PERGAMON

Transportation Research Part D 7 (2002) 265–284

TRANSPORTATION
RESEARCH
PART D

www.elsevier.com/locate/trd

Built environments and mode choice: toward a normative framework

Robert Cervero *

Department of City and Regional Planning, #1850 Hearst Field Annex, Building B, University of California, Berkeley, CA 94720, USA

Abstract

Compact, mixed-use, and walk-friendly urban development, many contend, can significantly influence the modes people choose to travel. Despite a voluminous empirical literature, most past studies have failed to adequately specify relationships for purposes of drawing inferences about the importance of built-environment factors in shaping mode choice. This paper frames the study of mode choice in Montgomery County, Maryland around a normative model that weighs the influences of not only three core dimensions of built environments – density, diversity, and design – but factors related to generalized cost and socioeconomic attributes of travelers as well. The marginal contributions of built-environment factors to a traditionally specified utility-based model of mode choice are measured. The analysis reveals intensities and mixtures of land use significantly influence decisions to drive-alone, share a ride, or patronize transit, while the influences of urban design tend to be more modest. Elasticities that summarize relationships are also presented, and recommendations are offered on how outputs from conventional mode-choice models might be "post-processed" to better account for the impacts of built environments when testing land-use scenarios.

Keywords: Mode choice; Built environment; Travel demand; Logit analysis; Land-use planning

1. Introduction

The volume of literature on how land-use patterns and built environments influence urban travel demand has exploded over the past decade (Cervero and Seskin, 1995; Handy, 1996; Crane, 2000; Boarnet and Crane, 2001; Ewing and Cervero, 2001). Spiraling interest in "smart growth", "transit villages", and "new urbanism" has spawned a veritable cottage industry of researchers

* Fax: +1-510-643-9576.
E-mail address: robertc@uclink.berkeley.edu (R. Cervero).

1361-9209/02/$ - see front matter
PII: S1361-9209(01)00024-4

who diligently probe and dissect the many ways in which urban form, neighborhood design, and the overall physical make-up of cities and regions shape how people get around.

Past studies of the built environment's impact on travel demand can be faulted on both theoretical and methodological grounds. (For recent critiques of this literature, see: Badoe and Miller, 2000; Crane, 2000; Boarnet and Crane, 2001; Ewing and Cervero, 2001.) To date, most models estimated to probe relationships have been incompletely specified, sometimes grossly so. This is partly because of modeling traditions and partly because of data limitations. Shortcomings are underscored by studies of transportation mode choice. Mode choice is usually treated as an application of consumer choice theory, grounded in the belief that people make rational choices among competing alternatives so as to maximize personal utility, or net benefit (Domencich and McFadden, 1975; McFadden, 1976; Ben-Akiva and Lerman, 1985; Small and Winston, 1999). Travelers are said to weigh the comparative travel times, costs, and other attributes of modes when deciding how get between point A and point B. Characteristics of the traveler, like the availability of a car, theory holds, also influence the selection. Many past studies on the travel-behavior impacts of built environments have inadequately expressed the influences of generalized costs (e.g., monetary costs and travel time expenditures) on mode choice, and sometimes have overlooked such factors altogether. More often than not, studies on the effects of housing densities, sidewalk provisions, and other built-environment attributes on modes of travel have failed to account for the simultaneous influences of factors like travel times and motoring prices.

In a similar vein, mode choice models used by regional planning organizations across the United States to forecast future travel demand are also often under-specified. In most multinomial logit formulations of mode choice, the systematic components of utility expressions weigh generalized costs of getting between points A and B as well as characteristics of trip-makers; rarely, however, do equations account for the influences of points A (origins) and points B (destinations) themselves in explaining mode choice. That is, the potential effects of densities, land-use mixtures, and urban designs in and around trip origins and destinations are left unsaid. This compromises the ability to test the possible transportation benefits of land-use initiatives, be they transit-oriented development, infill housing, neo-traditional towns, or clustered developments that promote efficient automobile circulation.

These oversights should not be dismissed lightly for the omission of relevant explanatory variables can lead to biased parameter estimates. For example, to the degree that bus and rail services to dense urban settings are more frequent, thus shortening transit travel times, omitting a density variable from a mode choice utility function can produce biased estimates of included variables that are related to density. This might be the case when factors that routinely accompany density (e.g., passenger amenities like protective shelters) and that are not explicitly captured in models have a bearing on mode choice. In such instance, omitting a density variable (even if it functions only as a proxy) from the utility expression could lead to an misstatement of the effects of travel time on mode of travel. [1] And, of course, it works the other way as well – omitting

[1] When a relevant omitted variable is positively correlated with an included variable, and the sign on the included variable is positive, then estimates will overstate the influence of the included variable. In a mode choice model that predicts the probability of patronizing transit, if the included variable "travel time differential between auto and transit modes" is positively related to the excluded but relevant variable "density", then the positive sign on the "travel time differential" variable will be overstated. For more on biased estimation, see Pindyck and Rubinfeld (1991).

measures of generalized cost from a model that gauges the effects of land use on mode choice is apt to give a distorted impression of how factors like density influence transit usage. Until travel research can lay bona fide claims to internal validity – namely, models that are well enough specified to support causal inferences – our understanding of how built environments shape travel demand will necessarily be incomplete and murky.

This paper seeks to overcome some of the deficiencies of past mode-choice analyses, particularly those that have focused on the effects of built environments, through an expanded specification of mode-choice utility. Using transportation and land-use data from Montgomery County, Maryland, mode-choice models are estimated that weigh the marginal contributions of land-use variables to a traditional expression of utility based on generalized costs and socio-economic factors. The built-environment is defined in terms of three core dimensions, or the "3 Ds": density, diversity, and design. In addition, results are summarized in elasticity form to shed light on the sensitivity of mode choice to changes in the built environment. The paper concludes that regional planning organization should give stronger consideration to including explicit measures of land-use variables in mode choice models, and correspondingly studies of land-use and travel demand should imbed measures of generalized costs in their model formulations.

2. Case context and data inputs

Montgomery County, Maryland, a fairly affluent county of 850,000 inhabitants adjacent to the District of Columbia, was chosen as a case context to empirically test normative models for predicting influences of the built environment on mode choice. This was partly because the county maintains fairly rich data on land-use characteristics of its 318 traffic analysis zones (TAZs). Additionally, Montgomery County residents enjoy a wide array of mobility options that are available in the Washington metropolitan area, providing a good setting to study variations in mode choice behavior.

To carry out the analyses, several data bases were merged to account for the full array of factors thought to influence mode of travel. Trip records for Montgomery County residents were drawn from the 1994 Household Travel Survey compiled for the Metropolitan Washington Council of Government (MWCOG) region, providing 5167 observations (representing multiple trips for multiple purposes among persons surveyed in each household). Data on the comparative travel times and travel costs of competing modes for each trip segment, along with variables measuring socio-demographic characteristics of trip-makers, were obtained from calibration files used in developing the Version 2 Model of the MWCOG mode choice models, and merged with the Montgomery County travel records. Of particular value were data on in-vehicle and out-of-vehicle travel times for the origin–destination combination of each trip record, defined for drive-alone, group-ride, and transit modes (based on minimum path skims across highway and transit networks). Added to these records were various land use, activity-location, urban design, and accessibility measures associated with the TAZs of the origin and the destination of each trip record. A number of additional variables (e.g., land-use diversity, gross densities) were created using input variables of each TAZ. The 5167 trip records of Montgomery County residents from the 1994 Household Travel were reduced in the analyses that follow in part because not all data were available for each trip record across the multiple data bases, and also because one of the analyses was carried out only for work trips.

