Structural Equations Model of Land Use Patterns, Location Choice, and Travel Behavior in Southern California

João de Abreu e Silva, Konstadinos G. Goulias, and Pamela Dalal

This paper continues a series of papers that address the relationship between travel behavior and land use patterns under a structural equations modeling framework in different contexts for comparative purposes. The proposed model structure in this paper is, by design, heavily influenced by a model developed for Lisbon, Portugal; Seattle, Washington; and Montreal, Canada, in addition to a revisited model for Lisbon that used more recent data. In all previous models, significant effects of land use patterns on travel behavior were found. The variables included in this and past models are multidimensional and include short-term decisions (number of trips by mode and trip scheduling) and long-term decisions (home location, car ownership, and mobility). The modeled land use variables measure the levels of urban intensity, density, diversity, and accessibility. The land use patterns are described at the residence and employment zones. To account explicitly for the self-selection bias, the land use variables are modeled explicitly as functions of the socioeconomic attributes of individuals and their households. The findings from Los Angeles, California, and the surrounding metropolitan region are presented in this paper and then compared with those from Lisbon, Seattle, and Montreal. The results show that, similarly to the other cases, land use patterns influence travel behavior significantly. Other commonalities were also found in all four environments, as were some important differences.

The integration of land use policies with car use policies is strongly advocated in many developed countries as a way to decrease fuel consumption and greenhouse gas emissions. This integration is particularly important for California because of its recent legislation aimed at stricter mobile-source emissions control and its plans to dramatically decrease greenhouse gas emissions, both of which emphasize the need for integrated land use and transportation policies (see http://www.ca-ilg.org/SB375Basics). This integration occurs through sustainable community strategies that require the understanding and changing of the household residential location and the promotion of environmentally friendly behavior. All of these factors create a need for better analytical tools to study policies.

J. de Abreu e Silva, Center for Urban and Regional Systems, Department of Civil Engineering, Architecture, and Georesources, Technical University of Lisbon, Room 3.27.4, Avenida Rovisco Pais, 1049-001 Lisbon, Portugal. K. G. Goulias, Room 5706, and P. Dalal, Room 3625, Department of Geography, University of California, Santa Barbara, Ellison Hall, Santa Barbara, CA 93106. Corresponding author: J. de Abreu e Silva, joao.abreu@civil.ist.utl.pt.

Transportation Research Record: Journal of the Transportation Research Board, No. 2323, Transportation Research Board of the National Academies, Washington, D.C., 2012, pp. 35–45.
DOI: 10.3141/2323-05

In the past 20 years, many research papers have demonstrated the need to assess these policies with modeling and simulation tools that use data about individuals and their households as decision-making units and provide more realism in the behavioral representations. In addition, because land use models are influenced by choices of residential and work location, the inclusion of the effects of self-selection, as a result of either socioeconomic characteristics or attitudinal aspects, is required in behavioral model systems for policy tools (*1, 2*). In a stream of analyses that has jointly examined location choices, car ownership, activity participation, and travel, model systems have been created for different urban environments; the models were based on endogeneity among variables (*1, 3–5*). These model systems include location attributes and land use variables that other researchers also consider to be important determinants of travel (*6–9*). Moreover, these empirical studies link travel behavior with land use patterns through the use of multiequation methods pioneered in travel behavior by Golob (*10, 11*) and used in similar contexts by Bagley and Mokhtarian (*2*).

In this paper, data from Southern California are used and the same, previously described general hypothesis, modeling framework, methodology, and estimation methods are employed to continue the comparison between different environments. The base model structure was first presented by de Abreu e Silva et al. using data from the Lisbon metropolitan area, Portugal, collected in 1994 (*1*). Later, the same modeling structure was used to test the relationships between travel behavior and land use patterns for Seattle, Washington, and Montreal, Canada, as well as new data from Lisbon (*3–5*). Many similarities in long-term (e.g., location choice) and short-term (e.g., daily travel) relationships were found, as were differences in the role that land use patterns and the level of service of transportation systems play across different urban contexts. The model presented here fills a very important need to understand these relationships. In this study, the land use factors are built in a way that is somewhat different from past analyses; in this approach, a comprehensive group of accessibility indicators are built using the intervening opportunities approach and are transformed into *z*-scores. These land use *z*-scores assume and measure dependence and heterogeneity over space, thereby reducing the estimation biases attributable to the effects of large-scale regional agglomeration and the spatial correlation between locations.

Although the overall modeling structure of these models is the same, some differences exist in the variables used in each of the models because the available data differed from case to case. The implications from the results obtained in these studies are important and far-reaching; the results help to validate and give more robustness to the conclusions obtained through the application of the same basic model in different urban contexts.

The main conclusions drawn from the previous models (*1, 3–5*) can be summarized:

- People who live and work in central and denser areas tend to use nonmotorized travel modes and transit more often and use the car less. Also, these people tend to have lower car ownership levels in their households.
- Working in central and denser areas tends to increase the commuting distance and attract people living in suburban and exurban areas, a sign of the polarizing power that the centers of these metropolitan regions have.

In this paper, the influence of land use patterns in the South California Association of Governments (SCAG) region is examined. This region includes the counties of Los Angeles, Imperial, Orange, Riverside, San Bernardino, and Ventura and encompasses a population of around 18.6 million. Besides the relevance attributable to the size of the SCAG region, this study is also important because Southern California is normally considered to be the archetype of a sprawling and car-dependent region with longer commutes and lower-density environments than European cities.

The remainder of the paper is organized as follows. First, the case study and the general model structure and its main hypothesis are presented. This is followed by a brief presentation of the modeling method used and a summary of findings. Finally, in the conclusions, a brief comparison with the results obtained in the other models is presented.

CASE STUDY AND MODEL DESCRIPTION

The present model uses data from the Southern California Household Travel Survey (*12*). This survey was conducted after the 2001 census and contains social and demographic data, as well as travel diary data from 39,264 individuals from 16,506 households who at the time of the survey resided within the SCAG region. The SCAG region is the largest U.S. metropolitan planning organization. From this survey, employed persons for whom complete data were available were selected (creating a sample of 6,897 individuals) and those persons' home and work locations were joined spatially to a U.S. census block. For each census block, detailed spatial attributes, which consisted of accessibility indicators, were available from a previous study (*13, 14*).

The model structure used here was as similar as possible to the one first developed for Lisbon and examines the relationships between socioeconomic characteristics, land use patterns, relative residential and employment locations, car ownership, public transit pass ownership, and travel behavior (*1*).

