This paper addresses the relationship between travel behavior and land use patterns through the use of a structural equations modeling framework and a more comprehensive modeling than in the past. The proposed model structure is by design heavily influenced by a model developed for Lisbon, Portugal, to allow comparisons. In a related paper about that model, the existence of significant effects of land use patterns in travel behavior was found. The travel behavior variables included in the proposed model are multidimensional and comprehend both the short term (number of trips and trip scheduling) and the long term (home location, car and pass ownership, and mobility decisions). The modeled land use variables measure the levels of urban intensity, density, and diversity, both in relation to types of uses and the mix between jobs and inhabitants and the public transport supply levels. The land use patterns are described at both the residence and the employment zones. To account for self-selection bias, the land use variables are explicitly modeled as functions of socioeconomic attributes of individuals and their households. The Seattle, Washington, findings are presented and then compared with the Lisbon findings. Many commonalities between the two environments were found as well as many important differences pointing to the need for policy initiatives that are local and tailored to the specific context.

Today urban mobility is strongly supported by the massive use of automobiles, inducing important environmental, socioeconomic, and territorial impacts, many of them perceived as strongly negative. This situation prompted several proposals of policies designed to tackle the negative impacts. The three most important types of policies are those advocating (a) the diffusion and use of new technologies, (b) economic measures to change travel behavior, and (c) land use changes to influence travel behavior. During the past 20 years, the debate between advocates of the two latter policies has been rather intense (1–8). Consequently, the study of the relations between land use patterns and travel behavior was the object of important attention from researchers. Because of this continuous attention, important theoretical and methodological innovations were made. The first generation of quantitative models tested the existence of these relations by means of aggregate models with important shortcomings. The first generation of studies was subjected to several criticisms (9–11), the most important their lack of behavioral basis. These criticisms paved the way for the appearance of disaggregate approaches and the application of models based on the utility theory (11, 12).

Within the framework of utility theory, travel demand is treated as a derived demand (13). By this reasoning, land use patterns influence travel behavior by changing generalized costs. This type of influence occurs either in long-term decisions (e.g., car ownership) or shorter-term decisions (e.g., mode or destination choice). Long-term decisions influence short-term decisions by restricting the alternatives available (14). Other recent methodological advances expanded the framework of utility maximization in the activity-based approach. In this case, the land use patterns are determinants of opportunities and restrictions posed in the pursuit of activities (15). However, the use of models that are based on the utility theory is plagued with difficulties. Using logit or probit models does not necessarily imply a utility theory–based model because it should reflect a theory–based specification (11). Cervero (16) points out that most of these models have been badly specified. These innovations also highlighted other shortcomings of the empirical models developed in this area. One of them is the endogenous relations that occur among behavioral variables such as self-selection (17) due to endogenous effects between land use variables and individual or family characteristics. A more radical hypothesis asserts that the differences in travel behavior found for residents in different urban environments are due to fundamentally different individual characteristics and not to characteristics of these environments. One solution to unravel all these relationships is to formulate many equations representing these behavioral facets and allow them to be correlated in their observed and unobserved components. In this way, causal inferences of mutual influence can be measured by estimated correlation among the variables in a system of equations.

Another important issue is the measurement of variables describing land use characteristics. One of the most widely used measurements is urban density, although it could not be the most adequate variable because it encompasses many diverse characteristics that cannot be easily replicated by simply changing density (9). Other land use variables more generally used include mix of employees and residents, mix and diversity of land use categories, urban design measures, housing characteristics, and accessibility variables. Important related issues are the multidimensionality of urban space and the interconnections that exist between land use variables (18, 19). The
former of these issues results from the necessity of having at the same
time an important number of land use variables that could encompass
the multidimensionality of urban space and from the need for a
reduction in the number of variables employed to capture the multi-
dimensionality of urban space. The interconnections and amplifica-
tion effects that could exist between land use variables mean that they
could present negligible effects when analyzed one by one and sig-
nificant effects when included in more comprehensive indexes (19).
These problems prompted the use of data reduction techniques (e.g.,
factor or cluster analysis) that allow the maintenance of the levels of
richness in the characterization of land use patterns (18).