Mode choice was limited to the three modal classifications used by MWCOG – drive-alone automobile, group-ride automobile, and transit – since variables capturing generalized costs among competing modes for each origin–destination pair were available only for this three-way breakdown. Thus, "motorized" mode choice was predicted (exclusive of walk and bike trips). For all trip purposes combined, the shares of trips made by Montgomery County residents in 1994 among motorized modes were: drive-alone – 72.8%; group-ride automobile – 22.1%; and transit – 4.6%. Stratifying trips by purpose reduced the number of sampled non-single-occupant trips to such a small number that only a binomial model could be estimated – specifically, a model that predicted the likelihood of driving alone versus sharing a ride (group-ride) or taking transit. Because very few available trip records for non-work purposes (i.e., home-based shop, home-based other, and non-home-based) consisted of transit trips, and because land-use factors were found to have only modest influences in the prediction of drive-alone versus group-ride travel, separate non-work mode choice analyses were not carried out.

Combining trip purposes yielded sufficient numbers of trips across modes to support a multinomial logit analysis. The multinomial model predicted the probability of drive-alone and the probability of group-ride travel, with transit functioning as the referent mode. Because of the particular attention given in recent years to transit-oriented development as a land-use strategy (Calthorpe, 1993; Bernick and Cervero, 1997), a binomial model was also estimated that gauged the relative importance of land-use factors in explaining whether Montgomery County residents opted for transit or not for all trip purposes combined.

It deserves mentioning that mode choice models reveal how built-environment factors influence market shares across modes, however, not necessarily whether the volume of vehicle travel changes. Compact, mixed-use neighborhoods might increase shares of non-auto trips, however, the total number of vehicle trips might remain the same. Handy (1992), for example, found neo-traditional neighborhoods averaged higher rates of walk trips than did neighborhoods with more auto-centric designs, however, differences in daily auto trip rates were indistinguishable across types of neighborhoods. This contrasts with other research (e.g., Cervero and Radisch, 1996) that uncovered evidence of substitution effects – notably, transit and walking trips appeared to have replaced some automobile trips in transit-oriented neighborhoods.

3. Model framework

The modeling framework used for estimating the probability a Montgomery County resident opted for a particular mode, accounting for the relative importance of land-use factors, took the following form:

$$P_{niod} = \exp(V_{niod}) \big/ \left[\Sigma_{j \in Cnod} \exp(V_{njod})\right], \forall V_{niod} = f(T_{iod}, \mathrm{SE}_n, \mathrm{BE}_o, \mathrm{BE}_d), \tag{1}$$

where P_{niod} is the probability of person n choosing mode i for traveling between origin o and destination d, C_{nod} is the choice set of modes available to person n traveling between origin o and destination d, V_{niod} is the utility function (systematic component) for person n traveling by mode i

between origin o and destination d, T_{iod} is the trip interchange vector for trips by mode i from origin o to destination d – including travel time and cost (i.e., generalized costs), SE_n is the socio-economic characteristics vector for trip-maker n – attributes such as income and vehicle availability, BE_o is the built environment vector for TAZ origin o, representing measures of land-use intensity, land-use mixture, land-use accessibility, and walking quality, among others, and BE_d is the built environment vector for destination d, comparable to the vector for origin o.

For purposes of gauging the marginal influence of the built environment vectors (BE_o and BE_d in Eq. (1)), the analysis was carried out as follows. A "basic" model was first estimated, followed by an "expanded" model. The basic model represents the traditional expression of utility in mode choice models, namely, in terms of comparative generalized costs of competing modes and socio-economic attributes of trip makers. Basic models therefore took the form:

$$P_{niod} = \exp\left(V_{niod} = f(T_{iod}, \mathrm{SE}_n)\right) \Big/ \left[\Sigma_{j\in Cnod} \exp\left(V_{njod} = f(T_{jod}, \mathrm{SE}_n)\right)\right]. \tag{2}$$

The expanded model retained the traditional measures of mode-choice utility but also added information on built-environment characteristics (both at trip origin and destination) that were thought to shape travel behavior. Expanded models were of the form:

$$P_{niod} = \exp\left(V_{niod} = f(T_{iod}, \mathrm{SE}_n, \mathrm{BE}_o, \mathrm{BE}_d)\right) \Big/ \left[\Sigma_{j\in Cnod} \exp\left(V_{njod} = f(T_{jod}, \mathrm{SE}_n, \mathrm{BE}_o, \mathrm{BE}_d)\right)\right]. \tag{3}$$

In this formulation, built-environment factors are assumed to directly influence travel demand, as in the case of recent mode-choice models that have accounted for the influences of jobs-housing mixes in greater Portland (Portland Metro, 1998) and metropolitan Washington (Milone, 2000). The commingling of retail uses and consumer services in suburban office parks, for example, is thought to *directly* induce carpooling and vanpooling by liberating some workers from the need for midday auto-mobility (Cervero, 1996). A continuous and integrated sidewalk network flanked by street trees, urban designers contend, *directly* stimulates transit riding by facilitating access and providing a visually attractive setting for getting between residences and rail stops (Untermann, 1984). Others (Boarnet and Sarmiento, 1998; Crane and Crepeau, 1998; Boarnet and Greenwald, 2000; Boarnet and Crane, 2001) have treated the influences of land-use factors, and particularly density measures, indirectly through their impacts on travel times and distances, however such formulations have focused on predicting variations in trip generation rates as opposed to mode choice. For predicting mode of travel, built-environment parameters are assumed to exert direct influences in the tradition of past mode-choice analyses (Pushkarev and Zupan, 1977; Cambridge Systematics, 1994; Parsons Brinckerhoff Quade and Douglas, 1996; Rodier et al., 2001).

Comparisons of Eqs. (2) and (3) allow the marginal effects of adding land-use variables to mode-choice utility expressions to be gauged. The degree to which an expanded model statistically improves upon a basic model is measured in terms of the change in the log likelihood function $\mathscr{L}$ relative to the change in degrees of freedom. The test statistic, I, follows a χ^2 distribution with k degrees of freedom (where k represents the increase in parameter estimates between the basic model and expanded model):

$$I = -2[\mathscr{L}(\text{basic model}) - \mathscr{L}(\text{expanded model})]. \tag{4}$$

The land-use variables introduced in the expanded models reflected those that incorporate the three core dimensions, or "3 Ds", of the built environment: density, diversity, and design (Cervero and Kockelman, 1997). An extensive literature on the potential impacts of built-environment factors on travel choice provided a compelling enough basis to include what were felt to be relevant built-environment variables as long as signs on coefficients were consistent with a priori expectations and statistical estimation problems like multicollinearity and heteroschedasticity were not present. In the spirit of gauging the marginal contributions of all three core dimensions of built environments on mode choice, restrictive entry criteria were not placed on built-environment variables, nor were they placed on other (more traditional) measures of utility like travel time and cost.

