A STRUCTURAL EQUATIONS MODEL OF LAND USE PATTERNS, LOCATION CHOICE, AND TRAVEL BEHAVIOR IN SOUTHERN CALIFONIA

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ABSTRACT

This paper continues the series of papers addressing the relationship between travel behavior and land use patterns using 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 (1), Seattle, Montreal, and a revisited model for Lisbon with more recent data. In all previous models the existence of significant effects of land use patterns on travel behavior was found. The variables included in this and past models are multidimensional and include both short term, number of trips by mode and trip scheduling, and long term, home location, car ownership, and mobility decisions. The modeled land use variables measure the levels of urban intensity, density, diversity, and accessibility. The land use patterns are described both at the residence and employment zones. In order to explicitly account for self selection bias the land use variables are explicitly modeled as functions of socioeconomic attributes of individuals and their households. The Los Angeles and surrounding metropolitan region findings are presented in this paper and then compared to Lisbon, Seattle, and Montreal findings. The results show that similar to the other cases land use patterns influence travel behavior in a significant way. Besides this other commonalities were found among all four environments are found but also some important differences.

1. INTRODUCTION

Integration of land use policies with car use policies are strongly advocated in many developed countries as a way to decrease fuel consumption and greenhouse gas (GHG) emissions. This is particularly important for California due to its recent legislation aiming at stricter mobile source emissions control and planning for dramatic decreases in Greenhouse gas emissions emphasizing the need for integrated land use policies with transportation policies (see http://www.ca-ilg.org/SB375Basics). This integration will happens through Sustainable Communities Strategies (SCS) that require understanding of and changing household residential location and promote a move to environmentally friendly behaviors. All this creates a need for better analytical tools to study policies.

In the past 20 years many research papers demonstrated the need to assess these policies with modeling and simulation tools that are based on data of individuals and their households as decision making units and more realistic in their behavioral representations. In addition, because land use models are also influenced by residential location and work location choices, the inclusion of self selection effects (2, 3, 1) in behavioral model systems for policy tools are required. In a stream of analyses that jointly examines location choices, car ownership, and activity participation as well as travel we created model systems for different urban environments that are based on endogeneity among variables (1, 4). These model systems include location attributes and land use variables that other researchers also consider important determinants of travel (see 5, 6, 7, 8). Moreover, these empirical studies link travel behavior with land use patterns using multi-equation methods pioneered in travel behavior by Golob, (9, 3), and used in similar contexts by Bagley and Mokhtarian(2).

In this paper using data from Southern California and employing the same modeling framework, methodology and estimation methods we continue the comparison among different environments. The base model structure was first presented by de Abreu e Silva et al (1) using data from the Lisbon Metropolitan Area collected in 1994. Later the same modeling structure was used to test the relations between travel behavior and land use patterns for Seattle in the United States (4), Montreal in Canada (10) and new data from Lisbon (11). Many similarities in long term (e.g., location choice) and short term (e.g., daily travel) relationships were found but also differences in the role of land use patterns and level of service of transportation systems play across different urban contexts. The model we present here from Southern California fills a very important need to understand these relationships. In this study the land use factors are built in a new way that is somewhat different from past analyses using a comprehensive group of accessibility indicators built using the intervening opportunities approach and transformed into z-scores accounting for spatial correlation.

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

The main conclusions drawn from each one of them can be summarized as:

- People living and working in central and denser areas tend to use more often non-motorized modes and transit and use less the car. 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, clearly a sign of the polarizing power that the centre of these metropolitan regions have, attracting people living in suburban and exurban areas.

In this paper we examine the influence of land use patterns on the SCAG (South California Association of Governments) region which includes the counties of Los Angeles, Imperial, Orange, Riverside, San Bernardino and Ventura, encompassing a population of around 18 million people. Besides the relevance due 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 long commutes and lower density environments when compared to European cities.

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

2. CASE STUDY AND MODEL DESCRIPTION

The present model uses data from the Southern California Household Travel Survey (12). This is a post-Census 2001 survey that contains social and demographic data as well as travel diary data from 39,264 individuals from 16,506 households that at the time of the survey resided with the Southern California Association of Governments (SCAG) region. The SCAG region is the largest U.S. Metropolitan Planning Organization with approximately 18.6 million residents. From this survey employed persons for whom complete data are available were selected (creating a sample of 6897 individuals) and their home and work locations were joined spatially to a US census block. For each census block detailed spatial attributes, consisting on accessibility indicators are available from a previous study (13, 14).