The model specification considers the land use patterns at the levels of the residential and employment U.S. census blocks. These land use patterns are treated as endogenous and allowed to be influenced by the socioeconomic characteristics of the individuals and their households, thus controlling for socioeconomic self-selection. Land use patterns and socioeconomic variables both influence the travel behavior of employed individuals. The model considers several travel behavior variables that range from long-term to short-term decisions. These variables include commuting distance and car ownership, which are considered to be longer-term decisions. These decisions, in turn, influence shorter-term decisions, such as the number of trips made daily by different modes, the distances traveled by mode, and the time between the first and last trips; the latter factor corresponds to the height of Hägestrand prism in time geography (*15*). Land use variables are also influenced by travel behavior variables. In this way, it is possible to test for the effects that result from travel behavior being one of the observed outcomes of individual preferences and for the feedback from the information that individuals have about optimal shorter-term decisions (*16*). Transit pass ownership was also considered for inclusion in the model as a variable but was excluded because of the very small percentage of pass owners (around 0.5%) and the potential multicollinearity problems.

The general model structure is presented in Figure 1. The variables in the boxes are the dependent variables; the arrows entering each box indicate which variables explain the dependent variable in the box. These relationships are tested statistically for their influence. In this type of model, it is also possible to differentiate between direct, indirect, and total effects (the latter being the sum of the direct and indirect effects).

The socioeconomic variables considered in the model include gender, age (although age did not influence any of the dependent variables), household total income, household size, average age of the household, average age of the adults in the household, households with only one member, households with only two members (to control for the nonlinear effects of household size), households with only teenagers and adults, fixed working schedules, and the number of workers in the household. With the exception of the last variable, these last four variables were built as dummy variables.

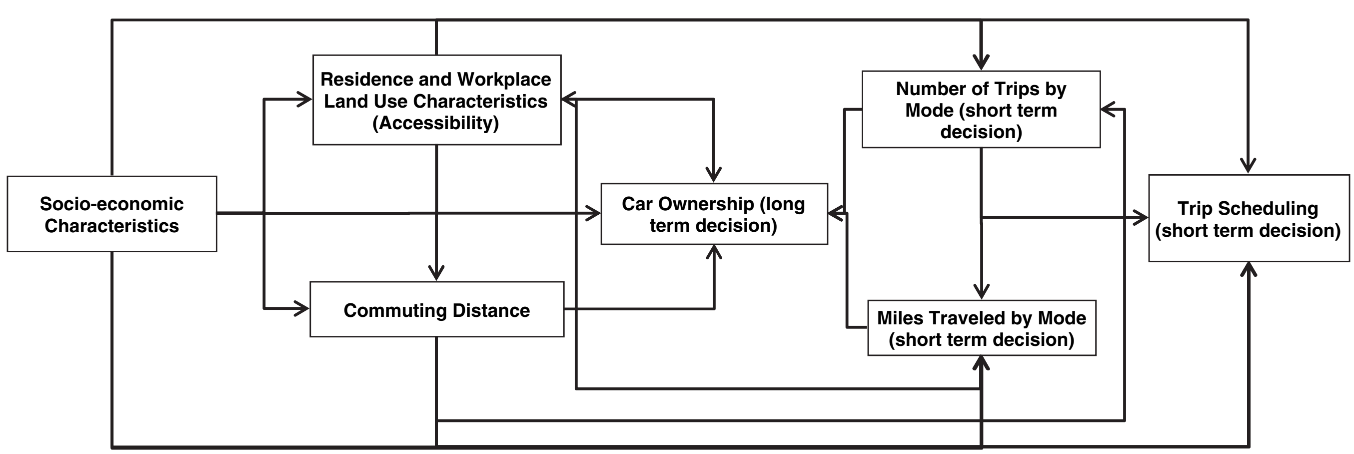

FIGURE 1 General structure of model.

This study used opportunity-based accessibility indicators at the level of the U.S. census block (203,191 U.S. census blocks cover the entire study area). These indicators represented the ease of reaching 15 types of industry (thereby representing the opportunities for activity participation) from each of these blocks within 10 min of roadway travel buffers from each of the 203,000 pegs (*13*). The types of industry included were (*a*) agriculture, forestry, fishing, hunting, and mining; (*b*) construction; (*c*) manufacturing; (*d*) wholesale trade; (*e*) retail trade; (*f*) transportation, warehousing, and utilities; (*g*) information; (*h*) finance, insurance, real estate, and rental and leasing; (*i*) professional, scientific, management, administrative, and waste management services; (*j*) educational; (*k*) health; (*l*) arts, entertainment, recreation, accommodation, and food services; (*m*) armed forces; (*n*) public administration; and (*o*) other services (except public administration). Different accessibility values were obtained for the morning peak period (6 to 9 a.m.), midday (9 a.m. to 3 p.m.), the evening peak period (3 to 7 p.m.), and the night (7 p.m. to 6 a.m.). In this way, the different roadway conditions and the opening and closing patterns of businesses and the arrival and departure patterns of employees in each industry were captured. Instead of using these indicators directly, a transformation was employed to account for spatial correlation among the blocks (*14*). All spatial aspects, such as employment density, are more influenced by the attributes of nearby locations than attributes from distant locations (*17*), thereby resulting in the nonindependence of the attributes of one location and neighboring locations; this concept is also called spatial correlation. The G^* transformation measured the intensity (or dispersion) of attributes over space as z-scores of positive or negative spatial correlation. A positive z-score meant that a block was surrounded by more blocks with similar attributes than would be expected at random. Conversely, a negative z-score indicated that a block was surrounded by more dissimilar blocks than would be expected at random. The outcome was 15 industry-specific z-scores for each block that revealed regional and local agglomeration based on spatial dependency and autocorrelation (*18*). Then, factor analysis was employed to identify 13 major dimensions for home and work locations from these z-scores, as explained later in the paper.

This process resulted in 13 factors that characterized the residential and employment locations (93% of the variation was captured; the Kaiser–Meyer–Olkin test value was 0.949) through the use of a principal components method. With the exception of two factors, there was a clear distinction between the factors that describe land uses in the residential and employment areas. The factors, the defining variables, and their z-scores are presented in Table 1.

The two factors "working in a block with strong accessibility to urban functions" and "living in a block with strong accessibility to urban functions" are very similar and point to high scores in accessibility to urban employment during all the periods of the day. Thus, these two land use factors describe well-mixed, dense, and potentially central urban environments.

The factor "living in a block with strong accessibility to industrial areas" presents high z-scores for manufacturing, construction, and wholesale retail employment, thus describing areas mainly occupied by the manufacturing industry and related activities.

The land use factor "working in a block with strong accessibility to construction areas" describes mainly monofunctional industrial-type areas and nonconsolidated expansion zones. The factor "working in a block with strong accessibility to logistical and manufacturing areas" describes port areas and other logistical and transportation-related zones. The factor named "living in a block with strong accessibility to logistical areas" accounts for high accessibility for people working in the transportation and logistics sector and, thus, describes residential areas near transportation facilities.