One relatively recent analytical innovation key to this paper is
structural equations modeling (SEM) (20, 21). SEM allows the param-
eterization of endogenous relations between variables that account
for self-selection effects (17, 21). It also allows the modeling of a
comprehensive framework of hierarchical relationships from long-
term to short-term decisions. Relatively new estimation algorithms
of SEM allow the estimation of discrete and censored variables, thus
permitting them to be used within the framework of utility theory (20).

All these methodological innovations were incorporated in the
model presented in this paper with a structure that replicates a previ-
ously developed model for the Lisbon, Portugal, metropolitan area
(1) to compare the results.

CASE STUDY AND MODEL DESCRIPTION

The present model used data from the Puget Sound Transportation
Panel (PSTP). Puget Sound is the region surrounding Seattle, Wash-
ington. PSTP contains a large number of waves, repeated observation
of the same persons, between 1989 and 2003 (22). The data used in
the study correspond to a sample taken from the ninth wave of this
panel survey, from 2000. This wave was chosen because of the avail-
ability of land use data of the same vintage [see also Goulias et al. (23,
24)]. This sample—1,025 observations—was made by selecting one
adult worker in each household interviewed in this wave. Table 1 con-
tains the individual and household variables and the travel behavior
variables used in this model.

<table>
<thead>
<tr>
<th>TABLE 1  Sample Travel Behavior and Socioeconomic Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Endogenous travel behavior variables</td>
</tr>
<tr>
<td>Time spent between first and last trips</td>
</tr>
<tr>
<td>No. of trips: nonmotorized</td>
</tr>
<tr>
<td>No. of trips: transit</td>
</tr>
<tr>
<td>No. of trips: car</td>
</tr>
<tr>
<td>Transit pass</td>
</tr>
<tr>
<td>No. of cars</td>
</tr>
<tr>
<td>Log commuting distance</td>
</tr>
<tr>
<td>Socioeconomic exogenous variables</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Gender: male (%)</td>
</tr>
<tr>
<td>Low income (%)</td>
</tr>
<tr>
<td>Medium income (%)</td>
</tr>
<tr>
<td>High income (%)</td>
</tr>
<tr>
<td>Household size</td>
</tr>
<tr>
<td>Average age</td>
</tr>
<tr>
<td>Household with two members (%)</td>
</tr>
<tr>
<td>Household with teenagers (%)</td>
</tr>
</tbody>
</table>

The model structure for both Seattle and Lisbon (1) examines the
relations among socioeconomic characteristics, land use patterns, rel-
ative residential and employment locations, car ownership, public
transportation pass ownership, and travel behavior.

The point of departure for model specification is as follows. Land
use patterns both around the residence and employment locations are
influenced by the socioeconomic characteristics of the individuals and
their households. Both land use patterns and socioeconomic variables
influence travel behavior of employed individuals. This influence is
assumed to be at least partly mediated by variables describing several
travel behavior–related decisions, going from long-term decisions to
shorter-term decisions. These variables include the distance between
employment and residence locations (commuting distance), car own-
ership, and transit pass ownership, 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 time
spent between the first and last trips, corresponding to the height of
the Hägestrand prism in time geography. Land use variables are
also influenced by travel behavior variables. In this way, one can
test for possible effects because travel behavior is one of the
observed outcomes of individual preferences and the feedbacks due
to the information that individuals have about optimal shorter-term
decisions (25).