The model structure used here is as similar as possible to the one first developed for Lisbon (1) which examines the relations among socioeconomic characteristics, land use patterns, relative residential and employment locations, car ownership, public transportation pass ownership, and travel behavior.

The model specification considers the land use patterns both at the residence and employment U.S. Census block levels. These are treated as endogenous and allowed to be influenced by the socioeconomic characteristics of the individual and it’s household. Both land use patterns and socioeconomic variables influence travel behavior of employed individuals. The model considers several travel behavior variables that range from long term to short term decisions. These variables include, the distance between employment and residence locations (commuting distance) and car ownership that are considered as being longer term decisions. These, in turn, influence shorter term decisions such as the number of trips made daily by different modes, and the distances travelled by mode and the time spent between the first and last trips, corresponding to the height of Hägestrand prism in time geography. Land use variables are also influenced by travel behavior variables. In this way, we can test for possible effects due to the fact that travel behavior is one of the observed outcomes of individual preferences and also the feedbacks due to the information that individuals have about optimal shorter term decisions (15). Pass ownership was also considered as a variable to be included in the model but due to the very short percentage of pass owners, around 0.5%, and potential multicollinearity problems was excluded.

The model general structure is presented in Figure 1. The arrows entering each box in the flowchart indicate variables used as explanatory variables for the variables in the box that are the dependent variables. 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 sum of direct and indirect effects).

The socioeconomic variables considered in the model include gender, age (although in the end age was not influencing 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 and households with only two members (to control for non linear effects of household size), households with only teenagers and adults, fixed working schedule and the number of workers in the household. With the exception of the last variable these last four variables were built as dummy variables.

As mentioned earlier variables describing the land use patterns, the present study used opportunity-based accessibility indicators. The opportunity-based accessibility indicators used here are at the level of the US Census block (203,191 US Census blocks cover the entire study area). These indicators represent the ease (or difficulty) of reaching 15 different types of industries (representing the opportunities for activity participation) from each of these blocks within 10, minutes of roadway travel buffers from each of the 203,000 pegs (13). The types of industries included are: (a) Agriculture, forestry, fishing and hunting and mining; (b) Construction; (c) Manufacturing; (d) Wholesale trade; (e) Retail trade; (f) Transportation and 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; (i) Arts, entertainment, recreation, accommodation and food services; (m) Armed forces; (o) Public administration; and (p) Other services (except public administration). Different accessibility values are obtained for the morning peak period (6 to 9 AM), midday (9 AM to 3 PM), evening peak period (3 to 7 PM), and at night (7 PM to 6 AM). In this way we capture the different roadway conditions and the patterns of opening and closing of businesses during the day by exploiting information for a travel survey with the arriving and departing patterns of employees in each industry. Instead of using directly these indicators a transformation was employed to account for spatial correlation among the blocks (13). Then, factor analysis was employed to identify thirteen major dimensions for home and work locations as explained later in the paper.