The land use factor "living in a nonurban block" has high loadings in the z-scores that represent accessibility to agriculture and military jobs, types of land use that are incompatible with urban occupation. The factor "working near military facilities" describes military facilities and their immediate surroundings, another type of use incompatible with urban occupation.

The land use factor "living and working in a rural area" is one of the two land use factors that are related to residential and employment places. The factor represents blocks with high accessibility to agriculture employment, thus describing rural areas. The factors "living in a block with accessibility to public services" and "working in a block with high accessibility to public services" describe the employment and residential blocks in urban areas that have high accessibility to public service employment.

The factor "living in a block close to a university campus," which presents high loadings in accessibility to education jobs, describes residential areas near the several university campuses that exist in the SCAG region (the University of California, Los Angeles, the University of Southern California, the Pomona colleges, the California Institute of Technology, the California State University campuses, etc.).

Finally, the land use factor "well-established areas, away from construction" describes zones with negative loadings on the accessibility to construction jobs, thus indicating that these areas are stabilized urban areas.

STRUCTURAL EQUATIONS MODELING

The modeling method used in the present work is structural equations modeling (SEM), which combines two types of statistical method: factor analysis and simultaneous equations models (*19*). In SEM, variables can be either exogenous or endogenous (*10, 11*). These characteristics allow SEM to handle indirect and multiple relationships and to study reverse relationships. Because of these characteristics, SEM is particularly adequate for modeling the complex relationships between travel behavior and land use patterns. The method is particularly useful in the identification of the direct impact of one variable on another and the variable's possible impact through a mediator.

In travel behavior analysis, SEM is becoming increasingly popular as a modeling method because of its ability to simultaneously estimate several endogenous variables and to include latent variables. In this way, SEM is particularly suited to modeling indirect and nonrecursive relationships (in which there are feedback loops). New estimation methods in SEM also allow the inclusion of discrete variables, which are common in travel behavior analysis. The model developed here is a structural equation model that uses only observed variables (often referred to as "path analysis" or "simultaneous equation modeling"). The estimation method used here is the weighted least squares, which was specifically developed to deal with discrete, ordered, and censored variables (*10, 11*). The weighted least squares method's genesis occurred with a multivariate probit developed by Muthén (*20*). Later, this method was generalized, also by Muthén, to accommodate structural equations with a mix of discrete, censored, and continuous variables (*21, 22*). Because the weighted least squares method uses correlation matrices, the resulting coefficients are standardized, thereby allowing a more direct comparison of the magnitudes of the effects.

TABLE 1 Factor Scores

Factor Name	Most Important z Score	Loading
Working in a block with strong accessibility to urban functions	Work arts a.m.	0.863
	Work construction a.m.	0.679
	Work educational a.m.	0.793
	Work finance a.m.	0.887
	Work health a.m.	0.905
	Work information technology a.m.	0.749
	Work manufacturing a.m.	0.623
	Work other services a.m.	0.845
	Work professional services a.m.	0.891
	Work public services a.m.	0.702
	Work retail a.m.	0.847
	Work wholesale a.m.	0.671
	Work construction md	0.750
	Work educational md	0.804
	Work financial md	0.902
	Work information technology md	0.769
	Work manufacturing md	0.620
	Work other services md	0.909
	Work professional services md	0.891
	Work public services md	0.722
	Work wholesale md	0.678
	Work health md	0.915
	Work retail md	0.837
	Work arts md	0.889
	Work arts nt	0.679
	Work educational nt	0.795
	Work finance nt	0.715
	Work health nt	0.884
	Work information technology nt	0.761
	Work other services nt	0.857
	Work professional services nt	0.536
	Work public services nt	0.719
	Work retail nt	0.815
	Work construction p.m.	0.736
	Work educational p.m.	0.822
	Work financial p.m.	0.896
	Work public services p.m.	0.701
	Work professional services p.m.	0.872
	Work other services p.m.	0.904
	Work information technology p.m.	0.734
	Work wholesale p.m.	0.669
	Work retail p.m.	0.819
	Work health p.m.	0.892
	Work arts p.m.	0.864
Living in a block with strong accessibility to industrial areas	Residence construction a.m.	0.644
	Residence manufacture a.m.	0.578
	Residence wholesale a.m.	0.557
	Residence construction md	0.572
	Residence manufacture md	0.505
	Residence arts nt	0.554
	Residence construction nt	0.716
	Residence professional services nt	0.721
	Residence wholesale nt	0.849
	Residence construction p.m.	0.550
	Residence wholesale p.m.	0.622
Working in a block with strong accessibility to construction areas	Work construction a.m.	0.654
	Work construction md	0.548
	Work construction nt	0.835
	Work professional services nt	0.727
	Work wholesale nt	0.800
	Work construction p.m.	0.533
Working in a block with strong accessibility to logistical and manufacturing areas	Work manufacturing a.m.	0.501
	Work transportation and logistics a.m.	0.783
	Work manufacturing md	0.547
	Work transportation and logistics md	0.795
	Work wholesale md	0.533
	Work transportation and logistics nt	0.779
	Work transportation and logistics p.m.	0.795
Living in a block with strong accessibility to logistical areas	Residence transportation and logistics a.m.	0.790
	Residence manufacturing md	0.547
	Residence transportation and logistics md	0.804
	Residence wholesale md	0.512
	Residence transportation and logistics nt	0.775
	Residence transportation and logistics p.m.	0.818
Living in a block with strong accessibility to urban functions	Residence arts a.m.	0.870
	Residence construction a.m.	0.646
	Residence educational a.m.	0.744
	Residence finance a.m.	0.875
	Residence health a.m.	0.886
	Residence information technology a.m.	0.863
	Residence manufacturing a.m.	0.524
	Residence other services a.m.	0.891
	Residence professional services a.m.	0.893
	Residence public services a.m.	0.628
	Residence retail a.m.	0.833
	Residence wholesale a.m.	0.561
	Residence construction md	0.721
	Residence educational md	0.745
	Residence financial md	0.888
	Residence information technology md	0.880
	Residence manufacturing md	0.529
	Residence other services md	0.915
	Residence professional services md	0.889
	Residence public services md	0.633
	Residence wholesale md	0.587
	Residence health md	0.892
	Residence retail md	0.814
	Residence arts md	0.917
	Residence arts nt	0.654
	Residence educational nt	0.737
	Residence finance nt	0.778
	Residence health nt	0.845
	Residence information technology nt	0.856
	Residence other services nt	0.872
	Residence professional services nt	0.506
	Residence public services nt	0.658
	Residence retail nt	0.798
	Residence construction p.m.	0.708
	Residence educational p.m.	0.757
	Residence financial p.m.	0.892
	Residence public services p.m.	0.612
	Residence professional services p.m.	0.872
	Residence other services p.m.	0.924
	Residence information technology p.m.	0.846
	Residence wholesale p.m.	0.547
	Residence retail p.m.	0.799
	Residence health p.m.	0.896
	Residence arts p.m.	0.897
Living in a nonurban block	Residence agriculture a.m.	0.646
	Residence armed forces a.m.	0.952
	Residence agriculture md	0.633
	Residence armed forces md	0.956
	Residence armed forces nt	0.937
	Residence agriculture p.m.	0.508
	Residence armed forces p.m.	0.945
Working near military facilities	Work armed forces a.m.	0.943
	Work armed forces md	0.946
	Work armed forces nt	0.925
	Work armed forces p.m.	0.939
Living and working in a rural area	Residence agriculture a.m.	0.583
	Residence agriculture md	0.588
	Residence agriculture p.m.	0.552
	Work agriculture a.m.	0.869
	Work agriculture md	0.868
	Work agriculture p.m.	0.836
Living in a block with accessibility to public services	Residence public services a.m.	0.638
	Residence public services md	0.622
	Residence public services p.m.	0.617
Working in a block with high accessibility to public services	Work public services a.m.	0.448
	Work public services md	0.432
	Work public services p.m.	0.446
Living in a block close to university campus	Residence educational a.m.	0.313
	Residence educational md	0.343
	Residence educational nt	0.315
Well-established areas, away from construction	Residence construction nt	–0.464
	Work construction nt	–0.341

