.32	0	1
Less than high school	11,822	0.09	0.28	0	1
High school graduate, some college	11,822	0.53	0.50	0	1
BA degree	11,822	0.22	0.42	0	1
Graduate degree	11,822	0.16	0.37	0	1
Sales or service	6,477	0.28	0.45	0	1
Clerical and administrative support	6,477	0.11	0.32	0	1
Manuf., const., maintenance, or farming	6,477	0.15	0.36	0	1
Professional–managerial	6,477	0.45	0.50	0	1
Other occupations	6,477	0.01	0.11	0	1
Household in urbanized area	14,392	0.93	0.25	0	1

NOTE: Obs. = observations; SD = standard deviation; min. = minimum; max. = maximum; manuf. = manufacturing; const. = construction. Commute mode variable has three values: 1 means driving POV; 2 means taking public transit; 3 means walking–biking. Travel mode variables for daily work trips and daily nonwork trips are all dummy variables. For daily work trips, each worker could use all three alternative travel modes in 1 day. Therefore, the means (percentages) of three alternative travel modes do not necessarily add up to 1. For daily nonwork trips, each individual could use all three alternative travel modes in 1 day. Therefore, the means (percentages) of three alternative travel modes do not necessarily add up to 1.

Results

Spatial Distribution of Smart Growth Neighborhoods and Socioeconomic Diversity in Los Angeles

Figure 1, a–d, shows the spatial distribution of smart growth neighborhoods in the Los Angeles CMSA, based on four different standardized factors. In the figure, neighborhoods (block groups)