The Seattle and Lisbon models’ general structure is presented
in Figure 1. The arrows entering each box in the flowchart indicate vari-
ables used as explanatory variables for the variables in the box that are
the dependent variables. These relationships are tested statistically
for their influence. In a model of this type, it is also possible to dif-
f erentiate between direct and indirect influences. In this way, the
influence land use variables have on trip making can be identified
directly by examining their magnitude and significance in the trip

\[ \text{Socioeconomic Characteristics} \]

\[ \text{Residence and Workplace Land Use Patterns} \]

\[ \text{Commuting Distance} \]

\[ \text{Travel Behavior} \]

\[ \text{Long Term Decisions} \]

\[ \text{Car Ownership} \]

\[ \text{Pass Ownership} \]

\[ \text{Short Term Decisions} \]

\[ \text{Number of Trips} \]

\[ \text{Trip Scheduling} \]

FIGURE 1 Model general structure.
making equations. The influence of land use variables on trip making can also be tracked through other variables such as car ownership. The total influence of land use on trip making is the sum of direct and indirect influences. The socioeconomic variables used in the model include gender, age, household total income (in three binary variables: low, medium, and high income), household size, average age of the household, an indicator for households with only two individuals, and another for households with teenagers.

In this model, the land use variables considered both the traffic analysis zone (TAZ) surrounding residence and work locations and a grid cell system of 750 × 750 m around the place of residence and employment of each individual, respectively labeled home and work. The land use variables included global population density (that considered both inhabitants and employees), built floor space density, and the density of arterial intersections in each grid cell. The distance of each TAZ to the Seattle Regional Centre was also included, and an entropy indicator was built by means of the built floor space of each type of land use, including residential, commercial and services, industry, and government–public services. This indicator measures the diversity balance between several categories of land uses, and it was first used by Cervero, Frank, and Pivo as cited in Kockelman (26). Transit supply variables were also created, including the number of bus services during the morning peak and at midday in each grid cell.

In a similar way as in the Lisbon model, all these land use variables were reduced to five factors that characterized both the residential and employment locations (capturing 77% of variation). With the exception of one factor, there was a clear distinction between factors describing land uses in the residence and employment areas. The factors, their defining variables, and their scores are presented in the Table 2.

The first two factors present high scores in variables describing the intensity and centrality of land uses. They are named employment and residence in central and denser areas, respectively. The third and fourth factors are clearly connected with transit supply, at both the residence and employment areas. They are named bus supply in the employment and residence areas. The fifth factor measures the balance of land uses at both the residence and employment areas. It is named mix of land uses. These five factors capture the most important dimensions of the home and work location and are used as five dependent variables in the model. In this way, the need to model spatial locations one by one is avoided, and they are converted into the five major latent characteristics.

<table>
<thead>
<tr>
<th>Land Use Factor</th>
<th>Most Important Variables</th>
<th>Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment in a central and denser area</td>
<td>Population density work</td>
<td>0.947</td>
</tr>
<tr>
<td></td>
<td>Building density work</td>
<td>0.966</td>
</tr>
<tr>
<td></td>
<td>Intersections density work</td>
<td>0.915</td>
</tr>
<tr>
<td></td>
<td>Distance form CBD work</td>
<td>−0.586</td>
</tr>
<tr>
<td>Residence in a central and denser area</td>
<td>Population density home</td>
<td>0.933</td>
</tr>
<tr>
<td></td>
<td>Building density home</td>
<td>0.917</td>
</tr>
<tr>
<td></td>
<td>Intersections density home</td>
<td>0.706</td>
</tr>
<tr>
<td></td>
<td>Distance form CBD home</td>
<td>−0.561</td>
</tr>
<tr>
<td>Bus supply in the employment area</td>
<td>Bus availability a.m. work</td>
<td>0.997</td>
</tr>
<tr>
<td>Bus supply in the residence area</td>
<td>Bus availability midday work</td>
<td>0.997</td>
</tr>
<tr>
<td>Mix of land uses</td>
<td>Entropy home</td>
<td>0.830</td>
</tr>
<tr>
<td></td>
<td>Entropy work</td>
<td>0.490</td>
</tr>
</tbody>
</table>

**BACKGROUND ON SEM**

SEM represents an evolution and a combination of two types of statistical methods: factor analysis and simultaneous equations models (27). In SEM, variables can be either exogenous or endogenous (20, 21). These characteristics allow SEM to handle indirect and multiple relationships. Due to these characteristics, SEM is particularly adequate as a tool to model the complex relationships between travel behavior and land use patterns.