NOTE: md = midday; nt = nighttime.

DISCUSSION OF ESTIMATION RESULTS

For reasons of space it is not possible to show all of the outputs of an SEM model (direct, indirect, and total effects). Therefore, the following tables present only the direct and total effects. The most important results from the model are mainly the ones that result from the total effects, although the direct effects give a clearer image of the model's structure. First, the effects between endogenous and exogenous variables are presented, followed by the total effects attributable to endogenous travel behavior variables; finally, the total effects attributable to the land use factors are presented.

Although all of the direct effects in the model were significantly different from zero (at a 95% level of significance), some of the total effects were not significantly different from zero; this result is attributable to contrary indirect effects that annul one another.

The estimated model showed a very good fit. The value of its chi-squared statistic was 250.3, with 331 degrees of freedom. The ratio between these two values means that the differences between the population covariance matrix and the model implied covariance matrix are small. An acceptable goodness of fit is obtained when this ratio is smaller than two and a very good fit is obtained when the ratio is close to one (*23, 24*). The standard Bayesian criteria (the Akaike information criterion and the consistent Akaike information criterion) indicate that this model is superior either to the independence or to the saturated models. All the other fit indicators for SEM indicate a very good fit (*20*): the normed fit index, the nonnormed fit index, the comparative fit index, the relative fit index, the goodness-of-fit index, and the adjusted goodness-of-fit index each have a value of one; the root mean square error of approximation is zero.

The main results from Table 2 are, in general, in accordance with what are commonly accepted as the main influences of socioeconomic variables on travel behavior. Globally, the direct and total effects have similar magnitudes and directions, meaning that, eventually, contrary indirect effects become insufficiently strong to significantly change the total effects.

It can be seen that men spend more time outside the home, travel further away by car, but make fewer trips, whereas women travel shorter distances but engage in more trips. Also, men travel more by transit and less by nonmotorized modes. Workers in households with higher levels of income travel more by car and less by transit; these workers also own more cars and have a higher commuting distance. These observations are in accordance with what has been reported in several studies.

The size of the household reduces the time spent outside the home and increases the number of trips using motorized modes versus nonmotorized ones. Household size also has a positive effect on car ownership. This finding supports the hypothesis that people who belong to larger households spend more time on in-home activities; thus, those people choose faster transportation modes.

Very small households, with just one individual, have a lower probability of owning more cars. Both one- and two-person households have a lower number of car trips. In the case of one-person households, car trips are substituted (at least in part) by nonmotorized trips; the two-person households substitute car trips with transit trips. Commuting distance is not influenced substantially by the effects of any variables.

The average age of the household and of the adults in the household have contrary total effects on some variables, although the factors are strongly correlated (0.89). Older households have a higher probability of owning more cars, whereas households with older adults own fewer cars. Also, households with younger adults more often use nonmotorized modes and transit, although some of the effects on the distances traveled are not significant.

People with fixed working schedules typically have a longer commuting distance, use transit more often, and use the car and nonmotorized modes less often. Usually, people without fixed working schedules commute more often during off-peak periods when the transit frequency is lower and, thus, less attractive. Because the commuting distance is higher, however, these people tend to travel longer distances; thus, a positive effect on all the distances traveled can be seen.

Households with only adults and teenagers have a higher probability of owning more cars, probably because (unique to the United States) persons as young as 16 years old may have a driver's license and, possibly, a car allocated to them. Workers in this type of household have longer commuting distances and travel more by transit and car and less by nonmotorized modes. These findings are a result of such workers locating (in terms of both employment and residence) less often in urban areas; these people are more likely to be suburban residents.

The increase in the commuting distance with an increase in the number of workers in the household is statistically significant, albeit weakly so. A higher number of workers increases the probability of the household owning more cars, increases the number of car trips, and reduces the number of trips in all other modes. In contrast, a higher number of workers significantly reduces the household distances traveled in all modes. This reduction could be a result of the errands necessary to household maintenance being divided among all the workers, thereby reducing the need to chain trips and, thus, decreasing the distances traveled.

The results from Table 3 show the existence of effects of self-selection attributable to socioeconomic characteristics. People who live and work in more urbanized areas and areas of higher accessibility tend to belong to smaller, older households, with, on average, younger adults and a smaller income. Also, these households have a smaller number of workers. If the areas with higher loadings in these factors could be considered to correspond to the central area of Los Angeles, the socioeconomic portrait does not show clear signs of gentrification as were deduced from the models developed for Seattle and Montreal (*3, 4*).

In general, income only positively affects the last land use factor, thus showing that people with higher income levels tend to locate themselves in more consolidated areas. Larger households tend to live and work in places with higher accessibility to public services. Larger households also tend to be located in nonurban areas; this finding is in accordance with the fact that households in more rural areas are larger. Households with only one member tend to live near university campuses in nonurban areas and work near military facilities. These effects may be attributable to military personnel and college students, who tend to live alone and locate themselves closer to their strong spatial daily anchors.

Workers with fixed schedules tend to live in the proximities and work in manufacturing, logistical, or rural areas. These effects are clearly explained by the fact that working in manufacturing and agriculture jobs is more subjected to fixed schedules than other types of occupation (e.g., information workers).

