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TRAVEL DEMAND AND THE 3Ds: DENSITY, DIVERSITY, AND DESIGN

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Abstract—The built environment is thought to influence travel demand along three principal dimensions—density, diversity, and design. This paper tests this proposition by examining how the '3Ds' affect trip rates and mode choice of residents in the San Francisco Bay Area. Using 1990 travel diary data and land-use records obtained from the U.S. census, regional inventories, and field surveys, models are estimated that relate features of the built environment to variations in vehicle miles traveled per household and mode choice, mainly for non-work trips. Factor analysis is used to linearly combine variables into the density and design dimensions of the built environment. The research finds that density, land-use diversity, and pedestrian-oriented designs generally reduce trip rates and encourage non-auto travel in statistically significant ways, though their influences appear to be fairly marginal. Elasticities between variables and factors that capture the 3Ds and various measures of travel demand are generally in the 0.06 to 0.18 range, expressed in absolute terms. Compact development was found to exert the strongest influence on personal business trips. Within-neighborhood retail shops, on the other hand, were most strongly associated with mode choice for work trips. And while a factor capturing 'walking quality' was only moderately related to mode choice for non-work trips, those living in neighborhoods with grid-iron street designs and restricted commercial parking were nonetheless found to average significantly less vehicle miles of travel and rely less on single-occupant vehicles for non-work trips. Overall, this research shows that the elasticities between each dimension of the built environment and travel demand are modest to moderate, though certainly not inconsequential. Thus it supports the contention of new urbanists and others that creating more compact, diverse, and pedestrian-orientated neighborhoods, in combination, can meaningfully influence how Americans travel. © 1997 Elsevier Science Ltd

1. INTRODUCTION

A host of urban design philosophies—new urbanism, transit-oriented development, traditional town planning—have gained popularity in recent years as ways of shaping travel demand. All share three common transportation objectives: (1) reduce the number of motorized trips, what has been called *trip degeneration*; (2) of trips that are produced, increase the share that are *non-motorized* (i.e. by foot or bicycle); and (3) of the motorized trips that are produced, *reduce travel distances* and *increase vehicle occupancy levels* (i.e. encourage shorter trips and more travel by transit, paratransit, and ride-sharing). An expected outcome of degenerating trips and weaning people from their cars, proponents hope, will be a lessening of the negative consequences of an automobile-oriented society—namely, reductions in air pollution, fossil fuel consumption, and class and social segregation (Banister and Lichfield, 1995; Dittmar, 1995).

New urbanists, neotraditionalists, and other reform-minded designers argue for changing three dimensions, or the 3Ds, of the built environment—density, diversity, and design—to achieve these objectives. While the effects of density on travel demand have long been acknowledged (e.g. Levinson and Wynn, 1963), the effects of diversity and design have just as long been ignored. This paper examines the connection between the 3Ds of the built environment and travel demand. Notably, it tries to sort through the relative influences of the three dimensions after controlling for other explainers, like travellers' demographic characteristics. It does this mainly by applying the technique of factor analysis to gauge the relative influence of each dimension as well as their collective impacts. The paper tests the propositions of the new urbanists and others that compact neighborhoods, mixed land uses, and pedestrian-friendly designs 'degenerate' vehicle trips and encourage residents to walk, bike, or take transit as substitutes for automobile travel, particularly for non-work purposes.

The underlying hypotheses addressed in this paper are outlined in Table 1. One, higher densities, richly mixed land uses, and pedestrian-friendly designs are thought to lower the rates of vehicular travel (i.e. trip degeneration), expressed in this paper as daily personal vehicle miles traveled per household. Two, these three dimensions are thought to be positively associated with the choices of shared-ride, transit, and non-motorized modes, what we call non-personal vehicular travel. Also, the 3Ds are thought to be associated with higher occupancy levels for personal vehicle travel (i.e. higher incidence of non-single occupant vehicle (non-SOV) travel). Moreover, density, diversity, and design are postulated to increase non-personal vehicle (non-PV) and non-SOV travel for both work and non-work trips. In the case of non-work trips, more compact settings with neighborhood retail outlets and pleasant walking environments are thought to induce more foot and bicycle travel and short-hop transit trips, especially for purposes like personal-business travel (where there is less of a need for a car to haul purchases). And in the case of work trips, pedestrian-friendly environments and the presence of convenience stores near residences are expected to induce commute trips via transit and non-motorized modes.

To test these hypotheses, we carry out statistical tests using variables that, individually and collectively, capture the three built environment dimensions for 50 neighborhoods in the San Francisco Bay Area. As used here, 'built environment' means physical features of the urban landscape (i.e. alterations to the natural landscape) that collectively define the public realm, which might be as modest as a sidewalk or an in-neighborhood retail shop or as large as a new town. Regardless of scale, however, all features of the built environment incorporate some elements or combinations of density, diversity, and design. Before presenting the research design and methodological approach to our study, it is instructive to briefly review some of the conceptual underpinnings and relevant findings from past research on the relationship between built environments and travel demand.

2. CONCEPTUAL FRAMEWORK

Within the past decade, a considerable amount of research has been carried out, at varying degrees of depth and sophistication, on how built environments influence travel demand. While motivated by movements like the new urbanism and transit village planning, the theoretical underpinnings of these works lie in traditional utility-based theories of urban travel demand. At the most rudimentary level, travel demand is a 'derived' demand in the sense that trips are made and distributed on the basis of the desire to reach places, whether office buildings, ballparks, or shopping centers. The characteristics of these places—i.e. their land uses, densities, design features—can affect not only the number of trips generated, but also modes and routes of travel. While characteristics of origin–destination interchanges, like the relative prices and service qualities of competing modes, are known to affect travel demand, so are features of the trip ends (i.e. origins and destinations) themselves—features that we have defined as the 3Ds of the built environment.

Normative explanations of how built environments can shape travel behavior, framed around traditional utility-based travel demand theories, can be found in Handy (1992) and Cervero and Seskin (1995). Take the dimension of density, for instance. Compact neighborhoods can degenerate vehicle trips and encourage non-motorized travel in several ways. One, by bringing origins and destinations closer together, there become many more opportunities for leaving one's car at home and walking or cycling to a destination. Moreover, compact neighborhoods tend to have less parking, better quality transit services, wider mixes of land uses, and larger shares of low-income

Table 1. Hypothesized direction of relationships between dimensions of built environments and travel demand

Dimension of built environments	Influences on		
		Non-SOV/non-PV mode choice*	
	Vehicle trip rates	Non-work trips	Work trips
Density	–	+	+
Diversity	–	+	+
Design	–	+	+

*SOV = single-occupant vehicle; PV = personal vehicle.

households, all factors that reduce car usage. Disentangling the relative contributions of these elements to trip-making requires far richer data than have been available to date; consequently, density is understood to be associated with these other potential explainers and together they are thought to reduce automobile travel. In view of data and methodological limitations (Handy, 1991; Crane, 1996), inquiries into the influences of built environments on travel behavior are necessarily tentative and exploratory. And since complete statistical control is never fully introduced, any relationships that are uncovered are necessarily associative rather than causal. The work we present aims to not only refine our understanding of these associations, but also to extend methodological approaches to measuring different attributes of the built environment and their relationship to travel demand.