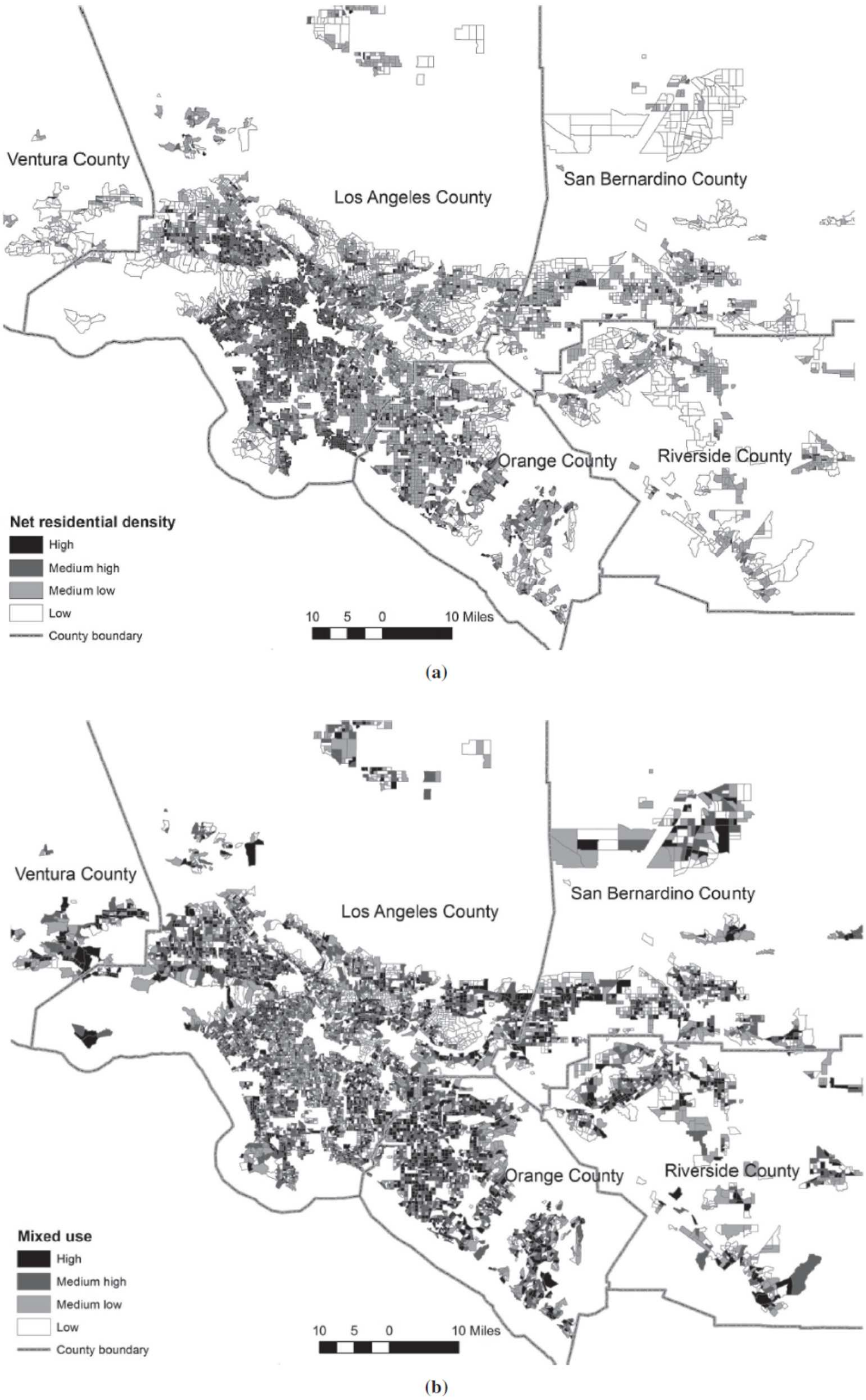

FIGURE 1 Spatial distribution of smart growth neighborhoods and socioeconomic diversity in Los Angeles CMSA: (*a*) residential density and (*b*) mixed use.

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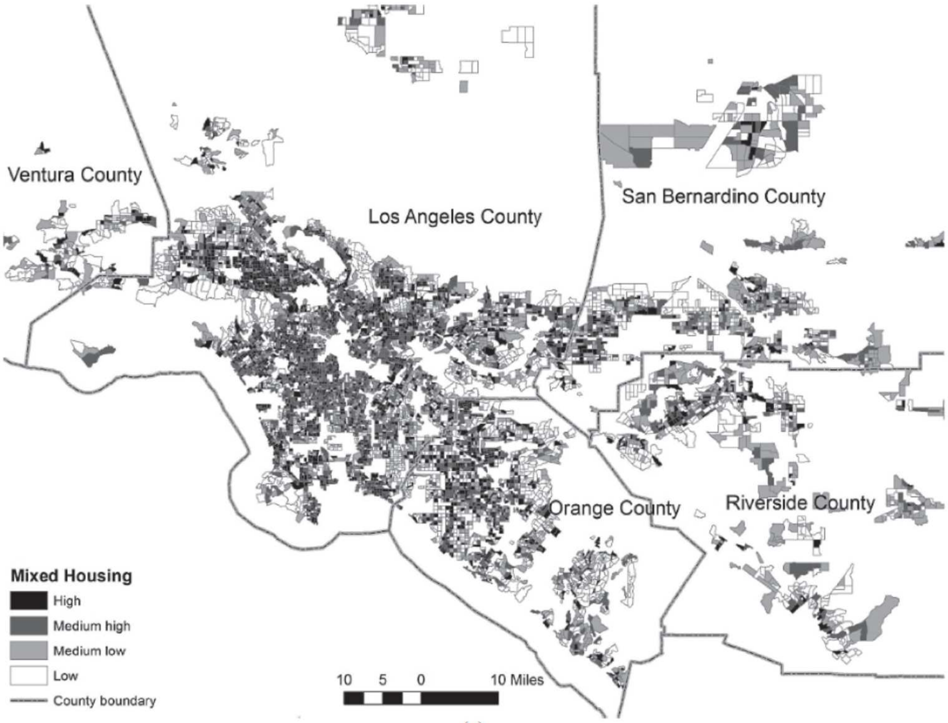
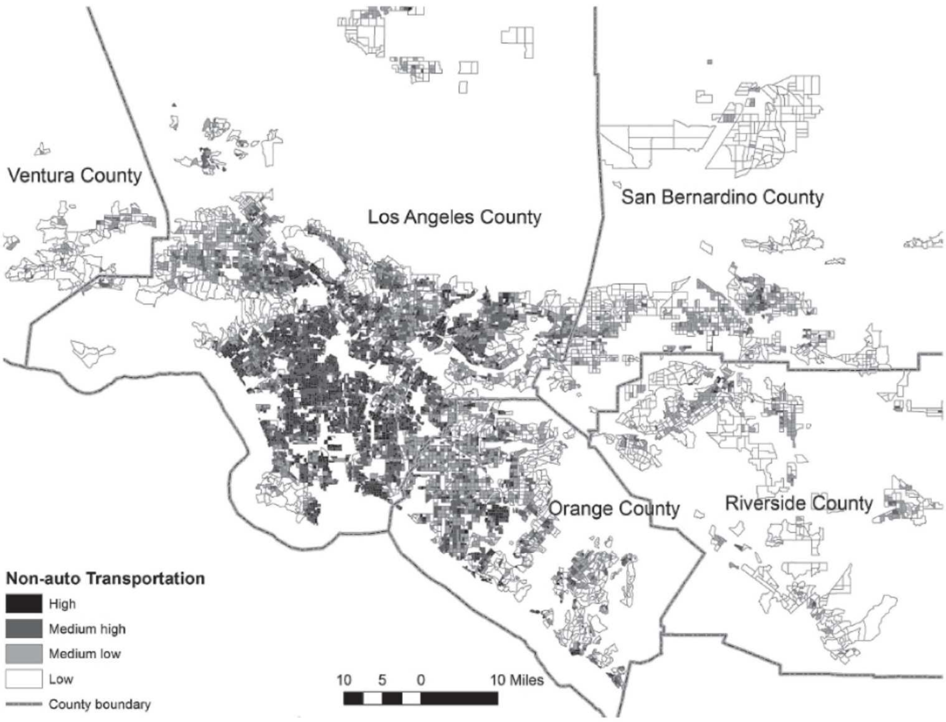