The effects of endogenous travel behavior variables show the existence of feedback effects from travel behavior variables on land use factors (Table 4). In this case, car ownership levels directly influence the first two land use factors, and the number of miles driven by car influences the land use factor "living in a block with strong accessibility to logistical areas." The first of these effects is common to all

TABLE 2 Effects on Travel Behavior Attributable to Exogenous Socioeconomic Variables

Dependent Variable	Type of Effect	Gender (1 if man)	Household Income	Household Size	Average Household Age	Average Adult Age	Household with One Member	Household with Two Members	Fixed Working Schedule	Household with Adults and Teens	Number of Workers
Time between the first and last trips	Direct	**0.210**	**–0.101**	—	**–0.072**	**0.299**	—	—	**0.103**	—	—
	Total	**0.156**	–0.038	**–0.006**	**–0.066**	**0.289**	0.001	**–0.036**	**0.088**	0.000	–0.001
Nonmotorized miles traveled	Direct	**0.012**	**0.068**	—	—	—	—	**0.006**	**0.028**	—	**–0.025**
	Total	–0.005	**0.056**	**–0.028**	**–0.061**	**–0.016**	**0.008**	0.004	**0.021**	**–0.023**	**–0.029**
Transit miles traveled	Direct	—	**0.021**	—	—	—	—	—	—	—	—
	Total	**0.020**	**–0.121**	**0.004**	**0.012**	–0.003	**–0.002**	**0.003**	**0.010**	**0.014**	**–0.001**
Car miles traveled	Direct	**0.063**	—	—	—	—	—	—	—	**0.016**	**–0.020**
	Total	**0.071**	**0.056**	**0.006**	**–0.011**	**0.041**	**–0.001**	**–0.016**	**0.008**	**0.019**	**–0.019**
Number of nonmotorized trips	Direct	**–0.015**	—	**–0.038**	**–0.136**	—	**0.015**	—	—	**–0.044**	—
	Total	**–0.038**	**–0.028**	**–0.047**	**–0.102**	**–0.033**	**0.014**	**–0.001**	**–0.013**	**–0.041**	**–0.004**
Number of transit trips	Direct	—	**–0.149**	—	—	—	**–0.006**	—	—	**0.018**	—
	Total	**0.015**	**–0.178**	**0.006**	**0.018**	**–0.016**	**–0.003**	**0.004**	**0.008**	**0.017**	**–0.003**
Number of car trips	Direct	**–0.131**	**0.142**	—	—	—	—	**–0.063**	**–0.043**	—	—
	Total	**–0.125**	**0.148**	**0.010**	**0.001**	**0.025**	**–0.003**	**–0.063**	**–0.043**	**0.007**	**0.002**
Number of cars in household	Direct	**0.051**	**0.241**	**0.495**	**0.686**	**–0.469**	**–0.047**	—	—	**0.085**	**0.187**
	Total	**0.060**	**0.270**	**0.488**	**0.685**	**–0.466**	**–0.049**	0.000	0.000	**0.086**	**0.191**
Log commuting distance	Direct	**0.140**	—	—	—	**0.049**	—	—	**0.067**	—	—
	Total	**0.147**	**0.005**	0.000	**–0.017**	**0.078**	0.001	**0.002**	**0.070**	**0.005**	**0.003**

NOTE: Number of individuals (N) = 6,897; coefficients significant at 95% presented in bold; — = no direct effect.

TABLE 3 Effects on Land Use Variables Attributable to Exogenous Socioeconomic Variables

Dependent Variable	Type of Effect	Gender (1 if man)	Household Income	Household Size	Average Household Age	Average Adult Age	Household with One Member	Household with Two Members	Fixed Working Schedule	Household with Adults and Teens	Number of Workers
Work StrongAccessUrb	Direct	**0.0310**	—	—	**0.3080**	**–0.1950**	**0.0310**	—	—	—	—
	Total	**0.0290**	**–0.0060**	**–0.0110**	**0.2920**	**–0.1840**	**0.0320**	0.0000	0.0000	**–0.0020**	**–0.0040**
Live StrongAccessUrb	Direct	—	—	—	**0.3510**	**–0.4400**	—	—	—	—	—
	Total	**–0.0080**	**–0.0370**	**–0.0670**	**0.2560**	**–0.3760**	**0.0070**	0.0000	0.0000	**–0.0120**	**–0.0260**
Live StrongAccessInd	Direct	**0.0450**	**–0.0960**	—	—	—	**0.0160**	—	—	—	**0.0910**
	Total	**0.0450**	**–0.0960**	—	—	—	**0.0160**	—	—	—	**0.0910**
Work StrongAccessConst	Direct	—	—	—	**0.0340**	**–0.1530**	—	**0.0280**	—	—	—
	Total	—	—	—	**0.0340**	**–0.1530**	—	**0.0280**	—	—	—
Work StrongAccessLogis&Manuf	Direct	**0.0260**	—	**–0.0460**	**–0.1040**	—	—	—	**0.0410**	—	—
	Total	**0.0260**	—	**–0.0460**	**–0.1040**	—	—	—	**0.0410**	—	—
Live StrongAccessLogis	Direct	—	—	**0.1110**	—	—	**0.0250**	—	**0.0400**	—	**–0.0300**
	Total	**–0.0030**	**–0.0030**	**0.1110**	**0.0000**	**–0.0020**	**0.0250**	**0.0010**	**0.0390**	**–0.0010**	**–0.0290**
LiveNonUrban	Direct	—	—	**0.0700**	—	—	**0.0270**	—	—	**–0.0590**	—
	Total	—	—	**0.0700**	—	—	**0.0270**	—	—	**–0.0590**	—
WorkMilitary	Direct	**0.0220**	—	—	—	—	**0.0130**	**0.0320**	—	**–0.0330**	—
	Total	**0.0220**	—	—	—	—	**0.0130**	**0.0320**	—	**–0.0330**	—
Live&WorkRural	Direct	—	—	—	—	—	—	—	**0.0310**	—	—
	Total	—	—	—	—	—	—	—	**0.0310**	—	—
LivebyPublicServices	Direct	**0.0270**	**–0.2000**	**0.0780**	—	—	—	—	—	—	—
	Total	**0.0270**	**–0.2000**	**0.0780**	—	—	—	—	—	—	—
Work StrongAccessPublicServices	Direct	**–0.0270**	—	**0.0200**	—	—	—	—	—	—	—
	Total	**–0.0270**	—	**0.0200**	—	—	—	—	—	—	—
LivebyUnivCampus	Direct	—	—	**0.0370**	—	—	**0.0210**	—	**0.0500**	—	—
	Total	—	—	**0.0370**	—	—	**0.0210**	—	**0.0500**	—	—
WellEstabAreasFarConst	Direct	—	**0.0610**	—	—	—	**0.0300**	—	**0.0290**	—	—
	Total	—	**0.0610**	—	—	—	**0.0300**	—	**0.0290**	—	—

NOTE: Coefficients significant at 95% presented in bold; — = no direct effect.