Numerous candidate measures of density, diversity, and design were available for the analysis, however, through exploratory analyses some were found to be superior to others (in terms of statistical goodness-of-fit and consistency with theory). Density reflects how intensively land is used for housing, employment, and other purposes; in the analyses that follow, "total activity density" of a TAZ of a trip end was used, expressed as the total of population and employment divided by total square miles of the TAZ. [2] Diversity generally reflects the degree of land-use mixture, with more heterogeneous settings thought to induce transit and non-drive-alone travel (Cervero, 1988). Several diversity indices were created for this analysis, including ones that compared the degree of jobs-to-population balance of a TAZ relative to the countywide average and ones that relied on entropy measures of mixtures across activity categories. Last, as used in studies of land-use and travel behavior, design generally reflects the quality of walking environment and the physical configurations of street networks. Among the several candidate variables considered for gauging walking quality, the one that consistently proved to be the best predictor of mode choice (defined across the three motorized mode options) was the ratio of sidewalk miles to centerline miles of roadway (serving as an index of sidewalk provisions). [3]

While the expanded model of Eq. (3) is thought to better gauge the marginal contributions of land-use variables on mode choice than traditional model formulations, one notable causal limitation is that it does not account for the possibility of self-selection. Land-use variables could very well act as proxies for attitudinal and lifestyle predispositions to using particular travel modes (Kitamura et al., 1997; Boarnet and Crane, 2001). One study, for example, found attitudinal measures explained travel behavior in the San Francisco Bay Area better than did land-use variables (Kitamura et al., 1997). This study did not model the relationship between travel preference and locational choice, though presumably one would expect those with a proclivity to commute via transit (e.g., in order to avoid the daily stress of driving) would most likely sort themselves into residential locations that are well-served by buses or trains. Accounting for such possible endogenous influences could very well further refine and enhance the specification of mode choice models.

[2] While separate measures of population density and employment density would have been preferable, "total activity density" was measured instead because secondary data on net area zoned and used for housing and net area zoned and used for employment were not available. Total activity density is used in the Smart Growth Index prepared for the US Environmental Protection Agency (Criterion Planners/Engineers, 2000).

[3] Factor analysis was carried out for purposes of extracting underlying factors that captured common characteristics of many different measures of urban design (see Cervero and Kockelman, 1997, for an example). Using a limited set of urban-design variables in their original forms provided better statistical fits, however, and thus were used for mode choice modeling.

4. Binomial model of drive-alone commuting

The initial analysis focused on the influence of built environments, at both the trip origin and destination, on the likelihood a Montgomery County resident solo-commuted versus got to work by some other motorized means. As noted, the limited sample size required the choice set to be dichotomized into simply driving alone or sharing a ride in a car, bus, or train.

4.1. Basic model

The choice to solo-commute was expressed in the basic model as a function of total travel time and cost differentials, car ownership levels, and the presence of a driver's license. Table 1 reveals positive cross-elasticities: the longer it took and the more it cost to commute by transit or carpool/vanpool relative to driving alone, the more likely a Montgomery County resident solo-commuted. The stronger relationship was with respect to travel cost; the travel-time variable was not statistically significant. Also, residing in a zero- or one-car household (relative to a two-plus car household) lowered the odds of solo-commuting while having a driver's license significantly increased them.

4.2. Expanded model

The right-hand side columns of Table 1 show the expanded model based on adding land-use attributes to the mode-choice utility function. Signs on the comparative travel-time and cost attributes as well as the trip-maker socio-economic characteristics remained the same in the expanded model (with the travel-time variable becoming more significant and the cost variable becoming less). [4] Clearly, numerous dimensions of the built environment improved the predictive power of the model. Of particular note, measures of the three core dimensions – density, diversity, and design – added significant marginal explanatory power, with signs matching expectations.

Higher gross densities lowered the odds of solo-commuting, especially at the trip destination. For work trips, this is to be expected since dense workplace destinations typically have more congested ambient traffic conditions. Also, transit options, especially grade-separated systems like Washington Metrorail, are more attractive when heading to jobs in dense areas.

Table 1 also reveals that high levels of accessibility via highway networks promoted drive-alone commuting. The two isochronic measures of accessibility represent cumulative counts of activities that can be reached within 45-min peak-period travel time over the region's highway network. In terms of trip origin (representing place of residence for home-based work trips), Montgomery County residents with comparatively large numbers of jobs within 45-min highway travel time were more likely to solo-commute, controlling for other factors (like gross density). This positive relationship likely reflected the joint influences of sub-regional jobs-housing balance (within a

[4] There are several possible explanations as to why the magnitude and prob-values of the travel-time differential and travel-cost differential variables might change upon entering built-environment factors like density. At higher densities, travel times via transit relative to automobile might increase proportionally more if in shared right-of-way settings buses disproportionately suffer from the effects of congested streets and transit boarding and alighting durations further increase. In terms of cost differentials, automobile expenses, notably for parking, could be expected to increase proportionally more in dense urban settings, narrowing the difference between transit and automobile costs.

Table 1
Comparison of binomial logit models for predicting drive-alone mode choice in montgomery county, work trips, 1994

Variables	Basic model			Expanded model		
	Coefficient estimate	Standard error	Prob-value	Coefficient estimate	Standard error	Prob-value
Comparative modal attributes						
Total travel time differential: average of transit & group-ride – automobile (min)[a]	0.0032	0.0036	0.3143	0.0122	0.0082	0.1369
Direct travel cost differential: average of transit & group-ride automobile (cents, 1980)[b]	0.0017	0.0008	0.0075	0.0036	0.0028	0.2811
Trip-maker attributes:						
Zero-car household: 0 = No, 1 = Yes	−1.5781	0.9718	0.1044	−2.2026	1.1012	0.0455
One-car household: 0 = No, 1 = Yes	−0.7168	0.2722	0.0086	−1.0889	0.2958	0.0002
Driver's license: 0 = No, 1 = Yes	2.9898	0.7848	0.0516	3.3049	0.8239	0.0001
Land-use attributes:						
Gross density, origin TAZ: (population + employment)/gross square miles, in 1000s	–	–	–	−0.0101	0.0085	0.2272
Gross density, destination TAZ: (population + employment)/gross square miles, in 1000s	–	–	–	−0.0174	0.0078	0.0248
Job accessibility, origin TAZ: number of jobs (in 1000s) within 45-min highway network travel time	–	–	–	0.0002	0.0002	0.2943
Labor-force accessibility, destination TAZ: number of households (in 1000s) within 45-min highway network travel time	–	–	–	0.0020	0.0009	0.0259
Land-use diversity, origin TAZ: retail employment and population relative to countywide ratio[c]	–	–	–	−0.5132	0.4428	0.2464
Land-use diversity, destination TAZ: normalized entropy index of households, retail employment, office employment, and other employment[d]	–	–	–	−0.9205	0.5132	0.0729
Ratio of sidewalk miles to road miles, origin TAZ[e]	–	–	–	−0.7282	0.2628	0.0056
Ratio of sidewalk miles to road miles, destination TAZ[e]	–	–	–	−0.8371	0.2664	0.0017
Constant	−2.5444	0.7427	0.0005	−4.4956	1.2491	0.0003
Summary statistics						
Number of Cases	427			427		
$-2\mathscr{L}(c)$: log likelihood function value, constant-only Model	469.512			469.512		
$-2\mathscr{L}(B)$: log likelihood function value, parameterized model	432.256			403.193		
Model χ^2 (probability): $-2[\mathscr{L}(c) - L(B)]$	37.256 (0.0000)			66.319 (0.0000)		