Explanations of how other dimensions of built environments, like diversity and design, influence travel demand follow similar logics. That placing convenience stores within neighborhoods can produce walk and cycling trips that substitute for external (i.e. out-of-neighborhood) vehicular trips is intuitive (Handy, 1993; Cervero and Radisch, 1996). So is the notion that siting restaurants, shops, and service outlets in suburban office settings can induce workers to ride-share by making midday destinations more conveniently reached, thus reducing the need to have a car on-site (Cervero, 1989). Perhaps less obvious is the possible benefit of in-neighborhood retail shops on residents' commuting mode. One view holds that conveniently siting grocery shops and the like between transit stops and residential neighborhoods can encourage transit commuting by allowing patrons to link work and shop trips, via foot, when en route to home in the evening.

The effects of design treatments, like aligning shade trees along sidewalks and siting parking lots in the rear of stores, on travel demand are thought to parallel the influences of density and diversity. Design schemes can not only make destinations more accessible and conveniently reached by foot (as with siting store entrances near curbsides and parking in the rear), but can also reward pedestrians, cyclists, and transit riders with amenities (like shade trees and civic squares). Some charge that such designs are not really amenities so much as basic provisions, i.e. providing pedestrians and cyclists with the same level of facilities provided to motorists, thus 'levelling the playing field'. Although many new urbanists are committed to reducing the dominance of the private car in America's suburbs, a stronger motivation seems to be the desire to increase suburbia's social and cultural diversity while also instilling a sense of community pride and attachment (Calthorpe, 1994; Downs, 1994; Katz, 1994). While charges of social engineering and environmental determinism have been levelled at these and other urban design movements, from the perspective of travel-demand theory, the physical make-up of places (i.e. trip origins and destinations) is unquestionably relevant to understanding travel behavior. Just as utility theory says that travel time differentials between car and bus can influence mode choice between origin–destination pairs, it also tells us that a dense, mixed-use, pedestrian-friendly downtown destination is more likely to induce transit riding than a sprawling, single-use, auto-oriented suburban one. That is, characteristics of trip ends, and not just trip interchanges, influence travel behavior and choices.

3. PRIOR RESEARCH

Research generally supports the theories of how built environments shape travel demand, though to varying degrees and with not altogether consistent findings. Much of the work to date has focused on how the designs of large employment sites influence commute trips. Consistent with theory, studies agree that pedestrian-oriented designs and on-site stores and services, like banks and shops, encourage non-auto travel. In a study of 59 large-scale employment centers in the U.S., Cervero (1989) found centers with on-site and nearby retail services averaged relatively high rates of midday walk travel and low rates of drive-alone commuting. More recently, Cambridge Systematics (1994) explored the connection between the work environment and workers' commute modes (across 330 companies in the Los Angeles region that had introduced transportation demand management measures in response to Regulation XV air quality mandates). The study found that transit captured 6.4% of commute trips in 'diverse-mix' employment areas, vs 2.9% of commute trips in 'no-mix' areas. Transit shares were 3.6 percentage points higher in areas with 'convenience-oriented services' vs those without.

While studies at the residential ends of trips have shown population density to be an important predictor of travel choice (Pushkarev and Zupan, 1977; Newman and Kenworthy, 1989; Dunphy and Fisher, 1996), only recently have other dimensions of the built environment been probed. Handy (1993) and Fehr and Peers Associates (1992) found substantially higher rates of foot and transit travel in traditional communities vs conventional suburban subdivisions of the San Francisco Bay Area, though factors like differing transit service levels were not controlled for. Recent studies of travel in Broward County, Florida (Ewing *et al.*, 1994) and Washington's Puget Sound (Frank and Pivo, 1994) further suggest mixed-use neighborhoods induce shorter, within-neighborhood travel. Ewing (1994) has argued that many of the benefits of density may in actuality be attributable to mixed land uses since the two usually co-exist.

Two studies which are particularly germane to our analysis—because they focused on the San Francisco Bay Area, examined multiple descriptors of the built environment, and introduced statistical controls—are those by Holtzclaw (1990, 1994) and Kitamura *et al.* (1994). Using data from smog-check odometer readings, Holtzclaw (1990) found vehicle miles traveled (VMT) per capita to be around two-thirds lower in dense, mixed-use settings than in suburban ones. A follow-up study of 28 Californian communities further substantiated these findings—statistical models suggested that VMT per household fell by one-quarter as densities doubled, and by around 8% with a doubling of transit services, controlling for factors like household income (Holtzclaw, 1994). Kitamura *et al.* (1994) concluded "neighborhood characteristics add significant explanatory power when socio-economic differences are controlled for"; however, the use of simple dummy variables to signify the presence of mixed land uses and pedestrian/bicycle facilities and respondents' perceptions of neighborhood features could explain why most of their built environment variables were insignificant.

The recent Land Use–Transportation–Air Quality (LUTRAQ) study conducted by Parsons Brinckerhoff Quade and Douglas, Inc. (1993) for the Portland, Oregon region has been one of the more ambitious efforts to date to gauge the travel impacts of 'pedestrian friendliness'. In the LUTRAQ study, neighborhoods were subjectively rated on a 1–5 scale by a panel of experts in terms of: (1) ease of street crossings; (2) sidewalk continuity; (3) local street characteristics (grid-iron vs cul-de-sac patterns); and (4) topography. While simple correlations showed that neighborhoods with highly-rated pedestrian environments averaged more transit trips, the 'pedestrian-friendliness' variable provided only marginal explanatory power in a regression model of neighborhood VMT.

4. DILEMMAS IN STUDYING THE TRANSPORT–LAND USE LINK

Researchers face a number of dilemmas in probing the links between the built environment and contemporary travel. One, transportation and land-use data are usually compiled by separate entities for different purposes and as a result are not always compatible. To study non-work travel at a disaggregate level, one has to turn to metropolitan travel surveys. (In contrast, disaggregate work-trip data are more readily available from the decennial census.) In the case of the San Francisco Bay Area, the most extensive regional travel survey is the Bay Area Travel Survey (BATS), last conducted by the Metropolitan Transportation Commission in 1990–1991.* Unfortunately, there are often too few travel-diary records for individual census tracts to support any rigorous modeling of how the built environments of those tracts shape travel demand. BATS, as with most metropolitan surveys, was conducted to support regional travel-demand forecasting, and thus is meant for macro-level, rather than neighborhood-scale, analyses. While census tracts can be combined to produce enough trip records to support modeling, this often ends up creating very large subareas, larger than what traditionally represents a residential neighborhood.

Another barrier to carrying out neighborhood-scale studies is the absence of rich, tract-level data on built environments. The U.S. census contains tract-level data on the densities, housing, and socio-demographic characteristics of tracts, though very little is available on specific land-use compositions or urban design features. In the San Francisco region, the Association of Bay Area Governments (ABAG) has a digital database on dominant land uses for hectare grid cells for the entire nine-county Bay Area, and we relied on these data for our study. However, there are no

*The 1990–1991 BATS compiled detailed single- and multiple-weekday travel-diary data for persons five years of age and older for 9359 Bay Area households. In addition, personal and household data were compiled and cross-coded for each trip record.

comprehensive databases that gauge the quality of walking environments, the sizes and types of commercial activity centers, parking supplies, landscaping provisions, and other detailed features that are thought to influence travel behavior, especially for more discretionary, non-work trips.