A structural equation system with observed variables only, as the one presented in this paper (no measurement submodels), can be expressed as

\[ y = \beta x + \Gamma x + \xi \]

where

\[ y = \text{vector of } p \text{ endogenous variables,} \]
\[ x = \text{vector of } q \text{ exogenous variables,} \]
\[ \xi = \text{vector of } p \text{ disturbances with variance–covariance matrix } \Psi, \]
\[ \beta = p \times p \text{ matrix containing the coefficients for the equations relating the endogenous variables, and} \]
\[ \Gamma = p \times q \text{ matrix containing the regression coefficients for the equations relating endogenous and exogenous variables.} \]

The model-replicated combined variance–covariance matrix of the observed endogenous \( (p) \) and exogenous \( (q) \) variables, arranged so that the endogenous variables are first, is given by the partitioned \((p + q \times p + q)\) matrix (20, 27).

\[
\sum(\theta) = \begin{bmatrix}
(I - \beta)' (I - \beta) & \phi \\
(I - \beta)' \phi & \phi
\end{bmatrix}
\]

where \( \Phi \) is the covariance matrix among exogenous variables. Estimation of SEM models is performed by using the covariance analysis method–method of moments (20). The objective function is to minimize the differences between the sample variance–covariance matrix \( S \) and the model-replicated matrix \( \sum(\theta) \). The methods used for model estimation are normal theory maximum likelihood, generalized least squares, and weighted least squares (WLS) (20, 21). WLS, used in this paper, was specifically developed to deal with discrete and censored variables. Its genesis occurred with a multivariate probit developed by Muthén (28). The latter was generalized (29) to accommodate structural equations with a mix of discrete, censored, and continuous variables (30).

WLS minimizes the following fit function (31):

\[
F(\theta) = (s - \sigma)' W^{-1} (s - \sigma)
\]

where

\[ s = \text{vector of the elements in the lower half, including the diagonal of the covariance matrix } S, \]
\[ \sigma = \text{vector of corresponding elements of } \sum(\theta) \text{ reproduced from the model parameters } \theta, \]
\[ W^{-1} = \text{positive definite weight matrix of order } u \times u, \]

where

\[
u = \frac{(P + q)(P + q + 1)}{2}
\]
and the weights are estimates of fourth-order moments (variances of covariances).

The direct effects in the SEM model are given by the parameters of the $\mathbf{B}$ and $\mathbf{I}$ matrices, can be interpreted in the same way as regression coefficients (27), and are the direct influence that one variable has on another. For an identified SEM model, the total effects of the exogenous variables on the endogenous variables are given by $(\mathbf{I} - \mathbf{B})^{-1} \mathbf{I}$ and the total effects of the endogenous variables on one another are given by $(\mathbf{I} - \mathbf{B})^{-1} - \mathbf{I}$ (20); they are deducted from the general model expression solved in order to $y$ (27). Total effects are the sum of both direct and indirect effects (27). The indirect effects are given by the differences between the total and direct effects. They capture the influence of a variable on another variable through a third mediating variable, thus helping to identify self-defeating policies due to contrary direct and indirect effects.

**DISCUSSION OF ESTIMATION RESULTS**

The model estimation results are presented in the following way. First, the direct effects between exogenous and endogenous variables (matrix $\mathbf{I}$) are presented in Table 3. Then, the direct effects between endogenous variables (matrix $\mathbf{B}$) are reported in Table 4. The total effects between land use variables and the other endogenous variables are presented last in Table 5.

The estimated model shows a good fit. The value of its chi-squared statistic is 100.15 with 104 degrees of freedom. The ratio between the standard Bayesian criteria (Akaike information criterion and consistent Akaike information criterion) indicate that this model is superior to either the independence or the saturated model.