Table 1 (*continued*)

Variables	Basic model			Expanded model		
	Coefficient estimate	Standard error	Prob-value	Coefficient estimate	Standard error	Prob-value
Goodness-of-fit (McFadden)	$\rho^2 = 0.079$; $\rho^2(\text{adjusted}) = 0.069$			$\rho^2 = 0.142$; $\rho^2_{(\text{adjusted})} = 0.114$		
Model improvement test: $-2[\mathscr{L}$ (basic model) $- \mathscr{L}$(expanded model)]	$\chi^2 = 29.063$, df $= 8$, prob. $= 0.001$					

[a] For transit travel, travel time consists of that occurring "in vehicle" (bus, metrorail, commuter rail), "out-of-vehicle" (including walk time for access and transfers and waiting time, both initial and transfer), and driving to access transit (if any). For drive-alone and group-ride automobile travel, total time consists of in-vehicle highway travel time plus attraction-end highway terminal time.

[b] For transit travel, direct cost comprises the transit fare. For drive-alone and group-ride automobile travel, direct cost equals the sum of operating cost (at 5.3 cents time highway distance), the toll (if any), and parking cost (if any).

[c] Diversity = 1 − {[ABS(population − retail employment)]/(population + retail employment)}.

[d] Normalized entropy $= \{-\Sigma_k[(p_i)(\ln p_i)]\}/(\ln k)$, where p_i = proportion of total land-use activities in category i (where the i categories are households, retail employment, office employment, other employment); and $k = 4$ (number of land-use categories).

[e] Ratio of sidewalk miles to centerline roadway miles. In measuring sidewalk miles, the following values were assigned to each segment of all public streets in a TAZ: 0 = no sidewalk; 1 = sidewalk on one side; 2 = sidewalk on two sides.

45-min commute-shed) and smoothly moving traffic on the decision to drive alone. More significant was labor-force accessibility, expressed as the cumulative count of households within a 45-min isochrone of a destination (which for home-based work trips typically represented the place of work). On balance, then, commuting from an origin with good highway accessibility to a destination with good highway accessibility increased the odds of Montgomery County residents solo-commuting.

Table 1 shows land-use diversity also mattered. Specifically, mixed-use settings at the origin and destination tended to work against driving alone and in favor of commute alternatives. As expected, the relationship was stronger for the workplace destination, reflecting the tendency for workers to rideshare and take transit when headed to a workplace with retail shops, consumer services, and other activities nearby. This finding is consistent with research showing mixed-use workplaces induce non-solo-commuting since, in contrast to single-use office parks and business centers, workers can take care of many midday personal activities when stores and restaurants are nearby (Cervero, 1989; Cambridge Systematics, 1994).

Somewhat surprisingly, the most statistically significant built-environment variable, namely, the sidewalk ratio, captured dimensions of urban design. Neighborhoods with fairly well developed sidewalk infrastructure appear to have influenced mode choice to some degree, ostensibly by providing more attractive settings for taking a bus or joining a vanpool.

Overall, the expanded model statistically outperformed the basic one. The pseudo-R^2 statistic of the expanded model was nearly twice that of the basic one, expressed in both unadjusted (as a McFadden ρ^2 statistic) and adjusted (reflecting loss of degrees of freedom) terms. [5] And based on

[5] The McFadden ρ^2 statistic is defined as $1 - [\mathscr{L}(B)/\mathscr{L}(c)]$, where $\mathscr{L}(B)$ is the log likelihood value of the fully parameterized model and $\mathscr{L}(c)$ is the value of the log likelihood value when all parameters, except for the constant term, are set to zero (Windmeijer, 1995). The adjusted ρ^2 statistic accounts for the loss of a degree of freedom for each predictor variable added to the model, expressed as: $1 - [(\mathscr{L}(B) - k)/\mathscr{L}(c)]$, where k = number of predictor variables.

the significant χ^2 statistic, the expanded model was found to significantly improve the prediction of how Montgomery County residents got to work.

5. Binomial model of transit mode choice

Modeling mode choice among all trip purposes significantly increased degrees of freedom. An initial analysis examined factors influencing the choice to travel by transit versus automobile (drive-alone or group-ride), modeled using a binomial logit formulation and maximum likelihood estimation. Because Montgomery County has a strong tradition of promoting transit-oriented development (see Carter and Mathias, 1995), with rail station areas like Bethesda and Silver Spring touted as successful transit-oriented suburban centers (see: Garreau, 1991; Bernick and Cervero, 1997), clarifying the marginal roles of land-use factors in shaping mode choice in such settings takes on particular importance.

5.1. Basic model

The basic model estimated for predicting transit choice, shown in the left-hand columns of Table 2, performed well, with all predictor variables statistically significant at the 0.05 probability level. A longer (in-vehicle and out-of-vehicle) travel time aboard transit relative to the private automobile lowered the odds of taking transit, consistent with theory. And where transit fares exceeded the direct cost of motoring (including tolls and parking fees), residents tended to travel by car. [6]

Several socio-economic factors also affected the propensity to patronize transit. Being from a zero-car household was strongly associated with transit dependency. Women in possession of driver's licenses were less inclined to patronize transit, all else being equal. The tendency for females to be more car-dependent likely reflects a combination of factors, including the need of many working women to use a car to chain trips between work, shops, and child-care centers. Car dependency tends to be particularly high in more affluent settings, like Montgomery County, where significant shares of professional women must balance job and child-rearing responsibilities (Pickup, 1989; Rosenbloom and Burns, 1995). Working full-time also promoted transit usage (presumably for the work-trip components of total trips). This likely reflected the fact that full-time workers are more likely to purchase monthly transit passes than part-timers, which in turn induces transit travel.

5.2. Expanded model

Adding land-use variables to the model enhanced predictability. All variables from the basic model retained their signs, however, there tended to be slight losses in statistical significance. By including relevant land-use variables in the model, the explanatory roles of modal and trip-maker attributes in predicting transit travel were attenuated.

[6] It is noted that in the measurement of both travel-time and travel-cost differentials, the base condition in Table 2 represents the combination of all forms of automobile travel – both drive-alone and shared-ride.