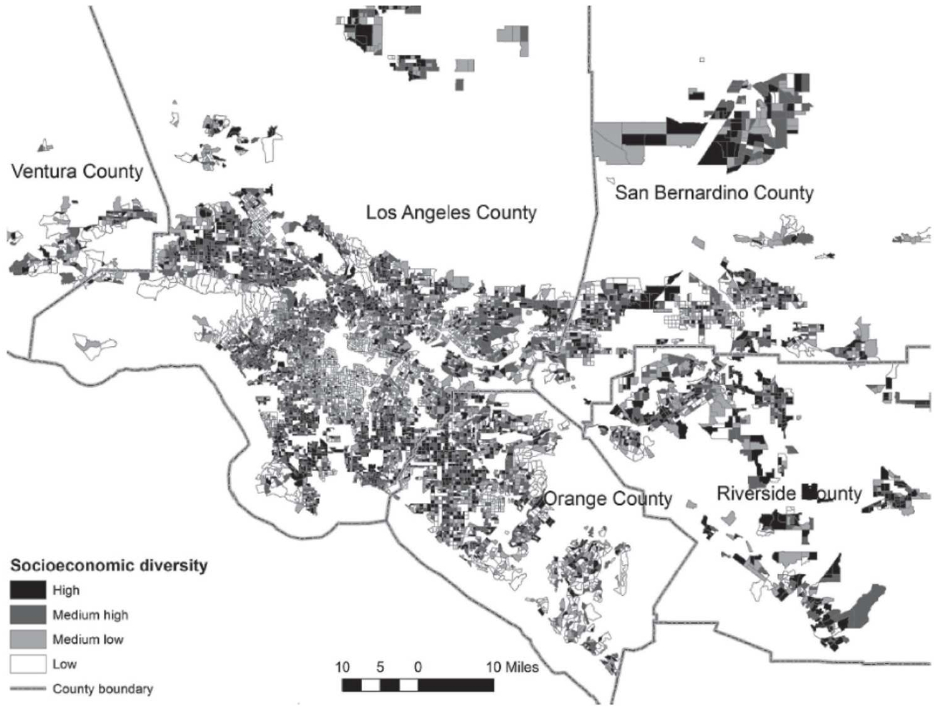
(c)



(d)

FIGURE 1 *(continued)* Spatial distribution of smart growth neighborhoods and socioeconomic diversity in Los Angeles CMSA: (*c*) mixed housing and (*d*) nonauto transportation infrastructure diversity and quality.