Even with larger, more comprehensive databases, it is questionable whether many built environment variables will show up as statistically significant. This is partly because of the colinearity between factors like neighborhood densities, mixed use levels, and pedestrian amenities—i.e. relatively dense neighborhoods tend to have a greater variety of land uses, shorter blocks, grid-like street patterns, sidewalk networks, and so on. Moreover, relatively coarse indices are normally used to measure built environments, often relying on subjective measures, such as ordinal 'pedestrian environmental factors' (Parsons Brinckerhoff Quade and Douglas, Inc., 1993) or simple dummy variables and respondents' perceptions of neighborhood quality (Kitamura *et al.*, 1994). In contrast, most control variables, such as household incomes and travel distances, are measured on a continuous ratio scale and thus enjoy a predictive advantage. Measurement invariably remains imperfect regardless of how many variables are used to capture elements of the built environment. For example, while the presence of street trees might serve as a proxy for an attractive walking corridor, the trees' value in providing shade might be limited to certain seasons and times of day that do not necessarily correspond to the periods when travel-diary data were compiled. And, of course, it could very well be that some factors, like urban design, indeed have little bearing on fundamental travel choices. In a study of transit-supportive designs across a number of U.S. cities, Cervero (1993, p. 220) concluded that "micro-design elements are too 'micro' to exert any fundamental influences on travel behavior; more macro-factors, like density and the comparative cost of transit vs automobile travel, are the principal determinants of commuting choices".

5. RESEARCH DATA BASE

To address the research questions posed, it was necessary to compile data from different sources and merge them into a single database. Travel data and socio-economic data were obtained from the 1990–1991 BATS and, for 50 sampled neighborhoods, data on land uses were compiled from field surveys, the ABAG land-use inventory, and the Census Transportation Planning Package (CTPP). Data on the design features of neighborhoods, such as block lengths and sidewalk provisions, were compiled for the 50 neighborhoods based on field surveys.

In building a database for this research, every person trip was treated as a data record.* Socio-economic and household data (from BATS) compiled for the person making the trip were appended to each record, as were the built-environment characteristics of the person's home neighborhood (from the census, ABAG land-use data, and field surveys). For several variables (e.g. employment density, accessibility indices), characteristics of the person's destination were likewise appended to each travel record. Thus, the following data were available for each person trip record:†

Travel data —from BATS (e.g. mode, trip length);
Personal data—from BATS (e.g. age, gender);
Household data—from BATS (e.g. number of persons, income);
Land-use data—from census (e.g. population density), CTPP (e.g. employment density), ABAG (e.g. dominant land uses), and field surveys (e.g. uses in activity centers);

*The BATS travel diaries typically recorded all trips made by each person above 5 years of age on a particular survey day. For travel demand modeling purposes, trips are treated as independent events both across trip-makers and members of households. Virtually all travel demand modeling work to date has invoked this assumption, usually implicitly, as a concession to the shortcomings, both theoretically and methodologically, of contemporary approaches for measuring and modeling urban travel behavior.

†Tract-level data on population densities were obtained from the U.S. census, Summary Tape File 3-A. Data on employment (e.g. number of jobs, occupational breakdowns, densities) at place of employment were obtained from the CTPP, Part II, for the San Francisco–Oakland–San Jose MSA. ABAG land-use data were used in developing indexes of land-use diversity. Data on transportation supplies, such as the lineal feet of freeway within or bordering a tract and number of intersections, were compiled from *Thomas Brothers Maps: Alameda-Contra Costa Counties, 1994.* Data on local bus services, such as revenue miles of bus service and average headways, were acquired from route maps and printed schedules provided by local transit operators (e.g. SamTrans, AC Transit).

Design data—from field surveys (e.g. block length, presence of street trees) and regional maps (e.g. proportion of intersections that are four-way);* and
Transportation supply data—from field surveys (e.g. availability of on-street parking), regional maps (e.g. distance to nearest freeway interchange), and transit schedules (e.g. transit service intensity).

Overall, then, three grains of data were used in the analysis—person information (trips, socio-demographics like age); household information (vehicles per person in household); and tract information (density and land use). All were tied to the most disaggregate level—the individual trip-maker. This meant there was less variation across the household-level variables, and even less variation across the built environment and urban design variables (i.e. only 50 possible data values).

6. STUDY CASES

Because of the need to collect fairly detailed and original data on the built environment, we limited our research to 50 neighborhoods in the San Francisco Bay Area which corresponded to census tracts. Having at least 50 neighborhoods was viewed as essential in recording enough variation in the built environment to support reasonably sophisticated modeling. Each neighborhood consisted of either a single census tract or a pair of adjoining tracts.†

Neighborhoods were selected to ensure each had at least 20 BATS household records and that, collectively, they were reasonably representative of built environments across the region. In light of the limited travel diary data for most census tracts, a purely random sample of census tracts was not possible.‡ However, since BATS household records were randomly sampled, linking our data cases to BATS ensured a high degree of randomness among selected neighborhoods.

As shown in Table 2, the selected neighborhoods were fairly representative of the region at large, though they tended to be slightly wealthier and had slightly smaller household sizes than the Bay Area average. Also, as shown in Fig. 1, the selected neighborhoods were geographically spread throughout the region, with at least one case from each of the nine Bay Area counties.§ The

Table 2. Comparison of mean household characteristics of Bay Area and Sample Cases, 1990 data

	Nine-county Bay Area	50 neighborhood cases*	Percentage difference
Mean household income, annual	$42,000†	$45,600	8.6
Mean household size (no. of members)	2.59‡	2.41	7.5
Mean household density (households per residential acre)	6.78‡	6.32	7.3

Sources: *Metropolitan Transportation Commission (1994) *1990–1991 Bay Area Travel Survey*. Metropolitan Transportation Commission, Oakland, CA. Association of Bay Area Governments (1993) *1990 Land Use Summary*. Association of Bay Area Governments, Oakland, CA.
†U.S. Census Bureau (1994) *1990 U.S. Census Summary: Social, Economic, and Housing Characteristics for California*. U.S. Census Bureau, Washington, D.C.
‡Association of Bay Area Governments (1994) *Projections '94*. Association of Bay Area Governments, Oakland, CA.

*The land-use and design data fell into three groups—general street data, non-residential land-use compositions, and residential neighborhood characteristics. Because it was not possible to study every street section within a tract, a random sample of 20 block faces was selected for each tract, from which measures such as the average block length and sidewalk width were recorded. The field survey also placed particular attention on detailing characteristics of activity centers—liberally defined as any collection of retail or service land uses that either comprise a land area over 10,000 square feet, or consists of three or more stores that either adjoin or lie within 200 feet of each other along the same street. For the most part, activity centers contained neighborhood and community retail activities. A 100% inventory of all activity centers within each surveyed neighborhood was compiled.

†Not every household recorded non-work, home-based trips by adult family members. Thus, in instances where fewer than 20 non-work trips were recorded for a tract, two adjoining census tracts were combined to produce at least 20 non-work, home-based trips.

‡A purely random sample could not be drawn since the majority of census tracts in the region had fewer than four household BATS records. A purely random sample would have also likely generated many similar suburban tracts that have little variation in their built environments, thus inhibiting model estimation.

§For each of the Bay Area's nine counties, the number of neighborhoods that we studied (and households within them with surveyed BATS travel data) were: San Francisco—13 (191 households); Marin—7 (132 households); Alameda—7 (120 households); San Mateo—6 (105 households); Contra Costa—6 (86 households); Santa Clara—5 (95 households); Napa—3 (137 households); Sonoma—2 (50 households); and Solano—1 (20 households).

higher concentration of sampled neighborhoods in denser, built-up parts of the Bay Area, like San Francisco and Oakland, reflects these cities' relatively high shares of regional population.