TABLE 4 Effects Attributable to Endogenous Travel Behavior Variables

Dependent Variable	Type of Effects	Nonmotorized Miles Traveled	Car Miles Traveled	Number of Nonmotorized Trips	Number of Transit Trips	Number of Car Trips	Number of Cars in Household	Log Commuting Distance
Time between the first and last trips	Direct			**0.136**	**0.090**	**0.580**		**0.155**
	Total	0.000	0.000	**0.053**	**0.100**	**0.569**	**–0.005**	**0.145**
Nonmotorized miles traveled	Direct		**0.070**	**0.592**				
	Total	**0.000**	**0.070**	**0.588**	**0.090**	**0.008**	**–0.006**	**–0.082**
Transit miles traveled	Direct				**0.803**			**0.049**
	Total	0.000	**–0.001**	**0.013**	**0.806**	**–0.087**	–0.002	**0.046**
Car miles traveled	Direct			**–0.031**	**–0.070**	**0.254**		**0.273**
	Total	**–0.001**	**0.000**	**–0.070**	**–0.083**	**0.263**	**0.012**	**0.286**
Number of nonmotorized trips	Direct				**0.159**			**–0.172**
	Total	**0.000**	**0.001**	**0.003**	**0.162**	**–0.017**	**–0.012**	**–0.173**
Number of transit trips	Direct					**–0.108**		
	Total	**0.000**	**–0.003**	**0.016**	**0.004**	**–0.109**	**–0.007**	**–0.004**
Number of car trips	Direct			**–0.145**				
	Total	**0.000**	0.000	**–0.146**	**–0.025**	**0.003**	**0.009**	**0.026**
Number of cars in household	Direct	**–0.041**	**0.028**		**–0.173**			**0.054**
	Total	**–0.041**	**0.028**	**–0.029**	**–0.180**	**0.027**	**0.003**	**0.067**
Log commuting distance	Direct							
	Total	**–0.001**	**0.001**	**–0.001**	**–0.003**	**0.000**	**0.018**	**0.001**
Work StrongAccessUrb	Direct						**–0.022**	
	Total	**0.001**	–0.001	**0.001**	**0.004**	**–0.001**	**–0.022**	**–0.001**
Live StrongAccessUrb	Direct						**–0.138**	
	Total	**0.006**	**–0.004**	**0.004**	**0.025**	**–0.004**	**–0.138**	**–0.009**
Live StrongAccessLogis	Direct		**–0.047**					
	Total	**0.000**	**–0.047**	**0.003**	**0.004**	**–0.012**	**–0.001**	**–0.013**

NOTE: Coefficients significant at 95% presented in bold.

TABLE 5 Effects Attributable to Endogenous Land Use Variables

Variable	Type of Effects	Work Strong AccessUrb	Live Strong AccessUrb	Live Strong AccessInd	Work Strong AccessConst	Work StrongAccess Logis&Manuf
Time between first and last trips	Direct	—	**0.081**	—	—	—
	Total	**0.023**	0.034	**–0.002**	–0.002	**0.017**
Nonmotorized miles traveled	Direct	—	—	—	—	—
	Total	**0.033**	**0.040**	**–0.019**	**–0.057**	**–0.006**
Transit miles traveled	Direct	**0.028**	**–0.025**	—	**–0.011**	**0.031**
	Total	**0.072**	0.000	**0.000**	**–0.052**	**0.052**
Car miles traveled	Direct	—	**–0.031**	**–0.022**	—	—
	Total	**0.020**	**–0.094**	**–0.019**	**0.026**	**0.027**
Number of nonmotorized trips	Direct	**0.063**	**0.047**	**–0.029**	**–0.081**	—
	Total	**0.054**	**0.079**	**–0.029**	**–0.100**	**–0.014**
Number of transit trips	Direct	**0.048**	**0.032**	—	**–0.053**	**0.020**
	Total	**0.049**	**0.040**	**–0.001**	**–0.055**	**0.020**
Number of car trips	Direct	—	**–0.055**	—	—	—
	Total	**–0.008**	**–0.067**	**0.004**	**0.015**	**0.002**
Number of cars in household	Direct	—	—	**0.019**	**0.035**	—
	Total	–0.004	**–0.019**	**0.020**	**0.051**	0.003
Log commuting distance	Direct	**0.101**	**–0.148**	—	**0.055**	**0.100**
	Total	**0.101**	**–0.148**	**0.000**	**0.055**	**0.100**
Work StrongAccessUrb	Direct	—	—	—	—	—
	Total	0.000	**0.000**	0.000	**–0.001**	0.000
Live StrongAccessUrb	Direct	—	—	—	—	—
	Total	0.001	**0.003**	**–0.003**	**–0.007**	0.000
Live StrongAccessLogis	Direct	—	—	—	—	—
	Total	**–0.001**	**0.004**	**0.001**	**–0.001**	**–0.001**

NOTE: Coefficients significant at 95% presented in bold; — = no direct effect.

the models developed in the studies using this analytical technique (Lisbon, Seattle, and Montreal) and suggests that people who intend to own more cars will not locate to more central and urbanized areas.

It can be seen that an increased commuting distance significantly increases car ownership levels and the number of trips by car, as well as the vehicle miles driven. A longer commuting distance reduces the number of trips by transit, increases the miles driven, and reduces the use of nonmotorized modes. A longer commuting distance also increases the time spent outside home. These effects are in perfect accord with what is commonly reported in the literature. Also, it is possible to see that commuting distance is not directly influenced by any other travel behavior variable, but mainly by land use factors, and indirectly passes its effects to shorter-term travel behavior variables.

Having more cars in the household has a positive total effect on commuting distance, which means that people who intend to own more cars have the means to look for work further from home. The other total effects of car ownership are also quite intuitive: higher car ownership leads to higher levels of car use and less transit and nonmotorized mode use.

In terms of the number of trips by mode, the existence of competition between the car and the other modes can be seen, as can the complementarity of transit and nonmotorized modes. These observations were common to all the other models. In terms of miles traveled by mode, it can be seen that the miles traveled by car are negatively influenced by the number of miles traveled by nonmotorized modes, but the number of miles traveled by car has a positive effect on the miles traveled by nonmotorized modes. This finding suggests that even with competition between car and transit, the nonmotorized modes could be complementary to both, although this complementarity is stronger for transit. Finally, the time spent outside the home is positively influenced by the number of trips, independent of the transport mode, although the car has a much stronger effect.