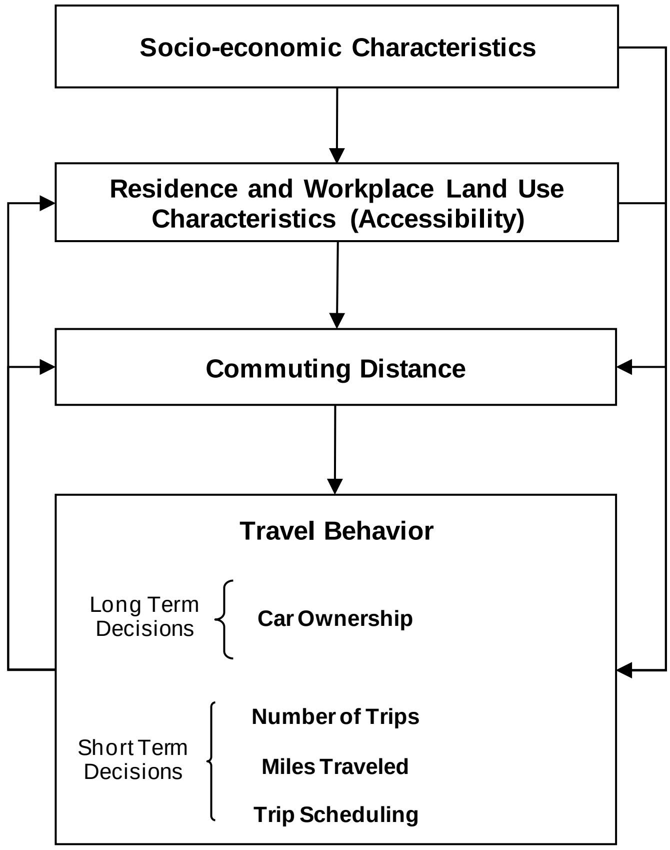

FIGURE 1 Model general structure

The z-scores obtained from the accessibility variables transformation were reduced to 13 factors, characterizing both the residence and employment locations (capturing 93% of variation and with a KMO of 0.949) using a principal components method. With the exception of two factors there was a clear distinction between factors describing land uses in the residence and employment area..

The first two factors were named “working in a block with strong accessibility to urban functions” (later labeled Work StrongAccessUrb) and “Living in a block with strong accessibility to urban functions” (Live StrongAccessUrb). They 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.

“Living in a block with strong accessibility to industrial areas” (Live StrongAccessInd) is the name of the third land use factor which presents high zscores to manufacturing, construction and wholesale retail employment, thus describing areas mainly occupied by manufacturing industry and compatible activities.

The fourth land use factor was named “Working in a block with strong accessibility to construction areas” (Work StrongAccessConst), which describes mainly mono-functional industrial type areas and also non consolidated expansion zones.

“Working in a block with strong accessibility to logistical and manufacturing areas” (Work StrongAccessLogis&Manuf) is the name of the fifth factor which describes port areas and other logistical and transportation related zones.

The sixth factor named “Living in a block with strong accessibility to logistical areas” (Live StrongAccessLogis) accounts for high accessibility to people working in transportation and logistics sector, thus describing residential areas near transportation facilities.

“Living in a non urban block” (LiveNonUrban) the name of the seventh land use factor has high loadings in the zscores representing accessibility to agriculture and military jobs, types of land use that are incompatible with urban occupation.

The eight land use factor “Working near military facilities” (WorkMilitary) 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” (Live&WorkRural) is one of the two land use factors that is both related with the residence and employment place. It represents blocks with high accessibility to agriculture employments, thus describing rural areas.

The next two factors “Living in a block with accessibility to public services” (LivebyPublicServices) and “Working in a block with high accessibility to public service” (Work StrongAccessPublicServices) describe both the employment and residence blocks in urban areas with high accessibilities to public services employment.

The factor “Living in a block close to university campus” (LivebyUnivCampus), which present high loadings to accessibility to education jobs, describes residential areas near the several university campuses (UCLA, USC, Pomona colleges, CalTech, the CalState system campuses, and so forth) that exist in the SCAG region.

Finally the last land use factor “Well established areas, away from construction” (WellEstabAreasFarConst) describes zones with negative loadings on the accessibility to construction jobs, thus indicating that these areas are consolidated.

3. STRUCTURAL EQUATION MODELLING

The modeling method used in the present work is Structural Equations Modeling (SEM) which represents a combination of two types of statistical methods, factor analysis and simultaneous equations models (16). In SEM variables could be either exogenous or endogenous (3, 9). These characteristics allow SEM to handle indirect and multiple relationships and also to study reverse relationships. Due to these characteristics SEM is particularly adequate as a tool to model the complex relationships between travel behaviour and land use patterns. The method is particularly useful when we want to identify the direct impact of a variable on another and its possible impact through a mediator.

In travel behavior analysis SEM is becoming increasingly popular as a modeling method due to its ability to estimate simultaneously several endogenous variables and also to include latent variables. In this way, it is particularly suited to model indirect and non recursive relationships (in which there are feedback loops). New estimation methods in SEM also allow including discrete variables, which are common in travel behavior analysis. The model developed here is a structural equation model using only observed variables (often referred to as path analysis or simultaneous equation modeling). Estimation of SEM models is performed by using the covariance analysis method – method of moments (3).The objective function is to minimize the differences between the sample variance-covariance matrix, S, and the model-replicated matrix $\Sigma(\theta)$. The methods used for model estimation are normal theory maximum likelihood (ML), generalized least squares (GLS) and weighted least squares (WLS) (3, 9). WLS, the method used to estimate the model presented in this paper was specifically developed to deal with discrete ordered and censored variables. Its genesis occurred with a multivariate probit developed by Muthen (17). Later this method was generalized also by Muthen (18) to accommodate structural equations with a mix of discrete, censored and continuous variables (19).