7. STUDY VARIABLES

The built environment variables compiled for this research sorted neatly into the '3Ds', and are listed in Table 3. While most of the selected variables related to density are similar to those used in prior studies (e.g. Holtzclaw, 1994; Frank and Pivo, 1994), our work incorporates many more measures of land-use diversity and urban design than most previous studies. Along the *density* dimension, besides population and employment density, accessibility is treated as an indicator of

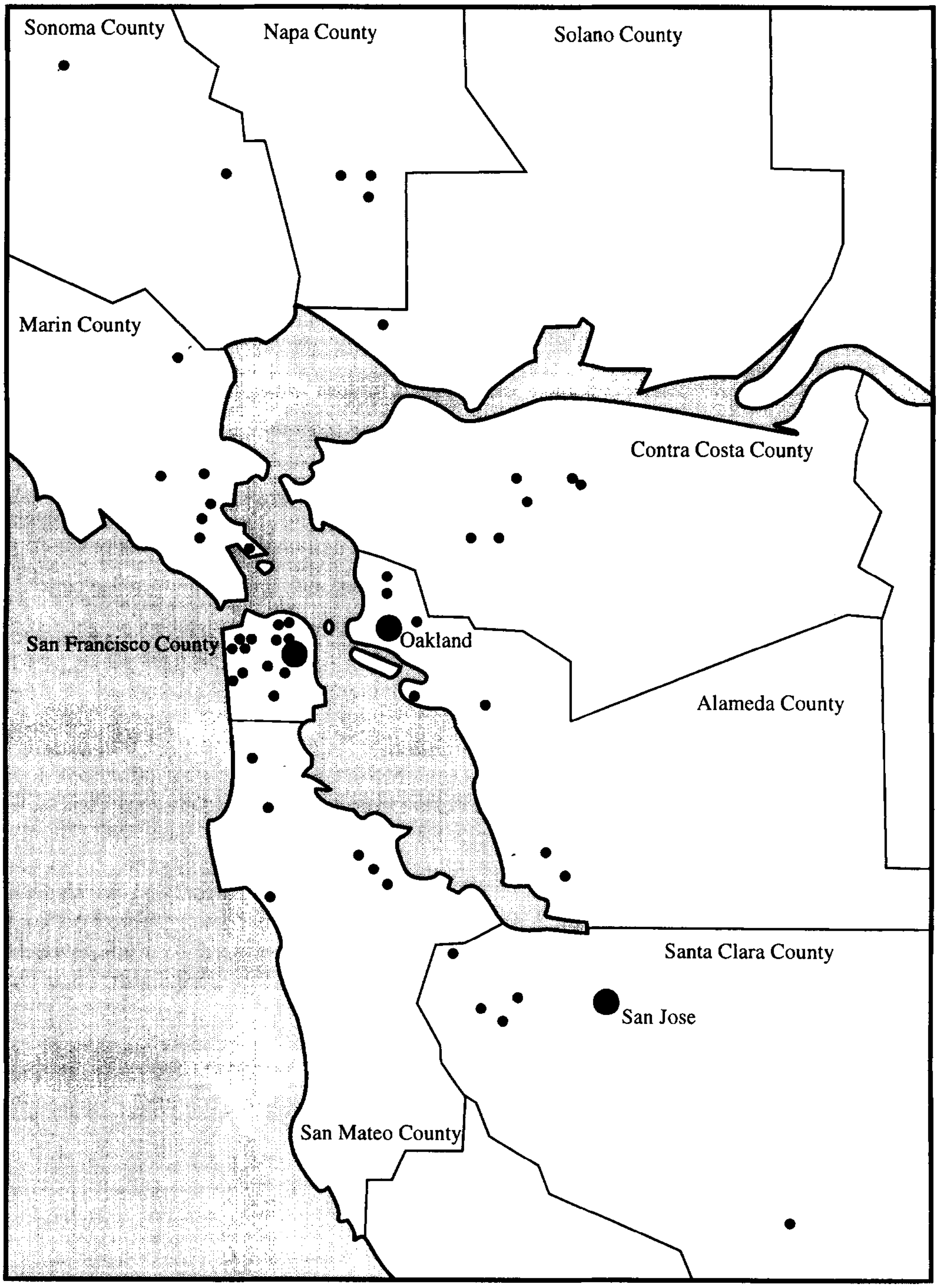

Fig. 1. Location of 50 case study neighborhoods, San Francisco Bay Area.

Table 3. Built environment variables

1. Density
- Population density: population per developed acre
- Employment density: employment per developed acre
- Accessibility to jobs: expressed in a gravity model form; for zone i, Accessibility Index = $\{\sum_j (\text{jobs})_j \exp[\lambda\ t_{ij}]\}$, where i = origin (residential) traffic analysis zone, j = destination traffic analysis zone, t_{ij} = travel time between zones i and j, and λ = empirically derived impedance coefficient. The accessibility index serves as a proxy of relative proximity and compactness of land uses

2. Diversity
- Dissimilarity index: proportion of dissimilar land uses among hectare grid cells within a tract. For each tract, computed as: $\{[\sum_j^k \sum_l^8 (X_l/8)]/K\}$, where K = number of actively developed hectare grid-cells in tract, and X_l = 1 if land-use category of neighboring (i.e. abutting or caddy-corner) hectare grid-cell differs from hectare grid-cell j (0 otherwise). (See Fig. 2)
- Entropy: mean entropy for land-use categories among hectare grid cells within a half mile radius of each hectare grid cell within a tract. For each tract, computed as: $\{\sum_k [\sum_j P_{jk} \ln(p_{jk})]/\ln(J)\}/K$, where: p_{jk} = proportion of land-use category j within a half-mile radius of the developed area surrounding hectare grid-cell k; j = number of land-use categories; and K = number of actively developed hectares in tract. The mean entropy ranges between 0 (homogeneity, wherein all land uses are of a single type) and 1 (heterogeneity, wherein developed area is evenly distributed among all land use categories)
- Vertical mixture: proportion of commercial/retail parcels with more than one land-use category on the site
- Per developed acre intensities of land uses classified as: residential; commercial; office; industrial; institutional; parks and recreation
- Activity center mixture: (1) entropy of commercial land-use categories computed across all activity centers within a zone; (2) proportion of activity centers with more than one category of commercial-retail uses; (3) proportion of activity centers with stores classified as: convenience; auto-oriented; entertainment/recreational; offices; institutional; supermarkets; service-oriented
- Commercial intensities, measured as per developed acre rates of: convenience stores; retail services; supermarkets; eateries; entertainment and recreational uses; auto-oriented services; mixed parcels
- Proximities to commercial-retail uses: (1) proportion of developed acres within 1/4 mile of: convenience store; retail-service use; (2) proportion of residential acres within 1/4 mile of: convenience store; retail-service use