(continued)



(e)

FIGURE 1 *(continued)* **Spatial distribution of smart growth neighborhoods and socioeconomic diversity in Los Angeles CMSA: *(e)* socioeconomic diversity.**

in the region were grouped into four quartiles according to each of the four indexes: residential density, mixed use, mixed housing, and availability of nonauto transportation. As Figure 1a indicates, the majority of high-density neighborhoods concentrate in urbanized areas throughout Los Angeles County and Orange County, especially in the city of Los Angeles and surrounding areas. In contrast, highly mixed use neighborhoods are dispersed throughout the whole region, as shown in Figure 1b. Similarly, neighborhoods with mixed housing are also dispersed, with many of them located in areas transitioning from high-density centers to low-density single-family home areas, as shown in Figure 1c. Figure 1d shows that neighborhoods with better nonauto transportation infrastructure diversity and quality maintain higher concentration in central areas of Los Angeles County. In addition to these four figures illustrating the spatial distribution of smart growth neighborhoods, Figure 1e demonstrates the distribution of neighborhoods according to their SDI. It shows that those socioeconomically diverse neighborhoods are found in urban centers and suburban areas. Downtown Los Angeles has relatively low socioeconomic diversity because its residents are predominantly minorities.

Commute Mode Choice

Table 3 presents results for commute mode choice using the multinomial logit model. Column 1 shows the coefficient estimates for commuting by public transit (bus and train), with respect to driving a POV. Column 2 shows the coefficient estimates for commuting by walking or cycling, with respect to using a POV.

TABLE 3 Multinomial Logit Model Results for Commute Mode Choice

Variable	Transit (Bus and Train)	Walking–Cycling
Nonauto transportation infrastructure	0.38*** (4.12)	0.24** (2.27)
Residential density	0.01 (0.08)	−0.01 (−0.08)
Mixed use	−0.07 (−0.77)	0.09 (0.87)
Mixed housing	0.04 (0.45)	0.17 (1.54)
Socioeconomic diversity	0.02 (0.18)	0.01 (0.10)
Vehicles per driver	−2.34*** (−9.59)	−1.47*** (−5.24)
Household income (log)	−0.36*** (−3.24)	−0.46*** (−3.78)
Age	0.00 (0.26)	−0.01** (−2.01)
Male	0.03 (0.18)	0.56*** (2.91)
Presence of child	0.11 (0.63)	−0.60*** (−2.85)
Medical condition	0.69* (1.77)	0.80* (1.90)
High school graduate, some college	−0.82*** (−3.34)	−0.57* (−1.75)
BA degree	−0.66** (−2.14)	−0.41 (−1.06)
Graduate degree	−0.61* (−1.71)	0.18 (0.43)
Sales or service	0.27 (1.12)	0.76** (2.30)
Clerical and administrative support	0.05 (0.14)	0.89** (2.27)
Professional–managerial	0.01 (0.02)	0.53 (1.47)
Other occupations	0.31 (0.48)	1.02 (1.49)
Household in urbanized area	−0.22 (−0.45)	−0.06 (−0.11)
Intercept	3.62*** (2.96)	3.26** (2.40)

Note: Observations = 4,934; pseudo-R^2 = .143. Z-statistics in parentheses. ***$p < .01$, **$p < .05$, *$p < .1$. Reference base in multinomial logit model is commuting by POV. In order to calculate the relative risk ratios, all coefficient estimates need to take exponential value. For education dummy variables, the reference is "less than high school." For occupation dummies, the reference is "manufacturing, construction, maintenance, or farming." BA = bachelor of arts.

Of the four smart growth indexes, the nonauto transportation infrastructure diversity and quality index has a statistically significant effect on commute mode choice. It is estimated that if the nonauto transportation infrastructure diversity and quality index increases by one standard deviation [for the convenience of model interpretation, the four smart growth indexes (first four variables) in all the empirical models are restandardized to mean 0 and standard deviation 1], the likelihood of taking public transit will be 46% higher relative to driving a POV, and the likelihood of walking or cycling will be 27% higher relative to using a POV. (Table 3 reports the coefficient estimates of the previous multinomial logit model. To determine the relative risk ratios, all coefficient estimates need to take their own exponential values.) These are significant effects in regard to the magnitude. Since the nonauto transportation infrastructure diversity and quality index is a variable extracted from multiple factors (transit availability, quality bike lane availability, street density, street intersection density) through the principal components analysis, this finding suggests that enhancing accessibility to public transit, providing safe cycling lanes and streets, and increasing street connectivity are important factors in increasing transit ridership and encouraging healthier travel modes (walking and biking) in people's commuting.

The other three smart growth indexes (residential density, mixed use, and mixed housing) and the SDI do not have statistically significant effects on commute mode choice after taking into account nonauto transportation infrastructure diversity and quality. It seems that, overall, these three aspects of the smart growth patterns in Los Angeles have only a limited effect on people's commute mode choice.