4. ESTIMATION RESULTS DISCUSSION

For reasons of space it's not possible to show all of the outputs of a SEM model (direct, indirect and total effects). Since the most important results from the model are mainly the ones resulting from the total effects, these are the only ones to be presented and discussed here. First the total effects between endogenous and exogenous variables are presented, followed by the total effects due to travel behavior endogenous variables, and finally the total effects due to the land use factors.

Although all of the direct effects in the model are significantly different from zero, it could and actually does occur that some of the total effects are not significantly different from zero, this is due to contrary indirect effects that might annul each other.

The estimated model shows a very good fit. The value of its chi-squared statistic is 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 2 and very good fit when it is close to 1 (20, 21). Also the standard Bayesian criteria (AIC and CAIC) indicate that this model is superior either to the independence or the saturated models.

TABLE 1 Total effects on travel behavior due to the exogenous socioeconomic variables

	Gender (1 if man)	Household Income	Household size	Average household age	Average adults age	Household with 1 member	Household with 2 members	Fixed working schedule	Household with adults and teens	No of workers
Time between the first and last trips	0.156	-0.038	-0.006	-0.066	0.289	0.001	-0.036	0.088	0.000	-0.001
	14.676	*-1.275*	*-2.139*	*-3.227*	*6.479*	*1.387*	*-6.618*	*9.325*	*-0.510*	*-1.239*
Miles traveled non-motorized	-0.005	0.056	-0.028	-0.061	-0.016	0.008	0.004	0.021	-0.023	-0.029
	-0.902	*6.741*	*-4.348*	*-4.686*	*-5.609*	*4.551*	*1.689*	*4.915*	*-10.198*	*-14.821*
Miles traveled transit	0.020	-0.121	0.004	0.012	-0.003	-0.002	0.003	0.010	0.014	-0.001
	14.326	*-34.339*	*4.444*	*5.222*	*-0.956*	*-1.992*	*5.811*	*9.495*	*6.062*	*-3.722*
Miles traveled car	0.071	0.056	0.006	-0.011	0.041	-0.001	-0.016	0.008	0.019	-0.019
	10.171	*7.320*	*4.700*	*-3.194*	*6.203*	*-3.413*	*-6.921*	*2.131*	*4.804*	*-3.559*
No of trips non-motorized	-0.038	-0.028	-0.047	-0.102	-0.033	0.014	-0.001	-0.013	-0.041	-0.004
	-5.481	*-17.564*	*-4.268*	*-4.570*	*-5.976*	*4.546*	*-2.905*	*-7.755*	*-10.458*	*-9.101*
No of transit trips	0.015	-0.178	0.006	0.018	-0.016	-0.003	0.004	0.008	0.017	-0.003
	10.776	*-18.146*	*5.836*	*5.990*	*-4.041*	*-2.356*	*6.299*	*6.599*	*6.111*	*-5.695*
No of car trips	-0.125	0.148	0.010	0.001	0.025	-0.003	-0.063	-0.043	0.007	0.002
	-14.135	*5.332*	*4.757*	*0.112*	*3.341*	*-5.516*	*-9.660*	*-4.764*	*9.762*	*3.832*
No of cars in the household	0.060	0.270	0.488	0.685	-0.466	-0.049	0.000	0.000	0.086	0.191
	4.710	*22.016*	*20.294*	*15.584*	*-11.562*	*-5.611*	*-0.748*	*-0.079*	*4.677*	*10.751*
Log Commuting distance	0.147	0.005	0.000	-0.017	0.078	0.001	0.002	0.070	0.005	0.003
	15.632	*7.425*	*0.085*	*-2.896*	*3.727*	*1.242*	*4.122*	*7.766*	*6.025*	*6.565*

Note: t statistics in italic

The main results from the previous table are in general in accordance to what is commonly accepted as the main influences of socioeconomic variables on travel behavior. It can be seen that men spend more time outside home, travel further away by car but make less trips whereas women travel smaller distances but engage in more trips. Also men travel more by transit and less by non-motorized modes. Workers in households with higher levels of income travel more by car and less using transit, they also own more cars and have a higher commuting distance, which is in accordance to what has been reported in several studies. The size of the household reduces the time spent outside home and increases the number of trips using motorized modes versus non-motorized ones. It has also a positive effect on car ownership. This supports the hypothesis that people belonging to bigger households spend more time in in-home activities thus they opt to choose for faster transportation modes.