3. Design
- Streets: (1) predominant pattern (e.g. regular grid, curvilinear grid); (2) proportion of intersections that are: four-way (proxy of grid pattern); (3) per developed acre rates of: freeway miles within or abutting tract; number of freeway under- and over-passes; number of blocks (proxy for the grain of road net); number of dead ends and cul-de-sacs; (4) averages of: arterial speed limits; street widths
- Pedestrian and cycling provisions: (1) proportion of blocks with: sidewalks; planting strips; street trees; overhead street lights; quadrilateral (i.e. rectangular or square) shape; bicycle lanes; mid-block crossings; (2) proportion of intersections with: signalized controls; (3) averages of: block length; sidewalk width; distance between overhead street lights; slope; pedestrian green lights at signalized intersections; (4) bicycle lanes per developed acre
- Site design: proportion of commercial–retail and service parcels with: off-street parking; off-street parking between the store and curb; on-street front or side parking; on-site drive-ins or drive-throughs

Sources: U.S Bureau of Census, Population and Housing, STF 3A; Census Transportation Planning Package, Parts I and II; ABAG, *1990 Land Use Summary*; ABAG, *Projection '94*; field surveys; and regional maps.

commercial intensity. As constructed here, it measures a neighborhood's relative proximity to activities, and thus reflects relative compactness. In constructing accessibility indicators, numbers of jobs were used as measures of destination attraction, and travel times between tracts were estimated on an unloaded regional highway network for the Bay Area using the MINUTP network package. Steiner (1994), Ewing (1994) and others argue that density's predictive value lies as a proxy for many difficult-to-measure variables that more directly affect travel behavior. Notably, as mentioned earlier, density is often associated with lower income households, limited parking supplies, more intensive bus services, and mixed land uses. Since these 'other' variables are directly controlled for in our analyses, we sought to isolate the individual effects of compactness in shaping travel demand.

We opted for a fairly wide array of variables to capture the *diversity* dimension. As used in earlier research on suburban activity centers (Cervero, 1989) and more recently by Frank and Pivo (1994), entropy provides a 0–1 index for gauging land-use heterogeneity.* While entropy quantifies the degree of mixing across land-use categories within a neighborhood, it is not a particularly good indicator of spatial inter-mixing at a finer grain, such as among parcels and city blocks. Accordingly, we developed a 'dissimilarity index' that gauges the degree to which uses abutting or

*To avoid bias against smaller tracts, in which there is relatively little area to accommodate a variety of land-use types (e.g. in densely developed San Francisco, some tracts have as few as 7 hectares), and to better reflect spatial mixing within a local neighborhood, a 'mean entropy' index was constructed.

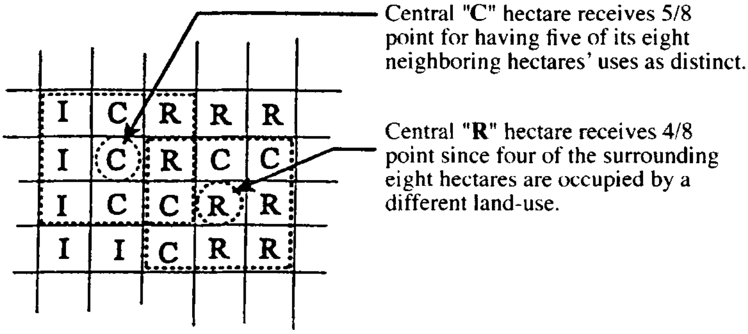

Fig. 2. Computation of the dissimilarity index.

diagonal to each hectare were different. As shown in Fig. 2, since one-eighth of a point is awarded for each of the adjacent hectares whose use differs from that of a particular hectare, the index varies between 0 and 1 when summed over and divided by the number of hectares in a tract. Supplementing both entropy and dissimilarity indices are variables that measure activity-center intensities, proximity to retail uses, and incidences of vertical land-use mixing within parcels.

Most of the *design* variables listed in Table 3 were compiled from field surveys. Design variables related to characteristics of streets (e.g. incidence of four-way intersections as a proxy for grid-like patterns), pedestrian and cycling provisions (e.g. share of block faces with sidewalks), and site design (e.g. proportion of retail parcels with front- and side-lot parking, reflecting wide setbacks and 'pedestrian-unfriendly' designs). Because design features can vary significantly within neighborhoods, for most variables used, we randomly sampled 20 block faces within each neighborhood to derive proportions and averages. Measuring 'average' design features of neighborhoods was necessitated by the need to tie these data to 'average' statistics on travel demand, density, diversity, and socio-economic characteristics for each of the 50 neighborhoods. While using smaller geographic units of analysis (e.g. city-block groupings) would have reduced the risks of aggregation bias, this would have been at the expense of reducing trip records to a few or none. As noted, empirical research into transportation–land use relationships necessarily involves trading off between the amount and precision of data.

The *control* variables used in our research are listed in Table 4. Standard demographic and household variables associated with travel demand, like possession of a driver's license and

Table 4. Control variables

1. Socio-demographics of trip-maker
- Age
- Gender: male status
- Employment: full-time or part-time status; professional occupation
- Race and ethnicity: racial-ethnic category; Caucasian status
- Possession of driver's license

2. Household of trip-maker
- Size: number of members; number of persons under 5 years of age (proxy for pre-school child dependency); number of persons 5 years of age and over (proxy for active household members)
- Vehicle ownership: number of automobiles, trucks, vans, and motorcycles per household
- Income
- Housing tenure (own or rent)

3. Transportation supply and services
- Transit service intensity: route miles of peak-hour revenue service divided by developed area of tract
- Distance to: nearest freeway-on ramp; nearest BART station; nearest commuter rail station; nearest light rail station; and nearest ferry landing
- Proportion of commercial–retail parcels with: paid on-street parking; paid off-street parking

4. Distance
- Euclidean distance between centroids of trip's origin and destination traffic analysis zones
- Euclidean distance: to downtown San Francisco; downtown Oakland; downtown San Jose.

Sources: MTC, 1990–1991 Bay Area Travel Survey (BATS); U.S. Bureau of Census, Population and Housing, STF 3A; Census Transportation Planning Package, Parts I and II; field surveys; schedules, maps, and reports from local transit agencies; and regional maps household income, were used. Transportation supply variables gauged each neighborhood's transit service levels, proximity to freeway interchanges and transit stations, and prevalence of paid parking. Lastly, all mode choice models controlled for trip distance. The Euclidean (or 'airline') distance of each trip was estimated using census tract centroid co-ordinates; a trip that did not leave a tract was assigned a distance of 0.20 miles, which served as a minimum expected trip distance.

While the BATS data supplied numerous dependent variables for measuring travel demand, we concentrated on two that were most germane to our central research questions—vehicle miles traveled (VMT) by personal vehicles (e.g. automobiles, trucks, and vans) and mode choice. Because the great majority of trips within the region were by private automobile, mode choice was defined using simply binary distinctions—whether by a personal vehicle or not, and whether by single-occupant vehicles (SOV) or not.*

Descriptive statistics for the built environment variables that, as shown in latter sections, proved to be the strongest predictors of travel demand are presented in Table 5. Basic statistics for dependent variables and control variables are summarized in Table 6.