From Table 5 it can be seen that land use factors significantly influence travel behavior, even in a region that is the stereotype of the car-oriented metropolis. By accounting for the dependency between neighboring locations, the land use factors describe the similarities and dissimilarities in urban structure and patterns present in the SCAG region. It is possible to see that indirect effects are not sufficiently strong to change the direction of the direct effects, although in some cases the indirect effects change the magnitude of the direct effects.

The effects of land use patterns on commuting distance show that, in a general way, the land use factors associated with employment tend to increase commuting distance, whereas the land use factors associated with the residential area tend to decrease commuting distance. This type of effect is the way the model captures the existence of a polarized region in which the employment is clustered around different central business districts of varied importance; the residences are generally located further away from these centers. Thus, people who tend to live in areas with stronger loadings in factors like "living in a block with strong accessibility to urban functions" have lower commuting distances because the effects of this land use counteract and surpass in magnitude the effects of the work land use factors.

The effects on car ownership indicate some level of car dependency based on land use patterns. The outcomes show that people who live and work in more mixed urban areas (e.g., working or living in a block with strong accessibility to urban functions) have lower car ownership levels. On the contrary, people who live or work in more specialized and monofunctional areas (e.g., living in a block with

Live Strong AccessLogis	LiveNonUrban	WorkMilitary	Live& WorkRural	LivebyPublic Services	Work StrongAccess PublicServices	LivebyUniv Campus	WellEstabAreas FarConst
—	—	—	—	—	—	—	—
0.004	**–0.009**	**–0.002**	**–0.007**	**0.006**	0.000	**–0.014**	0.000
—	—	—	—	—	**–0.031**	—	**0.003**
–0.012	**–0.015**	**0.004**	**0.006**	**0.005**	**–0.026**	**–0.011**	**0.003**
–0.020	**0.009**	—	—	—	**0.020**	—	—
0.020	**0.006**	**–0.023**	**0.006**	**0.045**	**0.048**	**0.002**	0.000
—	—	—	—	—	—	—	—
–0.003	**–0.013**	**0.002**	**–0.018**	**–0.005**	**–0.009**	**–0.005**	0.000
–0.029	**–0.032**	**0.012**	—	—	—	**–0.018**	—
–0.020	**–0.023**	**0.007**	**0.012**	**0.009**	**0.010**	**–0.018**	0.000
0.050	—	**–0.029**	**0.011**	**0.056**	**0.036**	—	—
0.050	0.000	**–0.029**	**0.011**	**0.057**	**0.036**	**0.002**	0.000
—	—	—	—	—	—	**–0.023**	—
0.003	**0.003**	–0.001	**–0.002**	**–0.001**	**–0.001**	**–0.020**	0.000
–0.048	**–0.031**	—	—	—	—	—	—
–0.056	**–0.033**	**0.005**	**–0.006**	**–0.010**	**–0.007**	0.000	0.000
—	**–0.051**	—	**–0.059**	—	**–0.021**	—	—
–0.001	**–0.052**	**0.000**	**–0.059**	**0.000**	**–0.022**	0.000	0.000
—	—	—	—	—	—	—	—
0.001	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	0.000	0.000
—	—	—	—	—	—	—	—
0.008	**0.005**	**–0.001**	**0.001**	**0.001**	**0.001**	0.000	0.000
—	—	—	—	—	—	—	—
0.000	**0.001**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	0.000

strong accessibility to industrial areas or working in a block with strong accessibility to construction areas) tend to own more cars. People who live and work in agricultural areas also tend to have lower levels of car ownership and, presumably, car share.

The first two land use factors, the ones more strongly connected with a dense urban environment, negatively influence the number of trips by car and increase the number of trips by transit and nonmotorized modes. The effects on the miles traveled by mode are not so clear; some of them are not significantly different from zero. Working in a central area increases the miles traveled by all modes, in great part because of the positive effect that the factor has on commuting distance. In contrast, living in a central area reduces the miles driven by car and increases the miles traveled using nonmotorized modes. The effects on transit mileage are not significant, although this is a case in which there is a negative direct effect that is annulled by indirect effects from the number of trips. Living in a central and denser area increases the use of transit modes, but because travel distances are lower as a result of higher accessibility, the effects on travel distance are not clear.

The effects from the other land use factors are in accordance with the type of urban characteristics associated with those factors. The land use factors that more closely describe denser and more diverse urban areas have a positive effect on transit and nonmotorized modes. The other factors more closely associated with suburban, industrial, or generally industrial areas have a positive effect on car use and a contrary effect on the usage of other modes.

COMPARISON OF LISBON, SEATTLE, AND MONTREAL MODELS AND CONCLUSIONS

In addition to understanding the endogeneity structure of long- and short-term choices, the study's objectives also include a comparison of the estimation results with similar models built for the cities of Lisbon, Seattle, and Montreal. Through the use of the same modeling structure and similar variables for all the city-specific models, it is possible to make comparisons. There were, however, differences in the data sets available, mainly as a result of the differences in the land use variables available, but also in the availability of some travel behavior variables. These differences are accounted for in the description and conclusions.

Despite these differences, the results obtained here and in the other models (Lisbon, Seattle, and Montreal) point to general similarities in conclusions, thus reinforcing the validity of those conclusions. First, in all analyses there is evidence of self-selection, exhibited by different socioeconomic characteristics of the individuals and their households. Also, in all the models, car ownership levels influence location preferences. This finding reinforces the thesis that travel behavior is, among other things, the visible result of personal preferences and lifestyles, and people choose bundles of options.

Generally, in all the previous models, the influence of land use on travel behavior passes clearly from long-term decisions to shorter-term ones. Although this also happens in the SCAG model presented in this paper, this influence is not as clear as in the previous studies. Also, in the two models that used distances traveled—namely, Lisbon and Montreal (*1, 4*)—the distance traveled was a direct function of the number of trips. This same result did not occur in the SCAG model; the model here points to a more complex behavior. Most likely the urban structure of the SCAG region plays a role because it is less polarized and more diffuse than the metropolitan regions of Lisbon and Montreal.

The same model general structure has produced similar global conclusions. The reason for this success is that the same global structure was applied, but at the same time, the specific details and links between variables were local-data driven. So there is a general structure that is consistent throughout all the models, but it is flexible enough to account for local specific relationships between variables, as long as those relationships are in accordance with the general structure. And so far in these analyses, the relationships have been consistently so. Generally, the conclusions regarding land use and sociodemographics drawn from this model are in accordance with the general conclusions taken from all the other case studies presented in the introduction. The main conclusion of all of these models is that land use patterns were found to significantly influence travel behavior. Thus, all of the models add weight to the argument in favor of using land use patterns as a policy tool to change travel behavior. It is not argued that policy makers should use land use policies instead of pricing or the support of technological changes. It is instead argued that land use policies should be considered as one of the main tools to change travel behavior and should be used jointly with other measures and policies to create coherent packages of strategic measures. This conclusion is consistent with five analyses (Lisbon, Seattle, Montreal, the more recent Lisbon analysis, and the Los Angeles analysis presented here).