The average age of the household and of the adults on the household have contrary effects on some variables. Older households have a higher probability of owning more cars whereas households with older adults own fewer cars. Also households with younger adults use more often non-motorized modes and transit, although some of the effects on the distances traveled are not significant.

Very small households, with just one or two individuals have a lower probability of owning more cars (although this effect is not significant for two person households). Both have a lower number of car trips, but whereas in the case of one person households those are substituted (at least in part) by non-motorized trips, the two person households substitute them by transit trips. Looking at the effects of all the variables about household size it is possible to conclude that in the SCAG region they almost do not influence commuting distance.

Having a fixed working schedule implies a higher commuting distance, using transit more often and the car and non-motorized modes less. But because the commuting distance is higher these people tend to travel longer distances thus we see a positive effect on all the distances traveled. The fixed working schedule makes the commuting travel patterns of these workers more compatible with the transit schedules.

Households with only adults and teenagers have a higher probability of owning more cars, probably due to the fact that (unique to the US) persons as young as 16 years may have a drivers license and possibly an allocated car to them. Workers in this type of households have higher commuting distances and travel more by transit and car and less by non motorized mode. This is due to the fact that they locate less (both in terms of employment and residence) in urban areas, thus they correspond to the suburbanite stereotype.

The number of workers in the household increases significantly but weakly the commuting distance. It increases the probability of owning more cars and the number of car trips and reducing the number of trips in all other modes. In contrast, it significantly reduces the travel distances traveled in all modes. This could be due to the fact that the errands necessary to the household maintenance could be divided among all the workers, reducing the need to chain trips and thus decreasing the distances traveled.

TABLE 2 Total effects on land use variables due to the exogenous socioeconomic variables

	Gender (1 if man)	Household Income	Household size	Average household age	Average adults age	Household with 1 member	Household with 2 members	Fixed working schedule	Household with adults and teens	No of workers
Work StrongAccessUrb	0.029	-0.006	-0.011	0.292	-0.184	0.032	0.000	0.000	-0.002	-0.004
	3.188	*-2.447*	*-2.417*	*17.870*	*-6.569*	*7.382*	*0.728*	*0.080*	*-2.150*	*-2.358*
Live StrongAccessUrb	-0.008	-0.037	-0.067	0.256	-0.376	0.007	0.000	0.000	-0.012	-0.026
	-4.461	*-11.944*	*-11.507*	*13.702*	*-13.474*	*5.158*	*0.747*	*0.079*	*-4.447*	*-8.752*
Live StrongAccessInd	0.045	-0.096				0.016				0.091
	5.239	*-19.846*				*3.683*				*16.716*
Work StrongAccessConst				0.034	-0.153		0.028			
				2.951	*-5.957*		*5.785*			
Work StrongAccessLogis&Manuf	0.026		-0.046	-0.104				0.041		
	2.821		*-4.278*	*-5.683*				*4.587*		
Live StrongAccessLogis	-0.003	-0.003	0.111	0.000	-0.002	0.025	0.001	0.039	-0.001	-0.029
	-5.559	*-5.104*	*17.954*	*2.932*	*-4.579*	*5.655*	*4.912*	*4.546*	*-3.972*	*-3.816*
LiveNonUrban			0.070			0.027			-0.059	
			7.141			*7.730*			*-8.168*	
WorkMilitary	0.022					0.013	0.032		-0.033	
	2.612					*3.422*	*6.937*		*-10.978*	
Live&WorkRural								0.031		
								3.845		
LivebyPublicServices	0.027	-0.200	0.078							
	3.169	*-10.159*	*18.050*							
Work StrongAccessPublicServices	-0.027		0.020							
	-3.118		*4.965*							
LivebyUnivCampus			0.037			0.021		0.050		
			8.058			*4.708*		*5.569*		
WellEstabAreasFarConst		0.061				0.030		0.029		
		15.019				*6.286*		*3.098*		

Note: t statistics in italic

The results from the previous table show the existence of self selection effects due to socioeconomic characteristics. People living and working in more urbanized and of higher accessibility areas tend to belong to smaller, older households, with on average younger adults and smaller income. Also these households have a smaller number of workers. Considering that the areas with higher loadings in these factors could be considered as corresponding to the central area of Los Angeles, the socioeconomic portrait does not show clear signs of gentrification as can be deduced from the models developed for Seattle (4) and Montreal (11).