Table 5. Descriptive statistics for the built environment variables most associated with travel demand, across 50 neighborhood cases

	Mean	Standard deviation	Range	
			Minimum	Maximum
Density				
Population per developed acre	18.20	18.79	4.38	141.70
Employment per developed acre	5.96	7.20	0.18	44.10
Accessibility Index (in 1000):*				
to all jobs (via auto)	93.92	60.18	4.53	252.25
to sales and services jobs (via walk)	0.55	0.46	0.00	2.31
Diversity				
Dissimilarity index*	0.13	0.08	0.00	0.30
Mean entropy*	0.32	0.11	0.14	0.52
Per developed acre rates of number of:				
retail stores	0.41	0.66	0.00	3.25
activity centers	0.01	0.02	0.00	0.13
parks and recreational sites	0.01	0.01	0.00	0.04
Proportion of commercial-retail parcels that are vertically mixed*	0.27	0.24	0.00	1.00
Proportion of residential acres within 1/4 mile of convenience or retail store	0.41	0.34	0.00	1.00
Design				
Proportion of intersections that are four-way	0.37	0.28	0.06	1.00
Proportion of blocks with:				
sidewalks	0.78	0.26	0.10	1.00
planting strips	0.42	0.30	0.00	0.95
overhead lights	0.87	0.23	0.05	1.00
flat terrain (< 5% slope)	0.80	0.23	0.30	1.00
quadrilateral shape	0.51	0.33	0.00	0.98
Block face length (feet)	579	162	345	1079
Sidewalk width (feet)	5.55	3.77	0.50	15.00
Distance between overhead lights (feet)	222	118	21	568
Proportion of commercial parcels with:				
paid parking	0.16	0.28	0.00	0.82
side- or front-lot on-street parking	0.42	0.31	0.00	1.00

*See Table 3 for definition of variable.

*It should also be pointed out that regional travel surveys, like BATS, rarely provide a complete portrait of travel, in part because sample data are normally compiled for a particular time of year and truly random samples are nearly impossible to collect. Moreover, one-day travel surveys likely undersample occasional trips, like walking and cycling, that occur most often on weekends. Any under-reporting of non-motorized travel invariably constrains analyses of how built environments influence walking and bicycling trips.

Table 6. Descriptive statistics for dependent variables and control variables most associated with travel demand

	Mean	Standard deviation	Range	
			Minimum	Maximum
Dependent variables				
Daily personal vehicle miles traveled per household (divided by vehicle occupancy):*				
all trips	27.13	29.64	0.00	228.52
non-work trips	21.47	28.94	0.00	228.52
Proportion of total home-based trips by:†				
non-personal vehicle	0.15	0.36	0.00	1.00
non-single-occupant vehicle	0.46	0.50	0.00	1.00
Proportion of non-work home-based trips by:†				
non-personal vehicle	0.18	0.39	0.00	1.00
non-single-occupant vehicle	0.66	0.49	0.00	1.00
Proportion of personal business home-based trips by non-personal vehicle†	0.14	0.34	0.00	1.00
Proportion of work home-based trips by non-personal vehicle†	0.09	0.27	0.00	1.00
Socio-demographics of trip-maker				
Age, years‡	38.7	17.1	5.0	90.0
Proportion male‡	0.50	0.50	0.0	1.0
Proportion employed‡	0.66	0.47	0.0	1.0
Proportion white‡	0.80	0.40	0.0	1.0
Proportion with drivers licenses‡	0.87	0.43	0.0	1.0
Household characteristics				
No. of members:*				
total	2.41	1.27	1.00	8.0
5 years and older	2.22	1.14	1.00	8.0
Annual income, dollars*	47,740	31,126	2500	175,000
No. of autos, vans, and trucks*	1.78	1.04	0.0	6.0
Transportation supply and distance				
Transit service level (revenue route miles per developed area)§	0.06	0.08	0.00	0.42
Trip distance, in miles, all trips‡	5.29	5.24	0.20	48.42

*Measured across all surveyed households.
†Measured across all trips within trip category.
‡Measured across all trips.
§Measured across 50 case neighborhoods.

8. RESEARCH APPROACH AND METHODS

8.1. Measuring incremental predictive power

In the analyses that follow, multiple regression was used to predict personal vehicle miles of travel and binomial logit analysis was used to predict the probability of a person traveling by a non-personal-vehicle or non-SOV mode. 'Base' models were initially estimated wherein only control variables were used as predictors. Statistically significant variables related to the built environment were then added to the base models to produce what we call 'built environment' models. Variables, including factor scores, were stepped into models based on their incremental explanatory power. Efforts were made to ensure at least one variable or factor related to each of the three dimensions entered each built environment model. Comparisons of incremental increases in the models' predictive powers revealed the explanatory significance gained by adding the dimensions of the built environment, based on the F statistic produced from the following formula (Chatterjee and Price, 1991):

$$\frac{[SSE(BM) - SSE(BEM)]/(p + 1 - k)}{SSE(FM)/(n - p - 1)} \tag{1}$$

where SSE = sum of squared errors; BM = base model; BEM = built environment model; k = number of predictors in base model; p = number of predictors in built environment model; n = sample size.

It should be noted that the predictive models are based largely on characteristics of trip ends (mainly the residential end) vs characteristics of trip interchanges (e.g. comparative prices and travel times of modes). However, some of the included variables, notably accessibility indexes and trip distance, were assumed to capture, and therefore control for, characteristics related to the interchange portion of trips. Trip distance, for instance, might be considered to be an appropriate control and proxy to the degree that travel-time differentials between, say, automobiles and bus transit are proportional to lengths of trips.

8.2. Factor analysis

As noted, a premise of our research is that built environments can be described principally along three main dimensions—density, diversity, and design. As suggested in Table 3, each dimension can be expressed by different variables, no one of which, alone, fully portrays that dimension, but which together more completely characterize the dimension. The design dimension, in particular, is a fairly qualitative concept that almost defies measurement and certainly requires more than a single variable to capture its full complexity and many subtleties. In light of the need to use sets of variables to capture the many-sided dimensions of built environments and to allow for colinearity, the multivariate technique of factor analysis was used.

Factor analysis creates a relatively small number of underlying factors that can be used to represent relationships among sets of many interrelated variables (Dunteman, 1984). In our case, it allowed variables like 'average sidewalk width', 'incidence of signalized street crossings', and 'intensity of planting strips and street trees' to be linearly combined to represent the dimension of 'pedestrian-oriented design'. As such, factor analysis helps elucidate some of the underlying, though not always observable or readily measurable, dimensions of the built environment. It enriches the analysis since multicolinearity among the many descriptors of the built environment can conceal the consequences of their individual contributions to travel demand. While factor analysis has been used to study the effects of employment centers' built environments on travel demand (Cervero, 1989; Cambridge Systematics, 1994), we are not aware of its use to date in studying how physical features of residential neighborhoods shape travel behavior.

We contend that it is futile to attempt to isolate the unique contribution of each and every variable that measures some fine aspect of the built environment. Quite simply, extreme multicolinearity prevents this in a statistical sense. As already pointed out, neighborhood attributes like compactness, diverse land uses, and pedestrian provisions co-exist. According to factor analysis principles, variables are often simply empirical manifestations of deeper dimensions, what Thurstone (1947), one of the founders of factor analysis, called 'deep structure'.

Initially, we sought to extract three underlying factors—density, diversity, and design.* Not all of the candidate variables representing these factors (shown in Table 3) ended up being used in the final extraction because some had low and indecipherable loadings. Based on an oblique (non-orthogonal) rotation of initial extracted factors, two intuitive and interpretable factors were extracted based on the inputs of 12 built environment variables.† These two factors accounted for around two-thirds of the total variation in these 12 variables; in other words, there was only around a 34% loss in information incurred by the 83% reduction in the number of 'variables' from 12 to 2.