Table 2
Comparison of binomial logit models for predicting transit mode choice in montgomery county, all trip purposes, all forms of transit, 1994

Variables	Basic model			Expanded model		
	Coefficient estimate	Standard error	Prob-value	Coefficient estimate	Standard error	Prob-value
Comparative modal attributes:						
Total travel time differential: transit – automobile (min)[a]	−0.0150	0.0044	0.0009	−0.0160	0.0028	0.0001
Direct travel cost differential: transit – automobile (cents, 1980)[b]	−0.0100	0.0027	0.0000	−0.0136	0.0059	0.0204
Trip-maker attributes:						
Zero-car household: 0 = No, 1 = Yes	2.4858	0.9534	0.0065	3.2044	0.9407	0.0007
Gender: 0 = Male, 1 = Female	−0.7368	0.2199	0.0215	−1.0543	0.4991	0.0346
Driver's license: 0 = No, 1 = Yes	−4.6847	0.5703	0.0000	−6.0511	0.7435	0.0000
Full-time employed: 0 = No, 1 = Yes	1.6734	0.7422	0.0242	1.2574	0.7538	0.0953
Land-use/location attributes:						
Gross density, origin TAZ: (population + employment)/gross square miles, in 1000s	–	–	–	0.0386	0.0009	0.0000
Gross density, destination TAZ: (population + employment)/gross square miles, in 1000s	–	–	–	0.0258	0.0116	0.0265
Land-use diversity, origin TAZ: employment and population relative to county ratio[c]	–	–	–	2.4393	0.9130	0.0075
Land-use diversity, destination TAZ: employment and population relative to county ratio[c]	–	–	–	1.5519	0.8576	0.0704
Ratio of sidewalk miles to road miles, destination TAZ[d]	–	–	–	0.4701	0.4512	0.2935
Washington, D.C., destination: 0 = No, 1 = Yes	–	–	–	0.7790	0.6580	0.2365
Constant	−0.8327	0.7413	0.2612	−2.6653	0.9306	0.0041
Summary statistics						
Number of Cases	1960			1960		
$-2\mathscr{L}(c)$: log likelihood function value, constant-only model	276.4289			276.4289		

(*continued on next page*)

Table 2 (*continued*)

Variables	Basic model			Expanded model		
	Coefficient estimate	Standard error	Prob-value	Coefficient estimate	Standard error	Prob-value
$-2\mathscr{L}(B)$: log likelihood function value, parameterized model	196.912			168.3570		
Model χ^2 (probability): $-2[\mathscr{L}(c) - \mathscr{L}(B)]$	79.5169 (0.0000)			108.071 (0.0000)		
Goodness-of-fit (McFadden)	$\rho^2 = 0.288$; $\rho^2_{(\text{adjusted})} = 0.266$			$\rho^2 = 0.391$; $\rho^2_{(\text{adjusted})} = 0.3048$		
Model improvement test: $-2[\mathscr{L}(\text{basic model}) - \mathscr{L}(\text{expanded model})]$	$\chi^2 = 28.554$, df $= 6$, prob. $= 0.001$					

[a] For transit travel, travel time consists of that occurring "in vehicle" (bus, metrorail, commuter rail), "out-of-vehicle" (including walk time for access and transfers and waiting time, both initial and transfer), and driving to access transit (if any). For drive-alone and group-ride automobile travel, total time consists of in-vehicle highway travel time plus attraction-end highway terminal time.

[b] For transit travel, direct cost comprises the transit fare. For drive-alone and group-ride automobile travel, direct cost equals the sum of operating cost (at 5.3 cents time highway distance), the toll (if any), and parking cost (if any).

[c] Diversity = 1 − [ABS(population − employment)]/(population + employment).

[d] Ratio of sidewalk miles to centerline roadway miles. In measuring sidewalk miles, the following values were assigned to each segment of all public streets in a TAZ: 0 = no sidewalk; 1 = sidewalk on one side; 2 = sidewalk on two sides.

Because many of Washington Metrorail and Metrobus services focus on the nation's capital itself, a dummy variable was introduced that denoted whether a trip by a Montgomery County resident was destined to the District of Columbia. Heading to Washington, D.C. increased the odds of transit travel. All else being equal, going to Washington, D.C. increased the odds ratio that a Montgomery County resident would patronize Metrorail or Metrobus 2.18 times [exp(0.7790)]. Although not significant at the 0.05 probability level, the inclusion of this trip-destination control variable improved the overall predictability of the model, and served to statistically isolate out the effects of this unique travel-market niche.

The remaining variables in the expanded model capture each of the three dimensions of the built environment – density, diversity, and design. Activity density at both the trip origin and destination significantly increased the odds of transit usage, consistent with findings of a vast literature (Pushkarev and Zupan, 1977; Frank and Pivo, 1994; Steiner, 1994; Dunphy and Fisher, 1996). As important was the relative mixture of land uses at the trip origin and destination, expressed in terms of the mix of population and employment of a TAZ. [7] The one design variable that entered the model, albeit with only modest predictive powers, gauged the degree of sidewalk provisions. Having relatively complete sidewalk networks at the trip destination promoted transit usage. Since all transit trips involve some degree of walking, the presence of sidewalks no doubt works to transit's favor. Still, design factors appear to have been far weaker than land-use density and diversity in shaping transit usage among Montgomery County residents. This finding is

[7] This measure of land-use diversity was also developed as part of the smart growth index, as reported in Criterion Planners/Engineers (2000).

consistent with other studies that have shown urban design to be a relatively weak land-use factor in shaping travel choice (Cervero, 1993; Handy, 1996; Crane and Crepeau, 1998).

Overall, the expanded model outperformed the basic one in predicting transit mode choice. With a substantially higher pseudo-R^2 statistic and a significant χ^2 model improvement test statistic, the expanded model strengthened the explanatory power of the binomial estimate of mode choice. As to whether this holds in a multinomial framework, we turn to the following section.

6. Multinomial analysis

For all trip purposes combined, sufficient cases were available to also support a multinomial analysis of mode choice across the three choice alternatives: drive-alone automobile, group-ride automobile, and transit. In the model presented, transit was treated as the referent mode, meaning coefficients on the utility function should be interpreted with reference to the transit option. Also, alternative-specific coefficients (including constant terms) were generally estimated under the premise that trip-makers perceive factors like travel time and pedestrian provisions differently among modal options. In the interest of parsimony, coefficients were constrained to be equal across alternatives when their alternative-specific counterparts were approximately equal.

6.1. Basic model

The basic model, shown in the left-hand side columns of Table 3, reveals that longer travel times and higher prices via transit between an origin–destination pair increases the odds of either driving alone or ride-sharing. Modal attributes were statistically significant except in the case of drive-alone travel costs.

All of the socio-economic variables in the basic model were significant predictors. The likelihood of drive-alone and group-ride automobile travel increased with vehicle ownership levels, the presence of a driver's license, and for female trip-makers. Full-time employment worked in favor of opting for transit, again ostensibly reflecting the propensity of full-time workers to have and use limitless-ride monthly transit passes.