In general it could be seen that income only affects positively the last land use factor, thus meaning that people with higher income levels tend to locate themselves in more consolidated areas. Bigger households tend to live and work in places with higher accessibility to public services. They also locate themselves on non-urban areas, which is in accordance with the fact that households in more rural areas are bigger. Households with only one member tend to live near university campuses, in non-urban areas and work near military facilities. These effects may be due to military personnel and college students, which tend to live alone and locate themselves closer to their stronger spatial daily anchors.

Workers with fixed schedules tend to live in the proximities and work in manufacturing and or logistical areas 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).

TABLE 3 - Total effects due to endogenous travel behavior variables

	Miles traveled non-motorized	Miles traveled in car	No of trips non-motorized	No of transit trips	No of car trips	No of cars in the household	Log Commuting distance
Timebetween the first and last trips	0.000	0.000	0.053	0.100	0.569	-0.005	0.145
	0.961	*-1.794*	*3.459*	*8.390*	*8.654*	*-0.997*	*2.974*
Miles traveled non-motorized	0.000	0.070	0.588	0.090	0.008	-0.006	-0.082
	3.429	*24.591*	*79.663*	*68.446*	*4.696*	*-10.330*	*-25.086*
Miles traveled in transit	0.000	-0.001	0.013	0.806	-0.087	-0.002	0.046
	1.401	*-7.764*	*17.406*	*110.199*	*-25.227*	*-1.533*	*36.103*
Miles traveled in car	-0.001	0.000	-0.070	-0.083	0.263	0.012	0.286
	-3.038	*3.118*	*-11.409*	*-23.647*	*11.155*	*9.378*	*19.200*
No of trips non-motorized	0.000	0.001	0.003	0.162	-0.017	-0.012	-0.173
	3.449	*2.357*	*15.540*	*92.873*	*-23.085*	*-11.326*	*-27.639*
No of transit trips	0.000	-0.003	0.016	0.004	-0.109	-0.007	-0.004
	2.825	*-5.927*	*17.049*	*16.808*	*-24.684*	*-5.719*	*-15.665*
No of car trips	0.000	0.000	-0.146	-0.025	0.003	0.009	0.026
	-2.350	*0.856*	*-16.738*	*-20.356*	*16.714*	*3.385*	*16.095*
No of cars in the household	-0.041	0.028	-0.029	-0.180	0.027	0.003	0.067
	-3.206	*2.504*	*-3.768*	*-4.252*	*5.731*	*9.438*	*6.399*
Log Commuting distance	-0.001	0.001	-0.001	-0.003	0.000	0.018	0.001
	-2.957	*2.421*	*-3.384*	*-3.659*	*4.583*	*7.982*	*5.291*
Work StrongAccessUrb	0.001	-0.001	0.001	0.004	-0.001	-0.022	-0.001
	2.035	*-1.689*	*2.146*	*2.258*	*-2.332*	*-2.435*	*-2.223*
Live StrongAccessUrb	0.006	-0.004	0.004	0.025	-0.004	-0.138	-0.009
	3.161	*-2.487*	*3.689*	*4.016*	*-5.269*	*-14.091*	*-5.967*
Live StrongAccessLogis	0.000	-0.047	0.003	0.004	-0.012	-0.001	-0.013
	2.774	*-6.752*	*5.254*	*6.517*	*-5.853*	*-5.453*	*-6.419*

Note: t statistics in italic

The total effects of travel behavior endogenous variables show the existence of feedback effects from travel behavior variables on land use factors. In this case car ownership levels influenced directly the first two land factors, and the number of miles driven by car influenced the land use factor "Living in a block with strong accessibility to logistical areas". The first of these effects is common to all the models developed in our studies using this same analytical technique (Lisbon, Seattle and Montreal), meaning that people that intend or expect to own more cars will not locate in more central and urbanized areas.