The control variables in this research, individual and household demographics and socioeconomic characteristics, have shown results that are consistent with many other studies. The more vehicles per driver in a household, the lower the likelihood of taking transit or walking and cycling for commuting trips, with respect to driving. As expected, higher household income increases the likelihood of driving and decreases the possibility of taking transit or walking or cycling. Older people are less likely to walk or bike to work although the size of the difference is quite small (1 year older in age reduces the likelihood of walking or cycling to work by roughly 1%). Male workers are more likely to walk or bike to work than are female workers. People are less likely to walk or bike if the household has children. Age, gender, and the presence of children all have no significant effect on the relative probability of taking public transit versus driving. Medical conditions have a negative effect on taking transit or walking or cycling to work. Workers with higher education generally are less likely to take public transit or walk or bike to work. In regard to a worker's occupation, those working in sales and service and clerical and administrative support sectors are more likely to walk and bike to work, compared with other occupations. A worker's occupation has no statistically significant effect on the relative probability of taking public transit versus driving. Whether a worker's household is located in an urbanized area has no statistically significant effect on the worker's commute mode choice after neighborhood residential density and nonauto transportation infrastructure quality are included in the model. ("Urbanized area" as an independent variable was not excluded because the correlation between neighborhood residential density and whether the household is in an urbanized area is very low.)

Daily Work Travel Mode Choice

Daily work trips include all "to/from work" trips and "work related business" trips in the randomly selected trip day. Unlike commute travel mode, which is calculated according to the question "How did you usually get to work last week?" daily work travel mode is calculated according to respondents' actual trips made on the trip day. Table 4 presents the logit model

TABLE 4 Logit Model Results for Daily Work Travel Mode Choice

Variable	Transit (Bus and Train)	Walking–Cycling
Nonauto transportation infrastructure	0.40*** (3.29)	0.23** (2.38)
Residential density	0.00 (0.05)	0.00 (0.04)
Mixed use	−0.01 (−0.08)	0.01 (0.06)
Mixed housing	0.09 (0.73)	0.17* (1.66)
Socioeconomic diversity	−0.15 (−1.19)	−0.14 (−1.40)
Vehicles per driver	−3.15*** (−9.81)	−0.30 (−1.46)
Household income (log)	−0.40*** (−2.69)	−0.02 (−0.15)
Age	−0.01 (−0.63)	−0.01** (−2.01)
Male	−0.02 (−0.08)	0.49*** (2.72)
Presence of child	0.09 (0.38)	−0.50*** (−2.66)
Medical condition	0.60 (0.96)	0.15 (0.25)
High school graduate, some college	−0.59* (−1.88)	−0.07 (−0.20)
BA degree	−0.96** (−2.30)	−0.05 (−0.13)
Graduate degree	−0.50 (−1.06)	0.59 (1.43)
Sales or service	0.76** (2.26)	0.42 (1.56)
Clerical and administrative support	0.41 (0.91)	0.20 (0.56)
Professional–managerial	0.63 (1.57)	−0.08 (−0.26)
Other occupations	0.75 (0.85)	−0.42 (−0.40)
Household in urbanized area	0.21 (0.27)	0.11 (0.25)
Intercept	3.80** (2.32)	−2.22 (−1.52)

NOTE: Observations = 3,334; pseudo-R^2: transit = .275 and walking–cycling = .035. Z-statistics in parentheses.
***$p < .01$, **$p < .05$, *$p < .1$. Model 1 examines whether the respondent chose transit or not in any daily work trips; Model 2 examines whether the respondent chose walking–cycling or not in any daily work trips. In order to calculate the odds ratios, all coefficient estimates need to take the exponential value. For education dummy variables, the reference is "less than high school." For occupation dummies, the reference is "manufacturing, construction, maintenance, or farming."

results for daily work travel mode choice. Column 2 shows the coefficient estimates for the logit model that examines factors affecting whether the respondent chooses transit in any daily work trips. Column 3 shows the coefficient estimates for the logit model that examines factors affecting whether the respondent chooses walking or cycling in any daily work trips.