The direct effects as presented in the $\mathbf{I}$ matrix are in general in accordance with what would be expected. Men and people with higher levels of income tend to spend more time outside the home. People belonging to older and larger households tend to spend more time at home. Younger people tend to make more trips by nonmotorized modes, and older people tend to make more transit trips; being a man reduces the probability of making transit trips. A higher income reduces the probability of making trips by transit and nonmotorized modes. Being a member of an older household reduces the number of trips by transit. Moreover, people belonging to larger households tend to make fewer nonmotorized trips. The contrary happens for households with only two members. There are no significant direct effects between socioeconomic variables and the number of trips made by car, as all the effects from the socioeconomic variables on car trips are mediated through other endogenous variables.

People in households with two members have a lower probability of having a transit pass, presumably due to the ability to share tasks and drive. As expected, bigger households and those with higher levels of income have a higher probability of owning more cars. Gender also affects the number of cars in the household because the presence of women in the labor market is not as high as for men, although this difference could be considered small. Being an older man increases the commuting distance. In American cities, suburbanization and sprawling is an older and more intense phenomenon than in Europe in general and Lisbon in particular. The effects of income show that neither higher nor lower income levels directly influence commuting distance.

The results show that land use variables are influenced by socioeconomic variables, thus revealing the existence of self-selection effects. Younger women tend to work in denser and central areas, and

### TABLE 3  Gamma Matrix: Direct Effects Between Endogenous and Exogenous Variables

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Gender (1 if man)</th>
<th>Low Income</th>
<th>Medium Income</th>
<th>High Income</th>
<th>Household Size</th>
<th>Average Age</th>
<th>Household with 2</th>
<th>No. Teens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time spent between first and last trips</td>
<td>0.107</td>
<td>-0.040</td>
<td>0.076</td>
<td>0.106</td>
<td>-0.087</td>
<td>-0.182</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.115</td>
<td>-3.926</td>
<td>5.043</td>
<td>5.695</td>
<td>-2.404</td>
<td>-3.674</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of trips nonmotorized</td>
<td>-0.162</td>
<td>-0.039</td>
<td>-0.037</td>
<td>-0.207</td>
<td>0.167</td>
<td>0.176</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-2.685</td>
<td>-3.992</td>
<td>-6.307</td>
<td>-0.199</td>
<td>5.819</td>
<td>6.532</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of trips transit</td>
<td>0.218</td>
<td>-0.044</td>
<td>0.013</td>
<td>-0.077</td>
<td>-9.036</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.854</td>
<td>-2.878</td>
<td>2.276</td>
<td>-8.669</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transit pass</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.066</td>
<td>-2.675</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of cars</td>
<td>0.113</td>
<td>-0.036</td>
<td>0.180</td>
<td>0.370</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.221</td>
<td>-2.345</td>
<td>7.372</td>
<td>14.607</td>
<td>-0.067</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log commuting distance</td>
<td>0.758</td>
<td>0.260</td>
<td>-0.037</td>
<td>7.327</td>
<td>-2.561</td>
<td>-3.058</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.924</td>
<td>10.683</td>
<td>-2.561</td>
<td>-3.058</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment in a central and denser area</td>
<td>-0.188</td>
<td>-0.133</td>
<td>-0.067</td>
<td>0.093</td>
<td>0.144</td>
<td>-0.225</td>
<td>-0.197</td>
<td>0.053</td>
<td></td>
</tr>
<tr>
<td>Residence in a central and denser area</td>
<td>0.041</td>
<td>0.082</td>
<td>-0.459</td>
<td>0.260</td>
<td>0.257</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bus supply in the employment area</td>
<td>-0.038</td>
<td>0.033</td>
<td>-0.023</td>
<td>-0.018</td>
<td>-31.363</td>
<td>-13.287</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-23.759</td>
<td>46.627</td>
<td>-31.363</td>
<td>-13.287</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bus supply in the residence area</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.020</td>
<td>-0.052</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.443</td>
<td>-5.726</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mix of land uses</td>
<td>0.085</td>
<td></td>
<td></td>
<td></td>
<td>0.087</td>
<td>8.079</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.627</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** $t$-statistics are presented in italic.
people with medium and higher levels of income and belonging to smaller and younger households tend to work in these types of areas. Men belonging to smaller households and with medium-income levels tend to reside in more dense and central areas. Women with lower-income levels and belonging to smaller households tend to work more frequently in areas better served by bus. The direct effects of socioeconomic variables on the levels of transit supply in the residence area are mainly those of income: higher levels of income have a negative impact, and medium levels of income have a positive one. In mix of land uses, only age and household size have significant impacts, both positive. These results show that generally younger, richer people and those belonging to smaller households tend to work in more central areas. In addition, people living in more central areas tend to belong to smaller households. This is what one would expect as a description of urbanites. These results show that people with generally lower levels of car availability tend to locate their residence and employment sites in areas better served by public transport.