For ease of interpretation, variables in Table 7 are listed in order of the size of their factor loadings (i.e. coefficients), first on factor 1, then on factor 2. Also, only those loadings higher than 0.30 are shown. From the loadings, it is clear that the first factor, which accounts for 47.6% of the total variation, represents *intensity* of land uses and thus captures the density dimension. Based on both the size and signs of loadings, one sees that *intensity* variables have been grouped to represent cases with: large numbers of retail stores, activity centers, and public parks per developed acre; high population densities; numerous shop-related destinations within walking distance (i.e. compactness); and closeness of public amenities like overhead street lights.

The second factor, explaining about 18% of the variation, clearly captures the *design* dimension, and more specifically, *walking quality*, of the sampled neighborhoods. It reflects the commonality

*Since our research focused on how the built environment shaped travel demand, factor analysis was carried out only for built environment, not control, variables.

†Oblique rotation was used because the factor dimensions themselves (e.g. density and design) were correlated. From the factor structure matrix, the correlation of the intensity factor and the design factor was 0.34.

Table 7. Factor loadings for intensity and walking quality factors, based on characteristics of 50 case neighborhoods

	Factor loadings on	
	Intensity factor	Walking quality factor
Retail store density	0.954	
Activity center density	0.949	
Retail intensity	0.874	
Walking accessibility	0.802	
Park intensity	0.806	
Population density	0.796	
Sidewalk provisions		0.851
Street light provisions		0.816
Block length		−0.746
Planted strips		0.728
Lighting distance		−0.724
Flat terrain		0.464

Summary
65.5% of variation of 12 variables explained by two factors, using oblimin (oblique) rotation—47.6% by the *intensity* factor and 17.9% by the *walking quality* factor.
Factor loadings under |0.30| are not presented.

Variable definitions
Retail store density = number of retail stores per active developed area (in acres), wherein active developed area excludes open space, forests, vacant land, cemeteries, large recreation sites, and public infrastructure space; retail represents any commercial parcel where goods are sold, including convenience stores, supermarkets, restaurants and eateries, general merchandise stores, specialty stops, and entertainment and recreational-oriented establishments.
Activity center density = number of activity centers per developed area (in acres), wherein an activity center is defined as any collection of retail or service land uses that either comprise a land area over 10 000 square feet, or consists of three or more stores that either adjoin or lie within 200 feet of each other along the same street.
Retail intensity = proportion of block (polygon) faces with retail-land uses, wherein a block face is the frontage of a block that is bounded on all sides by an intersecting street.
Walking accessibility = relative proximity to sales and service jobs (reflecting activities within a neighborhood that are likely to attract foot travel), measured as: $AI_i = \sum_j$ (sales and service industry jobs)$_j$ {exp[−0.19−1.52(walk travel time, in minutes)$_{ij}$]}, where AI = accessibility index, i = origin (residential) traffic analysis zone, j = destination traffic analysis zone, walk travel time is assumed to equal automobile (centroid-to-centroid) travel time multiplied by 8, and intrazonal walk trips are assumed to take 8 min (Levinson and Kumar, 1995).
Park intensity = Number of local and regional parks per developed area (in acres), including open space of more than 20 acres.
Population density = Population per developed area (in acres).
Sidewalk provisions = Proportion of block faces with paved sidewalks over the full length.
Street light provisions = Proportion of block faces with overhead street lights.
Planted strips = Proportion of block faces with planted strips between the street curb and sidewalk.
Block length = Mean distance (in feet) of block faces.
Lighting distance = Mean distance (in feet) between overhead street lights along block faces.
Flat terrain = Proportion of block faces with 'flat' terrain (< 5% slope).

among neighborhoods which have: sidewalk and street light provisions; plentiful planted strips; short average block lengths and distances between street lights; flat terrain; and high walking accessibility to neighborhood shops.

Overall, factor analysis was successful in providing a multi-variable description of two of the underlying dimensions—density and design—of the 50 sampled neighborhood built environments. The extracted factors and their relationships to original variables are logical and interpretable. Additionally, oblique rotation accounted for intercorrelation among the two factors themselves, i.e. many cases with high *intensity* scores also had high *walking quality* scores.

9. STUDY FINDINGS

9.1. Trip rates

The measure of vehicular trip rate used in this analysis was *personal vehicle miles traveled per household.* This represents daily mileage of all household members via private automobile, van, truck, motorcycle, or taxicab/limousine. Thus, this measure excludes public transit and non-motorized (walking, bicycling) travel. The measure is adjusted for vehicle occupancy, i.e. two household members traveling together by car over a 5-mile distance represents 5, not 10, personal vehicle miles of travel. The expectation, of course, is that density, diversity, and pedestrian-oriented design should lower personal vehicle trip rates, that is, 'degenerate' trips.

Both 'base' and 'built environment' models were produced for total trips (Table 8) and non-work trips (Table 9). For the total trip model, when controls—number of workers and vehicles,* annual income, and transit service levels in the neighborhood—are introduced, 14.1% of the variation in VMT is explained. The signs of control variables are consistent with *a priori* expectations, e.g. personal VMT falls with transit service levels. For the expanded model, neither of the built environment factors was a reasonably significant predictor of total VMT; rather, only two variables—accessibility (as a proximity and compactness measure) and quadrilateral patterning of blocks (as an indicator of grid-like design)—added significant marginal explanatory power. And, somewhat surprisingly, quadrilaterals were positively associated with personal VMT, perhaps reflecting some of the marginal advantages of facilitating vehicular traffic flows with regularity in block patterns. In fact, the results suggest a neighborhood with all rectangular or square blocks could be expected to average nine more daily personal vehicle miles traveled per household than one with no quadrilateral blocks, all else being equal. Rectangular blocks (and thus grid-like street patterns), it should be noted, likely facilitate driving only in large, superblock configurations; however, 'average block size' was too weak to enter the predictive model to reveal whether this was the case. It is also noteworthy that the density and design factors were not as powerful in explaining VMT as these primary explanatory variables, and thus did not enter the model.

When personal VMT was examined for non-work trips, Table 9 shows one of the two extracted factors, *intensity*, provided significant marginal explanatory power. This factor, along with a specific indicator of site-level diversity, 'vertical mixing', and two measures of design, 'four-way intersections' and 'quadrilaterals', added around 5% explanatory power to the base model. The F statistic of model differences, moreover, was highly significant. As expected, people living in dense

Table 8. Predictive models of daily personal vehicle miles traveled per household, all trips

Dependent variable: Vehicle miles traveled in personal vehicles by all household members for all trips*				
	Base model		Built environment model	
	Coefficient	Probability	Coefficient	Probability
Explanatory variables				
No. of workers in household (full- and part-time, non-students)	5.316	0.000	5.919	0.000
No. of automobiles and vans in household	7.795	0.000	6.184	0.000
Annual household income, in $1000	0.033	0.294	0.041	0.185
Transit service intensity†	−9.682	0.487	−23.377	0.117
Proportion of commercial parcels with paid parking	−0.049	0.991	−6.141	0.162
Accessibility index‡	—	—	−0.079	0.000
Proportion of neighborhood blocks that are quadrilaterals (i.e. with four straight sides, either square or rectangular)	—	—	9.861	0.003
Constant	14.82	0.112	9.758	0.003
Summary statistics	Base model		Built environment model	
No. of cases	896		896	
R squared	0.141		0.171	
F statistic (probability) of model differences = 14.43 (0.000)				

*Adjusted for (divided by) vehicle occupancy level, where personal vehicle is defined as an automobile, truck, van, motorcycle, or taxi.