6.2. Expanded model

The relationships between multi-modal choice and attributes of modes and trip-makers remained the same under the expanded model, although several of the socio-economic variables lost statistical significance. And as in the case of the binomial model, land-use variables in the expanded multinomial model improved overall predictability, although not as significantly. Drive-alone and group-ride automobile travel fell relative to transit riding as gross densities increased at both the trip origin and destination. And land-use mixtures at both trip ends lowered the probability of driving alone or ride-sharing versus taking a bus or train, ceteris paribus. High levels of sidewalk provisions also favored transit riding, although this relationship was not highly statistically significant. In addition, a variable that reflects the degree of transit-oriented development (TOD), specifically for multi-family housing, was found to influence mode choice, albeit fairly modestly. Having high shares of apartments and condominiums near one's place-of-residence

Table 3
Comparison of multinomial logit models for predicting drive-alone and group-ride mode choice relative to transit travel in montgomery county, all trip purposes, alternative-specific models, 1994

Variables	Basic model			Expanded model		
	Coefficient estimate	Standard error	Prob-value	Coefficient estimate	Standard error	Prob-value
Comparative modal attributes:						
Total travel time differential: transit – drive-alone (min), (*specific to drive-alone*)[a]	0. 079	0.020	0.000	0.092	0.008	0.000
Total travel time differential: transit – group-ride (min), (*specific to group-ride*)[a]	0. 069	0.013	0.000	0.083	0.025	0.001
Direct travel cost differential: transit – drive-alone (cents, 1980), (*specific to drive-alone*)[b]	0.005	0.003	0.188	0.010	0.007	0.197
Direct travel cost differential: transit – group-ride (cents, 1980), (*specific to group-ride*)[b]	0.016	0.007	0.017	0.019	0.008	0.017
Trip-maker attributes:						
Vehicle ownership: number of automobiles in household	0.385	0.223	0.084	0.339	0.244	0.145
Gender: 0 = Male, 1 = Female (*specific to drive-alone*)	0.667	0.478	0.191	1.310	0.532	0.022
Gender: 0 = Male, 1 = Female (*specific to group-ride*)	1.011	0.501	0.044	1.694	0.574	0.003
Driver's license: 0 = No, 1 = Yes (*specific to drive-alone*)	3.809	0.662	0.000	8.552	1.120	0.000
Driver's license: 0 = No, 1 = Yes (*specific to group-ride*)	1.314	0.283	0.000	5.547	0.901	0.000
Full-time employed: 0 = No, 1 = Yes (*specific to drive-alone*)	−1.812	0.841	0.031	−1.415	0.884	0.110
Full-time employed: 0 = No, 1 = Yes (*specific to group-ride*)	−1.931	0.813	0.017	−1.488	0.881	0.091
Land-use/location attributes:						
Gross density, origin TAZ: (population + employment)/gross square miles, in 1000s	–	–	–	−0.044	0.000	0.014
Gross density, destination TAZ: (population + employment)/gross square miles, in 1000s	–	–	–	−0.023	0.000	0.051
Land-use diversity, origin TAZ: employment and population relative to county ratio (*specific to drive-alone*)[c]	–	–	–	−2.488	1.033	0.016
Land-use diversity, origin TAZ: employment and population relative to county ratio (*specific to group-ride*)[c]	–	–	–	−2.679	1.035	0.011
Land-use diversity, destination TAZ: employment and population relative to county ratio, (*specific to drive-alone*)[c]	–	–	–	−1.984	1.002	0.048

Table 3 (*continued*)

Variables	Basic model			Expanded model		
	Coefficient estimate	Standard error	Prob-value	Coefficient estimate	Standard error	Prob-value
Land-use diversity, destination TAZ: employment and population relative to county ratio (*specific to group-ride*)	–	–	–	−2.222	1.005	0.027
Ratio of sidewalk miles to road miles, destination TAZ (*specific to drive-alone*)[d]	–	–	–	−0.610	0.508	0.230
Ratio of sidewalk miles to road miles, destination TAZ (*specific to group-ride*)[d]	–	–	–	−0.727	0.509	0.153
Proportion of multi-family households in origin TAZ within one-half mile of metrorail station (*specific to drive-alone*)	–	–	–	−1.64	0.814	0.151
Proportion of multi-family households in origin TAZ within one-half mile of metrorail station (*specific to group-ride*)	–	–	–	−0.984	0.767	0.183
Constant (*specific to drive-alone*)	−2.847	1.143	0.013	−0.930	1.286	0.470
Constant (*specific to group-ride*)	−0.816	0.926	0.378	1.400	1.101	0.204
Summary statistics						
Number of cases	1960			1960		
$-2\mathscr{L}(c)$: log likelihood function value, constant-only model	2868.210			2868.210		
$-2\mathscr{L}(B)$: log likelihood function value, parameterized model	2591.131			2522.860		
Model χ^2 (probability): $-2[\mathscr{L}(c) - \mathscr{L}(B)]$	277.079 (0.000)			345.350 (0.000)		
Goodness-of-fit(McFadden)	$\rho^2 = 0.097$; $\rho^2_{\text{(adjusted)}} = 0.084$			$\rho^2 = 0.121$; $\rho^2_{\text{(adjusted)}} = 0.113$		
Model improvement test: $-2[\mathscr{L}(\text{basic model}) - \mathscr{L}(\text{expanded model})]$	$\chi^2 = 68.271$, df = 10, prob. = 0.000					

[a] For transit travel, travel time consists of that occurring "in vehicle" (bus, metrorail, commuter rail), "out-of-vehicle" (including walk time for access and transfers and waiting time, both initial and transfer), and driving to access transit (if any). For drive-alone and group-ride automobile travel, total time consists of in-vehicle highway travel time plus attraction-end highway terminal time.

[b] For transit travel, direct cost comprises the transit fare. For drive-alone and group-ride automobile travel, direct cost equals the sum of operating cost (at 5.3 cents time highway distance), the toll (if any), and parking cost (if any).

[c] Diversity = 1 − {[ABS(population − employment)]/(population + employment)}.

[d] Ratio of sidewalk miles to centerline roadway miles. In measuring sidewalk miles, the following values were assigned to each segment of all public streets in a TAZ: 0 = no sidewalk; 1 = sidewalk on one side; 2 = sidewalk on two sides.

lowered the odds of driving along or ride-sharing relative to transit riding. This finding is consistent with research by JHK and Associates (1987, 1989) that revealed remarkably high rates of transit commuting among apartment and condominium dwellers who resided close to Washington Metrorail stations, with transit capturing over a 50% market share in the case of several apartment projects. High ridership rates among residents living near rail stops is partly due to residential sorting – households purposely self-selecting homes and apartments near stations for the very purpose of economizing on commuting (Voith, 1991; Cervero, 1994).

Overall, the expanded multinomial logit model out-performed the basic one. Based on both the ρ^2 goodness-of-fit statistic and the χ^2 model improvement test statistic, it appears that land-use variables contribute significantly in explaining the utilities and disutilities associated with multimodal options available to Montgomery County residents.

7. Synopsis: elasticities

In summary, the normative framework revealed that land-use factors significantly influenced mode choice among Montgomery County residents in 1994, even upon controlling for factors like modal travel times and costs. Higher densities and land-use mixtures consistently worked in favor of transit riding and against drive-alone automobile travel, all else being equal. The influences of urban design factors, represented by the sidewalk ratio variable, on mode choice were generally weaker, although the urban-design variables used in this analysis were admittedly far from being complete and perfect proxies. Thus, even though many studies in the past have failed to directly control for the influences of generalized costs when examining the impacts of land-use on mode of travel, the analyses above reveal that the general conclusions of many of these studies seem to hold – namely, that land-use matters, albeit to varying degrees. Still, only by specifying models so as to account for the relative importance of the many factors that shape mode choice can reasonably reliable estimates on the impacts of built environments be attained.