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### TABLE 4 Beta Matrix: Direct Effects Among Endogenous Variables

<table>
<thead>
<tr>
<th></th>
<th>Transit Pass</th>
<th>Log Commuting Distance</th>
<th>Employment in a Central and Denser Area</th>
<th>Residence in a Central and Denser Area</th>
<th>Bus Supply in the Employment Area</th>
<th>Bus Supply in the Residence Area</th>
<th>Mix of Land Uses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time spent between first and last trips</td>
<td>0.093</td>
<td>0.224</td>
<td>0.153</td>
<td>0.023</td>
<td>0.000</td>
<td>−0.016</td>
<td>0.000</td>
</tr>
<tr>
<td>No. of trips non-motorized</td>
<td>0.293</td>
<td>0.224</td>
<td>0.172</td>
<td>−0.082</td>
<td>0.019</td>
<td>−0.034</td>
<td>−0.073</td>
</tr>
<tr>
<td>No. of trips transit</td>
<td>0.519</td>
<td>0.224</td>
<td>0.382</td>
<td>0.248</td>
<td>0.019</td>
<td>−0.034</td>
<td>−0.345</td>
</tr>
<tr>
<td>Bus supply in the residence area</td>
<td>−0.044</td>
<td>0.224</td>
<td>0.172</td>
<td>0.023</td>
<td>0.000</td>
<td>−0.016</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NOTE: t-statistics are presented in italic.

### TABLE 5 Total Effects Among Endogenous Variables

<table>
<thead>
<tr>
<th></th>
<th>Transit Pass</th>
<th>Log Commuting Distance</th>
<th>Employment in a Central and Denser Area</th>
<th>Residence in a Central and Denser Area</th>
<th>Bus Supply in the Employment Area</th>
<th>Bus Supply in the Residence Area</th>
<th>Mix of Land Uses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time spent between first and last trips</td>
<td>0.093</td>
<td>0.000</td>
<td>0.023</td>
<td>0.000</td>
<td>−0.016</td>
<td>−0.034</td>
<td>0.000</td>
</tr>
<tr>
<td>No. of trips non-motorized</td>
<td>0.293</td>
<td>0.002</td>
<td>0.023</td>
<td>0.000</td>
<td>−0.016</td>
<td>−0.034</td>
<td>0.000</td>
</tr>
<tr>
<td>No. of trips transit</td>
<td>0.519</td>
<td>0.019</td>
<td>0.023</td>
<td>0.000</td>
<td>−0.016</td>
<td>−0.034</td>
<td>0.000</td>
</tr>
<tr>
<td>Bus supply in the residence area</td>
<td>−0.044</td>
<td>0.023</td>
<td>0.023</td>
<td>0.000</td>
<td>−0.016</td>
<td>−0.034</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NOTE: t-statistics are presented in italic.
The time spent between the first and last trips is positively influenced by both the commuting distance and the possession of a transit pass. Having a transit pass also influences negatively the number of trips by car and positively all the others, meaning the existence of some levels of mutual reinforcement between transit and nonmotorized modes. The number of trips using transit is also positively influenced by the land use factor employment in a denser and central area and negatively by the factor residence in a central and denser area, probably meaning that people residing in a place with a high score on this factor might use nonmotorized modes more than transit, presumably due to the distances involved between activity opportunities.