Finally, there is one conclusion specific to this model and the variables used in it that is related to the use of the G^* derived z-scores that account for spatial correlation. These z-scores describe the environment as a continuous space, accounting for interactions and dependencies between neighboring locations. The derived factors from the principal components analysis describe the differential local-level land use patterns and reveal important aspects of the relationship between the urban space and travel behavior. One conclusion is that land use policies should be more holistic and include transit supply and should not just think in terms of mixed land uses and density. In the case of SCAG specifically, the areas with higher loadings in the two first land use factors are the ones that correspond to the highest levels of transit accessibility. Another quite important conclusion that could be derived from this model is that even in a case study that is commonly presented as the archetype of the car-dependent, sprawling city, it is clearly seen that land use patterns do influence travel behavior.

ACKNOWLEDGMENTS

Funding for this project was provided by the Southern California Association of Governments, the University of California (UC) Laboratory Fees program through a grant to UC Santa Barbara on next-generation agent-based simulation, and the UC Multicampus Research Program Initiative on sustainable transportation. Past research grants to UC Santa Barbara from the UC Transportation Center (funded by the U.S. Department of Transportation, RITA, and the California Department of Transportation) have also supported the development of methods used in this effort.

REFERENCES

1. de Abreu e Silva, J., T. F. Golob, and K. G. Goulias. Effects of Land Use Characteristics on Residence and Employment Location and Travel Behavior of Urban Adult Workers. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1977,* Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 121–131.
2. Bagley, M. N., and P. Mokhtarian. The Impact of Residential Neighborhood Type on Travel Behavior: A Structural Equations Modeling Approach. *Annals of Regional Science,* No. 36, 2002, pp. 279–297.
3. de Abreu e Silva, J., and K. G. Goulias. Structural Equations Model of Land Use Patterns, Location Choice, and Travel Behavior: Seattle,

Washington, Compared with Lisbon, Portugal. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2135,* Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 106–113.
4. de Abreu e Silva, J., C. Morency, A. Darien, and K. G. Goulias. Using Structural Equations Modelling to Unravel the Influence of Land Use Patterns on Travel Behaviour of Workers in Montreal. Presented at 12th World Conference on Transport Research, Lisbon, Portugal, 2010.
5. de Abreu e Silva, J., L. Martinez, and K. G. Goulias. Using a Multi-Equation Model to Unravel the Influence of Land Use Patterns on Travel Behavior of Workers in Lisbon. Presented at 12th Conference in Computers in Urban Planning and Urban Management, Lake Louise, Alberta, Canada, 2011.
6. Kitamura, R., T. F. Golob, T. Yamamoto, and G. Wu. Accessibility and Auto Use in a Motorized Metropolis. Presented at 79th Annual Meeting of the Transportation Research Board, Washington, D.C., 2000.
7. Cervero, R., and K. Kockelman. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transportation Research Part D,* Vol. 2, No. 3, 1997, pp. 199–219.
8. Guo, J. Y., and C. R. Bhat. Operationalizing the Concept of Neighborhood: Application to Residential Location Choice Analysis. *Journal of Transport Geography,* Vol. 15, No. 1, 2007, pp. 33–45.
9. Bhat, C. R., and J. Y. Guo. A Comprehensive Analysis of Built Environment Characteristics on Household Residential Choice and Auto Ownership Levels. *Transportation Research Part B,* Vol. 41, No. 5, 2007, pp. 506–526.
10. Golob, T. F. Structural Equations Modeling for Travel Behavior Research. *Transportation Research Part B,* Vol. 37, No. 1, 2003, pp. 1–25.
11. Golob, T. F. Structural Equation Modeling. In *Transportation Systems Planning: Methods and Applications* (K. G. Goulias, ed.), CRC Press, Boca Raton, Fla., 2003.
12. *Post Census Regional Household Travel Survey: Data User's Manual.* Southern California Association of Governments, 2003.
13. Chen, Y., S. Ravulaparthy, K. Deutsch, P. Dalal, S. Y. Yoon, T. Lei, K. G. Goulias, R. M. Pendyala, C. R. Bhat, and H.-H. Hu. Development of Indicators of Opportunity-Based Accessibility. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2255,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 58–68.
14. Dalal, P., S. Ravulaparthy, Y. Chen, and K. G. Goulias. Dynamic Opportunity-Based Multipurpose Accessibility Indicators in California. Presented at Annual Meeting of the European Association of Geographers, Athens, Greece, 2011.
15. Pendyala, R. M. Time Use and Travel Behavior in Space and Time. In *Transportation Systems Planning: Methods and Applications* (K. G. Goulias, ed.), CRC Press, Boca Raton, Fla., 2003.
16. Domencich, T. A., and D. McFadden. *Urban Travel Demand: A Behavioral Analysis.* North–Holland Publishing, Oxford, United Kingdom, 1975.
17. Tobler, W. A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography,* Vol. 46, 1970, pp. 234–240.
18. Getis, A., and J. Ord. The Analysis of Spatial Autocorrelation by Use of Distance Statistics. *Geographical Analysis,* Vol. 24, No. 3, 1992, pp. 189–206.
19. Kaplan, D. *Structural Equation Modeling: Foundations and Extensions.* Sage Publications, Thousand Oaks, Calif., 2000.
20. Muthén, B. A Structural Probit Model with Latent Variables. *Journal of the American Statistical Association,* Vol. 74, No. 368, 1979, pp. 807–811.
21. Muthén, B. A General Structural Equation Model with Dichotomous, Ordered Categorical, and Continuous Latent Variable Indicators. *Psychometrika,* Vol. 49, No. 1, 1984, pp. 115–132.
22. Golob, T. F., and A. Regan. Trucking Industry Adoption of Information Technology: A Multivariate Discrete Choice Model. *Transportation Research Part C,* Vol. 10, 2002, pp. 205–228.
23. Jöreskog, K., and D. Sörbom. *LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language.* Scientific Software International, Lincolnwood, Ill., 1993.
24. Schermelleh-Engel, K., H. Moosbruggrer, and H. Müller. Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. *Methods of Psychological Research Online,* Vol. 8, No. 2, 2003, pp. 1–22. http://www.dgps.de/fachgruppen/methoden/mpr-online/. Accessed Nov. 2008.

The Traveler Behavior and Values Committee peer-reviewed this paper.