We can see that increasing commuting distance increases significantly car ownership levels and the number of trips by car as well as the vehicle miles driven. It reduces the number of trips by transit but increases the miles driven, and reduces the use of non-motorized modes. It also increases the time spent outside home. These effects are in perfect accordance to what is commonly reported in the literature.

Having more cars in the household also increases commuting distance, meaning that people that intend to own more cars have the means to look for work farther from home. The other effects of car ownership are also quite intuitive, higher car ownership leads to higher levels of car use and lower levels of transit and non-motorized modes use.

Looking at the number of trips by mode we can see the existence of competition between the car and the other modes and the complementarity of transit and non-motorized modes.

Considering the miles traveled by mode it can be seen that the miles traveled by car are negatively influenced by the number of miles traveled by non-motorized modes, but we can see that the number of miles traveled by car has positive effect on the miles traveled by non-motorized modes. This suggests that although we could consider only the existence of competition between car and transit, the non-motorized modes could act as complementary to both motorized modes, although this complementarity is stronger for transit.

Finally the time spent outside home is positively influenced by the number of trips, independently of the transport mode, although the car has a much stronger effect.

TABLE 4 Total effects due to endogenous land use variables

	Work StrongAccessUrb	Live StrongAccessUrb	Live StrongAccessInd	Work StrongAccessConst	Work StrongAccessLogis&Manuf	Live StrongAccessLogis	LiveNonUrban	WorkMilitary	Live&WorkRural	LivebyPublicServices	Work StrongAccessPublicServices	LivebyUnivCampus	WellEstabAreasFarConst
Time between the first and last trips	0.023	0.034	-0.002	-0.002	0.017	0.004	-0.009	-0.002	-0.007	0.006	0.000	-0.014	0.000
	4.203	*0.899*	*-3.424*	*-0.583*	*3.303*	*3.119*	*-2.870*	*-4.768*	*-2.299*	*7.551*	*0.235*	*-3.899*	*0.898*
Miles traveled non-motorized	0.033	0.040	-0.019	-0.057	-0.006	-0.012	-0.015	0.004	0.006	0.005	-0.026	-0.011	0.003
	11.550	*11.167*	*-9.702*	*-22.355*	*-7.307*	*-5.321*	*-9.674*	*2.067*	*6.499*	*16.794*	*-11.574*	*-6.438*	*2.219*
Miles traveled transit	0.072	0.000	0.000	-0.052	0.052	0.020	0.006	-0.023	0.006	0.045	0.048	0.002	0.000
	30.894	*-0.081*	*-7.413*	*-48.399*	*39.386*	*17.987*	*18.928*	*-49.503*	*15.699*	*18.641*	*49.841*	*3.392*	*1.242*
Miles traveled car	0.020	-0.094	-0.019	0.026	0.027	-0.003	-0.013	0.002	-0.018	-0.005	-0.009	-0.005	0.000
	6.409	*-12.634*	*-3.583*	*9.403*	*9.202*	*-3.990*	*-4.837*	*5.833*	*-5.728*	*-14.153*	*-3.280*	*-2.761*	*-1.863*
No of trips non-motorized	0.054	0.079	-0.029	-0.100	-0.014	-0.020	-0.023	0.007	0.012	0.009	0.010	-0.018	0.000
	10.864	*12.836*	*-8.803*	*-22.073*	*-7.965*	*-5.205*	*-9.160*	*1.989*	*6.376*	*17.636*	*5.200*	*-6.055*	*1.957*
No of transit trips	0.049	0.040	-0.001	-0.055	0.020	0.050	0.000	-0.029	0.011	0.057	0.036	0.002	0.000
	8.470	*4.912*	*-6.641*	*-13.457*	*3.915*	*8.405*	*-1.614*	*-43.070*	*11.793*	*18.210*	*7.513*	*3.392*	*1.850*
No of car trips	-0.008	-0.067	0.004	0.015	0.002	0.003	0.003	-0.001	-0.002	-0.001	-0.001	-0.020	0.000
	-9.066	*-3.380*	*8.473*	*14.281*	*7.189*	*3.912*	*7.325*	*-1.897*	*-6.180*	*-12.925*	*-5.130*	*-3.332*	*-1.665*
No of cars in the household	-0.004	-0.019	0.020	0.051	0.003	-0.056	-0.033	0.005	-0.006	-0.010	-0.007	0.000	0.000
	-1.462	*-9.285*	*2.355*	*5.812*	*1.822*	*-6.591*	*-4.343*	*3.904*	*-5.294*	*-4.011*	*-3.264*	*-0.273*	*-1.912*
Log Commuting distance	0.101	-0.148	0.000	0.055	0.100	-0.001	-0.052	0.000	-0.059	0.000	-0.022	0.000	0.000
	9.889	*-13.575*	*2.280*	*5.722*	*11.338*	*-4.952*	*-5.659*	*3.423*	*-5.853*	*-3.532*	*-2.245*	*-0.273*	*-1.844*
Work StrongAccessUrb	0.000	0.000	0.000	-0.001	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	1.494	*2.346*	*-1.703*	*-2.238*	*-1.375*	*2.315*	*2.132*	*-2.204*	*2.238*	*2.201*	*2.012*	*0.270*	*1.560*
Live StrongAccessUrb	0.001	0.003	-0.003	-0.007	0.000	0.008	0.005	-0.001	0.001	0.001	0.001	0.000	0.000
	1.447	*9.101*	*-2.337*	*-5.408*	*-1.820*	*5.820*	*4.187*	*-3.712*	*4.950*	*3.824*	*3.158*	*0.272*	*1.894*
Live StrongAccessLogis	-0.001	0.004	0.001	-0.001	-0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000
	-4.719	*5.886*	*3.072*	*-5.413*	*-5.408*	*3.736*	*4.013*	*-4.521*	*4.381*	*6.172*	*2.961*	*2.585*	*1.814*