The number of trips by car is negatively influenced by the transit supply levels in the area of employment and positively by the factor employment in a denser and central area. Although this direct effect might appear contrary to what might be expected, this could be at least partly a compensation effect because this factor positively influences the probability of having a transit pass. Nevertheless, the number of cars in the household is influenced by income levels as is also the land use factor employment in a central and denser area. This could mean that, although density and centrality could act as a deterrent to car ownership levels, the levels of income combined with the fact that public transport in Seattle is mainly built around a bus network could act as an impediment to a more widespread use of public transport by people working in central locations.

Pass ownership is influenced negatively by the number of cars in the household and the levels of bus supply in the employment area. This variable is positively influenced by both the commuting distance and residence and employment in central and denser areas. Both indications may lead to different markets for transit agencies to tap. The number of cars in the household is negatively influenced by land use factors employment in a denser and central area, bus supply in the employment area, and mix of land uses. The commuting distance is positively influenced by number of cars in the household, employment in a denser and central area, and bus supply in the employment area. These effects are consistent with the hypothesis of a more intense suburbanization if the population is more centralized. Two land use factors are directly affected by travel behavior variables. One is the residence in a denser and central area, which is negatively influenced by the commuting distance, and the other is the bus supply in the residence area, which is negatively influenced by the number of cars in the household. People who prefer to live closer to their workplace tend to choose more central and denser locations, and people who prefer to own fewer cars tend to locate their residence in a place better supplied with public transport.

The direct effects between pairs of endogenous variables show in general the confirmation of the following hypotheses:

- Land use variables directly affect travel behavior.
- The relationships between travel behavior variables are consistent with the hypothesis that long-term decisions condition shorter-term ones. With three exceptions, the direct effects are all above the diagonal of the $\mathbf{B}$ matrix.
- Land use variables are also directly influenced by travel behavior variables.

Table 5 shows the total effects between endogenous variables. Interpreting a model with the direct effects provides misleading conclusions when the direct and the total effects are very different. It is the total effects that should be used in identifying the impact that land use variables have on travel behavior.

The overall finding is that total effects from land use factors to the travel behavior variables show the existence of significant influences. In fact, people working in more central, denser, and mixed areas and with higher levels of transit availability tend to own fewer cars. In contrast, car ownership is not influenced by the residential area land use characteristics. People living and working in more central, denser, and mixed areas tend to have a higher probability of owning a transit pass. In contrast, the levels of bus supply have negative total effects, although with a much lower level of magnitude.

The total effects of land use factors on the number of trips show that density and centrality at both residence and employment areas increase the number of trips in transit and in slow modes. The effects on the number of trips by car are negative in the case of the land factor residence in a denser and central area and not significantly different from zero in the case of the land use factor employment in a denser and central area. The variable mix of land uses influences negatively the number of trips by car and positively the number of trips by other modes. The levels of bus supply both at residence and employment locations tend to influence negatively the number of trips by every mode, with the exception of bus supply in the residence area, which has a positive effect on the number of trips by car. This is an indication that simply increasing bus services will not be sufficient to attract ridership and may have negative impacts (e.g., residents of an area giving rides to bus riders for their long-haul trip). The effects of land use patterns on the time spent between the first and last trip go also in two directions: the residence and employment in denser and central areas influences positively this trip scheduling variable, and the levels of bus supply in the residence areas influence it negatively.