As useful as logit models are for predicting mode choice behavior, it is difficult to judge the relative importance of particular explanatory variables from model outputs. To do this, it is best to translate and summarize the results in elasticity form. Disaggregate elasticities represent the sensitivity of an individual's choice probability to a change in the value of some attribute (Ben-Akiva and Lerman, 1985). They were imputed by systematically increasing one built-environment variable at a time by 1% and applying each of the expanded models to measure the corresponding percentage change in mode-choice probabilities, setting values for all other variables in the utility function at their statistical means (in the case of ratio-scale variables) or modes (in the case of categorical-scale variables). [8] Estimates represent mode-choice point elasticities for the "typical" Montgomery County traveler. [9] Mathematically, the elasticity (E) of the probability of person n choosing mode i (P_{ni}) as a function of a change in the value of variable X_k for person n and mode i (X_{kni}), with all other variables set at their mean or modal values, equals:

[8] For the work trip analysis, the following mean values were used in calculating binomial probabilities: travel time differential = 24.3; travel cost differential = 70.3; gross density = 16.25; land-use diversity (based on comparative population and employment ratios) = 0.30; land-use diversity (based on normalized entropy index) = 0.234; sidewalk ratio = 0.585; and street density = 9.0. For the work trip analysis, mode values were: zero-car households = 0; one-car households = 0; driver's license = 1. For the analysis of combined trip purposes, the following mean values were used in calculating binomial and multinomial probabilities: travel time differential = 25.3; travel cost differential = 49.2; gross density = 14.3; land-use diversity (based on normalized entropy index) = 0.29; sidewalk ratio = 0.585; and proportion of multi-family housing within a half-mile of a rail station = 0.19. Mode values for the analysis of combined trip purposes used in estimating elasticities were: zero-car households = 0; female gender = 1; driver's license = 1; and full-time employment = 1.

[9] It should be noted that these estimates do no represent the average elasticities among individual travelers but rather elasticities calculated for average values of variables contained in utility expressions. Because logit functions capture non-linear relationships, elasticities based on the average representative utility are not necessarily the same as the average of individual elasticities. For further discussions, see Train (1986).

Table 4
Point elasticity estimates imputed from mode choice models: percentage change in probability of choosing mode with a 1% increase in built-environment factor

Built-environment factors:	Home-based work trips Drive-alone	All trip purposes Drive-alone	Group-ride	Transit
Gross density, origin	−0.151	−0.163	−0.124	+0.511
Gross density, destination	−0.259	−0.137	−0.096	+0.268
Land-use diversity, origin	−0.141	−0.340	−0.361	+0.615
Land-use diversity, destination	−0.197	−0.291	−0.165	+0.452
Sidewalk ratio, origin	−0.390	–	–	–
Sidewalk ratio, destination	−0.448	−0.366	−0.062	+0.327
Transit-oriented multi- family housing, origin	–	−0.052	−0.066	+0.195
Job accessibility, origin	+0.141	–	–	–
Labor accessibility, destination	+0.290	–	–	–

$$E^{P_{ni}}_{X_{kni}} = (\partial P_{ni}/\partial X_{kni})(X_{kni}/P_{ni}), \forall V_{ni} = f(\bar{x}_{1ni}, \bar{x}_{2ni}, \ldots, \bar{x}_{k-1ni}, \bar{x}_{k+1ni}, \ldots). \tag{5}$$

Table 4 presents the point elasticities stratified by type of trip and mode. Consistent with the logit model results, transit usage was found to be most sensitive to changes in land-use attributes. Among the "3 Ds" of the built environment, the dimensions of density and diversity exerted the strongest influences on the probability of selecting a mode. The influences of design factors (represented by the sidewalk ratio variable) on mode choice were more modest, as were the affects of accessibility and transit-oriented housing. In general, these elasticity estimates align with those reported in previous studies of land-use impacts on built environments (Cervero, 1991; Cervero and Kockelman, 1997; Walters et al., 2000; Ewing and Cervero, 2001).

One practical application of mode-choice elasticities is to post-process mode-choice models that are incompletely specified for purposes of studying policy initiatives like transit-oriented development (TOD). This was done in a recent study of a proposed busway and rail transit system in Charlotte, North Carolina. Charlotte's *2025 Integrated Transit/Land-Use Plan* called for compact, mixed-use development around proposed transit stations to generate ridership sufficient to justify the billion-dollar-plus investment that went before Charlotte voters in a November 1998 sales-tax referendum. Unfortunately, Charlotte's four-step travel-demand forecasting model, calibrated in the late 1960s, was not up to the task of estimating the ridership impacts of TOD scenarios. Neither trip generation nor mode choice models included density or any other land-use variables. Time constraints and data limitations precluded the recalibration of models to directly account for built-environment influences. Accordingly, mode-choice estimates for the proposed Charlotte plan were "post-processed" by using transit-boarding elasticities as functions of densities and other factors based on experiences of 285 light rail stations throughout the United States and Canada (Parsons Brinckerhoff Quade and Douglas, 1996). Elasticity estimates were used to pivot off of baseline projections to better account for the likely impacts of proposed TODs. The results helped to build broad-base support for the proposed transit program, culminated by Charlotte voters agreeing to tax themselves over the next 20 years, one of the few cities where transit tax referenda have passed in recent years.

8. Conclusion

Producing estimates of the likely travel-demand impacts of changes to the built environment has never been easy. Regardless, numerous studies have attempted to do so based on models that leave lots of room for improvement. Model mis-specification leads analysts to read too much or too little into estimated relationships. Statistically, the influences of omitted variables get soaked up by the modeled variables – which means (by ignoring land-use factors) most regional travel-demand models end up overstating or understating the importance of travel time and cost, while studies of land use impacts on travel demand end up misinterpreting (by ignoring generalized costs) the importance of the built environment.

The results of this research argue for the explicit inclusion of land-use variables in the utility expressions of mode choice models in urbanized settings. They also reveal the importance of including economic attributes of competing modes, notably travel time and price variables, in the specification of models that test the influences of land-use factors on travel demand. A logical extension of the work presented in this paper would be to account for the possible influences of self-selection on mode choice. This might take the form of testing the influences of three blocks of variables on mode of travel: (1) traditional travel time, cost, and demographic variables; (2) attitudinal and lifestyle preference variables; and (3) built-environment factors. Such a formulation would allow the marginal contributions of land- use variables on mode choice to be more fully gauged after the two vectors of variables are controlled for (similar to work carried out by Kitamura et al., 1997, in evaluating marginal contributions of land-use factors on trip generation).

Recalibrating mode choice models to incorporate characteristics of built environments is no easy task, in part because in many metropolitan areas variables related to land-use diversity and urban design are not readily available. A second-best approach is to incorporate land-use factors in the post-processing of travel-demand forecasts. Elasticities provide a useful basis for refining modal split estimates by pivoting off of the forecasts generated from under-specified models.

Continuing interest in "growing smart" and sustainable forms of urbanization promises that the study of built environments and their influences on travel behavior will not wane in importance. If policy-makers are to make informed decisions on land use and transportation proposals, it is incumbent that a normative analytical framework, ideally rooted in the traditions of consumer choice and travel demand theories, be adopted.

Acknowledgements

I thank Rick Hawthorne and Tom Harrington of the Montgomery County Planning Department for making the data available to support this research and for providing helpful comments on the models that were estimated. I also thank Reid Ewing for assisting with the organization of data used in this research. Lastly, I thank an anonymous reviewer for providing very thorough and constructive comments on this paper.