The model shows that nonauto transportation infrastructure diversity and quality continue to play an important role in making daily work travel mode choice. With the nonauto transportation infrastructure diversity and quality index increasing by one standard deviation, the likelihood of taking public transit for daily work trips will increase by 49%, or the likelihood of walking or cycling for daily work trips will increase by 26%. The other three smart growth indexes and the SDI do not have statistically significant effects on daily work travel mode choice. This finding is similar to previous results in the commute mode choice model. At the 90% confidence level, mixed housing (i.e., tenure diversity, structure diversity, size diversity, and value and rent diversity) in a neighborhood tends to increase the likelihood of walking or cycling. The control variables—individual and household demographics and socioeconomic characteristics—have shown coefficient estimates similar to previous results on commute mode choice. That result is not surprising given that commuting trips make up the majority of daily work trips for most workers.

Daily Nonwork Travel Mode Choice

Daily nonwork trips include shopping trips, other family and personal business trips, school and church trips, medical and dental trips, visiting friends and relatives trips, and other social and recreational trips in the randomly selected trip day. The sample in this section includes workers and nonworkers. Table 5 presents the logit model results for daily nonwork travel mode choice. Column 1 shows the coefficient estimates for the logit model that examines factors affecting whether the respondent chooses transit in any daily nonwork trips. Column 2 shows the coefficient estimates for the logit model that examines factors affecting whether the respondent chooses walking or cycling in any daily nonwork trips.

Similar to previous findings of this research, nonauto transportation infrastructure diversity and quality have the most substantial (and statistically significant) effect on daily nonwork travel mode choice. If the nonauto transportation infrastructure diversity and quality index increases by one standard deviation, the likelihood of taking public transit for daily nonwork trips is estimated to increase by 38%, or the likelihood of walking or cycling for daily nonwork trips is estimated to increase by 23%.

The other three smart growth indexes (residential density, mixed use, mixed housing) and the SDI do not statistically significantly affect the likelihood of taking public transit in people's daily nonwork trips. Even after one controls for nonauto transportation infrastructure diversity and quality in the model, the mixed housing index and SDI still have a significant effect on the likelihood of walking or cycling when people make their daily nonwork trips. It appears that with one standard deviation increase in the housing mix index (i.e., tenure diversity, structure

TABLE 5 Logit Model Results for Daily Nonwork Travel Mode Choice

Variable	Transit (Bus and Train)	Walking–Cycling
Nonauto transportation infrastructure	0.32*** (4.05)	0.21*** (6.96)
Residential density	0.02 (0.32)	0.02 (0.76)
Mixed use	−0.01 (−0.18)	0.03 (1.00)
Mixed housing	0.04 (0.46)	0.10*** (3.25)
Socioeconomic diversity	−0.05 (−0.55)	−0.13*** (−4.39)
Vehicles per driver	−1.96*** (−10.66)	−0.32*** (−5.33)
Household income (log)	−0.50*** (−6.10)	−0.13*** (−3.63)
Age	−0.02*** (−4.98)	−0.00*** (−2.75)
Male	−0.25* (−1.70)	0.03 (0.56)
Presence of child	0.10 (0.57)	−0.20*** (−3.17)
Medical condition	0.72*** (3.69)	−0.10 (−1.10)
High school graduate, some college	−0.19 (−0.96)	−0.26** (−2.56)
BA degree	−0.41 (−1.52)	−0.01 (−0.13)
Graduate degree	−0.46 (−1.39)	0.23* (1.94)
Household in urbanized area	0.91 (1.51)	0.02 (0.13)
Intercept	3.90*** (3.88)	1.15*** (2.84)

NOTE: Observations = 8,181; pseudo-R^2: transit = .222 and walking–cycling = .025. Z-statistics in parentheses.
***p < 01, **p < .05, *p < .1. Model 1 is whether the respondent chose transit or not in any daily nonwork trips; Model 2 is whether the respondent chose walking–cycling or not in any daily nonwork trips. In order to calculate odds ratios, all coefficient estimates need to take the exponential value. For education dummy variables, the reference is "less than high school."

diversity, size diversity, and value and rent diversity) in a neighborhood, the likelihood that its residents choose to walk or bike for daily nonwork trips increases by roughly 11%. Meanwhile, if the SDI (i.e., household income diversity, racial and ethnic diversity, and household type diversity) of a neighborhood increases by one standard deviation, the likelihood that its residents choose to walk or bike for daily nonwork trips will decrease by roughly 12%. These findings might suggest that a mix of different housing structures, sizes, and values may provide some aesthetic benefits to the neighborhood and in turn increase people's willingness to walk or bike for some nonwork trip purposes, such as visiting friends or relatives trips and other social or recreational trips. On the contrary, a more socioeconomically diverse smart growth neighborhood means, as defined here, a higher mixture of different household types, different income groups, and different races and ethnicities. This mix may impair people's sense of safety and, in turn, reduce people's willingness to walk or bike in such a neighborhood. The control variables, individual and household demographics and socioeconomic characteristics, have shown results that are close to those in daily work travel mode choice models.