**COMPARISON WITH LISBON MODEL AND CONCLUSIONS**

One of the main objectives for building this model was to compare its results with a similar model built for the Lisbon Metropolitan Area (1). This comparison is presented mainly in relation to model structure and estimation results because the variables used in both models are not the same due to different data availability in the two areas studied. In addition, the travel behavior variables used in both models are almost the same, with the exception of the number of kilometers traveled by mode, available only for Lisbon. Variables describing individuals and household characteristics were also similar. The most important differences were in the number and breadth of land use variables that in the Lisbon model were vaster but measured at the zonal level. In spite of these differences, the estimation results obtained in both models point to similar global conclusions. People with different socioeconomic characteristics and income levels tend to work and live in places of different urban environments. Furthermore, land use patterns in the areas of employment, residence, or both are influenced by travel behavior variables, presumably capturing the impact of desired mobility and lifestyles on the choice of places to live and work. Both models lead to the conclusion that land use variables affect travel behavior in a significant way. Moreover, both models show that the effects of land use are in great part “passed-through” variables influencing longer-term decisions like commuting distance, car ownership, and transit pass ownership. Equally important is that both models account for self-selection effects due to socioeconomic characteristics. The results show that land use affects travel behavior even when self-selection is taken into account.

There are, however, some important differences between the Lisbon and Seattle models. In the Lisbon model, car ownership is
a function of pass ownership, but in Seattle, it is the other way around. This could be explained by the fact that Lisbon has a much more developed public transport network and less generous parking supply, thus offering more transit options and imposing heavier restrictions on car ownership levels. In Seattle, it is exactly the opposite. When a commuter cannot purchase a car he or she relies on transit. In the Lisbon model, the number of trips by mode is a function of car ownership and transit pass ownership, and they are a function of one another, an evidence of competition between modes. In the Seattle model, the number of trips by mode has only direct effects from transit pass ownership. There is no evidence of direct competition between modes. In relation to the total effect from transit pass and car ownership, they tend to have the same signal.

The direction of total effects from commuting distance on the number of trips by mode is different in each model. In Lisbon, the commuting distance positively affects the number of trips by car and transit and negatively affects the number of trips by nonmotorized modes. In Seattle, commuting distance positively affects the number of trips by transit and nonmotorized modes and negatively affects the number of trips by car. This points to the possibility of a strong market for Seattle transit, such as long-distance commuters, who are a neglected market segment in the United States.

Although a direct comparison between Lisbon and Seattle cannot be made for the size of the land use effects on travel behavior, the results tend to point generally to similar conclusions: (a) living and working in central, denser, and mixed areas tends to reduce the number of car trips and car ownership chances of owning a transit pass; (b) living in denser, central, and mixed areas tends to reduce the number of car trips and car ownership levels in a household; and (c) working in central and denser areas tends to increase the commuting distance, which is a sign of the polarizing power that the center of both metropolitan regions have, attracting people living in suburban and exurban areas. In relation to this last effect, it can be seen that in the Seattle model the total effects of car ownership on commuting distance are positive, contrary to what was found in Lisbon. This can be again explained by the fact the public transport network, particularly the regional rail network, in Lisbon is much more developed than the one in Seattle, which relies mainly on a bus network with ferries serving few specific locations. Thus, for people living in the suburbs and working in the center of Lisbon, public transportation is a more convenient option than for those in Seattle. This fact highlights the importance of public transport supply levels together with land use patterns. In addition, socioeconomic variables in both models stress the impact that income has on travel behavior. Both models show that higher levels of income tend to have a positive effect on commuting distance and car ownership levels. The total effects of income on transit pass ownership are different. In Lisbon, there is a negative relationship with income, and in Seattle, that relationship is positive but not significant.

The results presented in this model are strong evidence in favor of employing land use regulation and land use change as a tool to change travel behavior. Increases in public transportation supply are not supported by our model results except if tailoring to markets is applied (e.g., long-distance commuters in Seattle). The impact of these policies will be different depending on local circumstances. It is still not known, however, whether the commonalities with and differences between the two metropolitan areas here are due to local peculiarities of generally valid relationships. This question motivates the expansion of this study to other urban environments and the repetition of the analysis by using variables measured at the same scale and with the same content.

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REFERENCES


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