Note: t statistics in italic

From the previous table we can see that land use factors can significantly influence travel behavior even in a region that is the stereotype of the car oriented metropolis. It can also be argued that the use of accessibility indicators is useful to capture the differences in urban structure and patterns present in the SCAG region.

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 effects show the existence of a polarized region were the employment is clustered around different CBDs with variable importance and the residences are generally located farther 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" or "Living in a block with strong accessibility to logistical areas" have lower commuting distances.

The effects on car ownership show that people living and working in more urban areas (e.g. the first two land use factors) have lower car ownership levels. On the contrary, people living or working in more specialized and nonfunctional areas (e.g. the fourth and fifth land use factors) tend to own more cars. People living and working in agricultural areas 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 influence negatively the number of trips by car and increase the number of trips by transit and non-motorized 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 due to the positive effect that has on commuting distance. In contrast, living in a central area reduces the miles driven by car and increases the miles traveled using non-motorized modes. The effects on transit mileage are not significant.

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

5. COMPARISON WITH THE LISBON, SEATTLE, AND MONTREAL MODELS AND CONCLUSIONS

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

Despite these differences the results obtained here and in the other similar models (Lisbon, Seattle and Montreal) point to general similar 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 also the location preferences. This reinforces the thesis that travel behavior is among other things the visible result of personal preferences and lifestyles and people choose bundles of choices.

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 ones. Also in the other two models that used distances traveled – namely Lisbon and Montreal (1, 10), distance traveled is a direct function of the number of trips. This does not happens in the SCAG model here. This is an important difference that points to a more complex behavior. Most likely the urban structure of the SCAG region also plays a role, by being 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 of this success is that the same global structure is applied but at the same time specific details and links among variables are local data driven. So there is a general structure that is consistent throughout all models but it is flexible enough to account for local specific relations between variables as long as they are in accordance with the general structure. And so far they have been consistently so. Generally the conclusions that could be drawn from this model are in accordance with what was presented in the introduction about the general conclusions taken from all the other case studies. And this is the main conclusion in all of these models land use patterns were found to influence significantly travel behavior. Thus all of them add weight to the argument in favor of using land use patterns as a policy tool to change travel behavior. Also because in all the cases the land use factors included at least in an implicit way accessibility and transit supply indicators, we argue that land policies should be more holistic and include transit supply and not just think in terms of mixed land uses and density. Taking 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. Although we are not arguing that policy makers should use land use policies instead of pricing or support of technological changes. Our argument is 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 different analyses (Lisbon, Seattle, Montreal, more recent Lisbon, and Los Angeles here). 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.

Finally there is one conclusion specific with this model and the variables used in it and which is related with the use of the z-scores that account for spatial correlation. They showed to be a good tool to describe and differentiate land use patterns and so encompass and describe the multidimensionality and variability of the urban space.

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