Conclusion

With the individual trip diary from the recent 2009 National Household Travel Survey (NHTS), an analysis was done on the effect of neighborhood-level smart growth patterns and socioeconomic diversity on commute mode choice, daily work travel mode choice, and nonwork travel mode choice for individuals living in different neighborhoods in the Los Angeles CMSA, an area often considered as a synonym for "sprawl." Model results consistently show that nonauto transportation infrastructure diversity and quality are the most important aspects of smart growth patterns and have substantial effects on all travel mode choices. As a variable extracted from multiple factors through the principal components analysis, the nonauto transportation infrastructure diversity and quality index incorporates several factors, such as transit availability, quality bike land availability, street density, and street intersection density. That fact suggests that enhancing the neighborhood accessibility to public transit and providing pedestrian and cyclist "friendly" streets (such as providing safe cycling streets and increasing street walkability) tend to be the most realistic strategies to increase transit ridership and encourage walking and biking, at least in Los Angeles. In the literature the terms "pedestrian and cyclist friendly" and "walkability" also imply a number of design strategies such as crosswalks, sidewalks, plantings, traffic calming, signage, and the like. In future research, these measures could be incorporated in the nonauto transportation infrastructure diversity and quality index to provide a more comprehensive view of how these features affect travel mode choice.

After the nonauto transportation infrastructure diversity and quality index is controlled for, other smart growth indexes—residential density and mixed land use—have only a limited (statistically insignificant) effect on commute mode choice, as well as daily work and nonwork travel mode choice. This finding is in line with the findings of Boarnet and Sarmiento, who also found that, on net, land use variables do not influence travel in their southern California sample (4). Overall, increasing density or land use mix, by itself, will have little bearing on people's travel mode choice. Development needs to be focused near transit and design communities to be more transit friendly, pedestrian friendly, and bike friendly. Without a diverse, convenient, and safe transportation infrastructure, increasing the residential density or land use mix itself will probably only marginally increase the likelihood of taking transit or walking or cycling, and thus only marginally reduce automobile dependency. This finding does not conflict with other research that found that higher residential density and land use mix significantly reduce the distance of automobile travel since density brings everything closer. In addition, there needs to be recognition of the fact that density also makes investment in public transit more viable.

Moreover, the mixed housing index and the socioeconomic diversity index (SDI) both show some effect on travel mode choice. Housing mix in a neighborhood increases the likelihood of choosing walking and cycling for daily work trips and daily nonwork trips. Higher socioeconomic diversity of a neighborhood reduces the likelihood of choosing walking or cycling for daily nonwork trips. As discussed earlier, a mix of different housing structures, sizes, and values may provide some aesthetic benefits to the neighborhood and, in turn, increase people's willingness to walk and bike. However, a more socioeconomically diverse neighborhood, which has a higher mixture of different household types, different income groups, and different races and ethnicities, may impair people's sense of safety and, in turn, reduce their willingness to walk or bike in such a neighborhood. This finding appears to suggest that people living in socioeconomically diverse neighborhoods tend to walk and bike less, not more. Of course, the finding is determined by one's definition of socioeconomic diversity and the factors included in the SDI. If different factors were included in the index, the findings might be different.

The results of this study are based on residents living in Los Angeles. A smart growth neighborhood in Los Angeles might look different from one in Portland, Oregon. Therefore, the findings here may have limited applications to other metropolitan statistical areas (MSAs). However, even in an MSA that is often regarded as a synonym for "sprawl," there are still some aspects of the smart growth pattern that are strongly associated with people's travel mode choice. Overall, people living in smart growth neighborhoods in Los Angeles do travel "smarter," in regard to using environmentally more sustainable (bus and train) and healthier (walking and cycling) travel modes.

Ultimately, enhancing neighborhood accessibility to public transit, providing safe cycling streets, and increasing street walkability in neighborhoods are more urgent and realistic objectives in achieving the goal of smart growth and environmental sustainability in Los Angeles. In times of insufficient transportation funding at the federal and the state levels, these findings have important policy implications for how to prioritize the use of limited resources (47).

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