References

Badoe, D., Miller, E., 2000. Transportation-land use interaction: empirical findings in North America, and their implications for modeling. Transportation Research D 5 (4), 235–263.

Ben-Akiva, M., Lerman, S., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press, Cambridge, MA.

Bernick, M., Cervero, R., 1997. Transit Villages for the Twenty-First Century. McGraw-Hill, New York.

Boarnet, M., Sarmiento, S., 1998. Can land use policy really affect travel behaviour? Urban Studies 35 (7), 1155–1169.

Boarnet, M., Greenwald, M., 2000. Land use, urban design, and nonwork travel: reproducing other urban areas' empirical test results in Portland, Oregon. Transportation Research Record 1722, 27–37.

Boarnet, M., Crane, R., 2001. Travel by Design: The Influence of Urban Form on Travel. Oxford University Press, New York.

Calthorpe, P., 1993. The Next American Metropolis: Ecology Community and the American Dream. Princeton Architecture Press, New York.

Cambridge Systematic. 1994. The effects of land use and travel demand management strategies on commuting behavior. US Department of Transportation, US Environmental Protection Agency, US Department of Energy, Washington, D.C. Report prepared for the Travel Model Improvement Program.

Carter, J., Mathias, J. 1995. transit-supportive land use in Montgomery County, Maryland. Paper presented at the 1995 APA/CIP Conference, Toronto, April.

Cervero, R., 1988. Land use mixing and suburban mobility. Transportation Quarterly 42, 429–446.

Cervero, R., 1989. America's Suburban Centers: The Transportation-Land Use Link. Unwin-Hyman, Boston.

Cervero, R., 1991. Land uses and travel at suburban activity centers. Transportation Quarterly 45 (4), 479–491.

Cervero, R. 1993. Transit-supportive development in the United States: experiences and prospects. US Department of Transportation, Federal Transit Administration, National Technical Information Service,Washington, D.C.

Cervero, R., 1994. Transit-based housing in California: evidence on ridership impacts. Transportation Policy 1 (3), 174–183.

Cervero, R., 1996. Mixed land-uses and commuting: evidence from the American housing survey. Transportation Research A 30 (5), 361–377.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3 Ds: density, diversity, and design. Transportation Research D 2 (3), 119–219.

Cervero, R., Radisch, C., 1996. Travel choices in pedestrian versus automobile-oriented neighborhoods. Transport Policy 3 (3), 127–141.

Cervero, R., Seskin, S., 1995. An evaluation of the relationship between transit and urban form. Research Results Digest, No. 7. Transit Cooperative Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Crane, R., 2000. The influence of urban form on travel: an interpretative review. Journal of Planning Literature 15 (1), 3–23.

Crane, R., Crepeau, 1998. Does neighborhood design influence travel? A behavioral analysis of travel diary and GIS data. Transportation Research D 3, 225–238.

Criterion Planners/Engineers, with Fehrs & Peers Associates. Smart growth index: a sketch tool for community planning, reference guide. Report prepared for the US Environmental Protection Agency, July 2000.

Domencich, T., McFadden, D., 1975. Urban Travel Demand: A Behavioral Analysis. North-Holland, Amsterdam.

Dunphy, R., Fisher, K., 1996. Transportation, congestion, and density: new insights. Transportation Research Record 1522, 89–96.

Ewing, R., Cervero, R. 2001. Travel and the built environment. Paper presented at the Annual Meeting of the Transportation Research Board, Washington, D.C.

Frank, L., Pivo, G., 1994. Impacts of mixed use and density on utilization of three modes of travel: single-occupant vehicle, transit, and walking. Transportation Research Record 1446, 44–52.

Garreau, J., 1991. Edge City: Life on the New Frontier. Doubleday, New York.

Handy, S., 1992. Regional versus local accessibility: neo-traditional development and its implications for non-work travel. Built Environment 18 (4), 253–267.

Handy, S., 1996. Methodologies for exploring the link between urban form and travel behavior. Transportation Research D 1 (2), 151–165.

JHK and Associates, 1987. Development-Related Ridership Survey I. Washington Metropolitan Area Transit Authority, Washington, D.C.

JHK and Associates, 1989. Development-Related Ridership Survey II. Washington Metropolitan Area Transit Authority, Washington, D.C.

Kitamura, R., Mokhtarian, P., Laidet, L., 1997. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay area. Transportation 24, 125–158.

McFadden, D., 1976. The mathematical theory of demand models. In: Stopher, P., Meyberg, A. (Eds.), Behavioral Travel-Demand Models. Lexington Books, Lexington, MA.

Milone, R. 2000. Version 2 Travel Model Calibration Report. Metropolitan Washington Council of Governments and the National Capital Regional Transportation Planning Board, Washington, D.C.

Parsons Brinckerhoff Quade and Douglas. 1996. Transit and Urban Form, vol. 1. Transportation Research Board, Transit Cooperative Research Program, Washington, D.C., Report 16.

Pindyck, R., Rubinfeld, D., 1991. Econometric Models & Economic Forecasts. McGraw-Hill, New York.

Pickup, L., 1989. Women's travel requirements: employment, with domestic constraints. In: Grieco, M., Pickup, L., Whipp, R. (Eds.), Gender, Transport, and Employment. Gower, Brookfield, Vermont.

Portland Metro. 1998. Technical Specifications for the March 1998 Travel Demand Model. Portland Metro, Portland, Oregon, p. 7.

Pushkarev, B., Zupan, J., 1977. Public Transportation and Land Use Policy. Indiana University Press, Bloomington.

Rodier, C., Abraham, J., Johnston, R. 2001. Anatomy of induced travel using an integrated land use and transportation model in the Sacramento Region. Paper presented at the 80th Annual Meeting of the Transportation Research Board, Washington, D.C.

Rosenbloom, S., Burns, E., 1995. Why working women drive alone: implications for travel reduction programs. Transportation Research Record 1459, 35–41.

Small, K., Winston, C., 1999. The demand for transportation: models and applications. In: Gómez-Ibáñez, J., Tye, W., Winston, C. (Eds.), Essays in Transportation Economics and Policy: A Handbook in Honor of John R. Meyer. Brookings Institution Press, Washington, DC, pp. 11–55.

Steiner, R., 1994. Residential density and travel patterns: review of the literature. Transportation Research Record 1466, 43–47.

Train, K., 1986. Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand. MIT Press, Cambridge, MA.

Untermann, R., 1984. Accommodating the Pedestrian: Adapting Towns and Neighborhoods for Walking and Bicycling. Van Nostrand Reinhold, New York.

Voith, R., 1991. Transportation, sorting and house values. American Real Estate and Urban Economics Association 19 (2), 117–137.

Walters, G., Ewing, R., Schroeer, W., 2000. Adjusting computer modeling tools to capture effects of smart growth, or poking at the project like a lab rat. Transportation Research Record 1722, 17–26.

Windmeijer, F., 1995. Goodness-of-fit measures in binary choice models. Econometric Reviews 14 (1), 101–116.

Robert Cervero is Professor of City and Regional Planning at the University of California at Berkeley.