†Transit service intensity = Total route miles of revenue service over the 8–9 am peak period within the tract (or along its borders), divided by developed active area (in acres) of tract, measured as:{ $60\ [\sum_i (M_i/H_i)]\}/A_i\}$, where M = route miles of revenue service within or bordering tract, from 8–9 am, H = average headways of bus routes within tract, A = developed active area, in acres (e.g. excluding public parks, vacant land, cemeteries, public infrastructure space, etc.), and i = origin (residential zone).

‡Accessibility index, zone $i = \{\sum_j$ (total jobs)$_j$ exp[−0.4−0.15 (automobile travel time, in minutes)$_{ij}$]}/1000, where i = origin (residential) traffic analysis zone, j = destination traffic analysis zone, and intrazonal travel time is assumed to be 3 min; index is factored by a constant value of 1000 (Levinson and Kumar, 1995).

*The relationship between control variables like vehicle ownership levels and built environment variables could be endogenous, e.g. compact settings reduce vehicle ownership. However, the availability of cross-sectional data precluded any efforts to simultaneously estimate equations to control for possible estimation biases. If the influences of built environments on vehicle ownership levels were explicitly accounted for in model estimation, the built environment variables would likely emerge as even more significant explainers since they most likely modify vehicle ownership in ways consistent with their expected impacts on travel behavior.

neighborhoods featuring within-building mixing (e.g. offices and residences above ground-floor shops) and four-way intersections averaged significantly less personal VMT. All other things held constant, Table 9 reveals: a neighborhood where all retail stores are vertically mixed vs one where no retail stores are vertically mixed averages 11.1 fewer personal VMT per household; and one with all four-way intersections vs one with only three-way intersections averages 32 fewer personal VMT per household each day. The co-existence of 'four-way intersections' and 'quadrilaterals' in the model suggests that while regularity in block patterns might be conducive to automobile driving in built-up areas, the existence of numerous four-way intersections encourages walking and other non-motorized trips by providing for the conditions of controlled street crossings and more access points.

Overall, the premises of vehicle-trip degeneration, more frequent non-motorized trip-making, and shorter motorized trips provided by compact, mixed-use, pedestrian-friendly development are supported by the estimated trip-rate models. Thus, experiences in the San Francisco Bay Area lend support to the contentions of new urbanists and other proponents of traditional neighborhood designs though, clearly, design treatments, in and of themselves, fail to powerfully influence vehicle trip rates.

9.2. Non-work mode choice

9.2.1. Non-SOV model. Traditional neighborhoods are also thought to reduce auto-dependency, particularly drive-alone travel. For non-work trips, the model results in Table 10 largely support this, though contributions of built environment variables to SOV reductions were fairly modest, adding only a percentage point in explanatory power (which, nonetheless, was a statistically significant increase). In the built environment model, both the intensity and pedestrian quality factors entered as reasonably significant predictors. The positive signs on both factors

Table 9. Predictive models of daily personal vehicle miles traveled per household, non-work trips

Dependent variable: Vehicle miles traveled in personal vehicles by all household members for non-work home-based trips*

	Base model		Built environment model	
	Coefficient	Probability	Coefficient	Probability
Explanatory variables				
No. of persons in household over 4 years of age	1.499	0.123	1.072	0.107
No. of workers in household (full- and part-time, non-students)	3.034	0.014	4.053	0.001
No. of automobiles and vans in household	6.953	0.000	5.752	0.000
Transit service intensity†	−72.498	0.000	−18.975	0.250
Intensity factor‡	—	—	−3.450	0.002
Proportion of parcels with vertical mixing§	—	—	−11.209	0.013
Proportion of intersections that are four-way (e.g. not T or Y intersections)	—	—	−34.343	0.000
Proportion of neighborhood blocks that are quadrilaterals (i.e. with four straight sides, shaped as either squares or rectangular)	—	—	19.509	0.000
Constant	5.918	0.009	9.970	0.968
Summary statistics	Base model		Built environment model	
No. of cases	904		868	
R squared	0.154		0.203	

F statistic (probability) of model differences = 13.51 (0.000)

*Adjusted for (divided by) vehicle occupancy level, where personal vehicle is defined as an automobile, truck, van, motorcycle, or taxi.

†Transit service intensity = Total route miles of revenue service over the 8–9 am peak period within the tract (or along its borders), divided by developed active area (in acres) of tract, measured as: $\{60\,[\sum_i(M_i/H_i)]\}/A_i\}$, where M = route miles of revenue service within or bordering tract, from 8–9 am, H = average headways of bus routes within tract, A = developed active area, in acres (e.g. excluding public parks, vacant land, cemeteries, public infrastructure space, etc.), and i = origin (residential zone).

‡See Table 7 for definition of intensity factor.

§Vertical mixing = Proportion of parcels with more than one land use category on the site, with use categories defined as residential, office, or retail/services; since different uses typically occupy different floors of a structure (e.g. ground-floor retail and upper-level housing), this reflects the degree of vertical mixing within buildings.

Table 10. Models for predicting probability of traveling by a non-single occupant vehicle mode for non-work, home-based trips

Dependent variable: Non-work trip by all means except non-single occupant vehicle (1 = yes, 0 = no)				
	Base model		Built environment model	
	Coefficient	Probability	Coefficient	Probability
Explanatory variables				
No. of automobiles, trucks and vans in household per person over 4 years of age	−0.5577	0.000	−0.0387	0.000
Annual income per person (over 4 years of age) in household, in $1000	−0.0213	0.000	−0.0288	0.000
No. of children under 5 years of age in household	0.2091	0.010	0.2222	0.009
Male (1 = yes, 0 = no)	−0.2653	0.001	−0.2831	0.001
Age, in years	−0.0096	0.000	−0.0086	0.002
Possess a driver's license (1 = yes, 0 = no)	−2.4675	0.000	−2.5497	0.000
Employed, full-time or part-time, non-student (1 = yes, 0 = no)	−0.4778	0.000	−0.3927	0.000
Trip distance (Euclidean miles, centroid-to-centroid)	−0.0165	0.020	−0.0162	0.021
Intensity factor*	—	—	0.1841	0.157
Walking quality factor†	—	—	0.1308	0.032
Land use mixing (dissimilarity index)‡	—	—	2.1289	0.049
Proportion of intersections that are four-way (e.g. not T or Y intersections)	—	—	0.8131	0.006
Proportion of non-residential parcels with front- or side-lot on-site parking	—	—	−0.7578	0.000
Constant	3.1687	0.000	4.6063	0.000
Summary statistics	Base model		Built environment model	
No. of cases	2850		2850	
Rho (pseudo-R squared)	0.1794		0.1900	
F statistic (probability) of model differences = 7.43 (0.000)				

*See Table 7 for definition of intensity factor.
†See Table 7 for definition of walking quality factor.
‡Dissimilarity index: proportion of dissimilar land uses among hectare grid cells within a tract. For each tract, computed as: $\{[\sum_j^k \sum_l^8 (X_l/8)]/K\}$, where: K = number of actively developed hectare grid-cells in tract, and $X_l = 1$ if land-use category of neighboring (i.e. abutting or diagonal) hectare grid-cell differs from hectare grid-cell j (0 otherwise); 12 land-use categories were used: residential, general commercial, retail and wholesale, office, industrial, mixed commercial–industrial, health, institutional (including civic and religious), educational, ports and airports, commercial–recreational, and public parks–outdoor recreational.

reveal neighborhoods that are denser and more pedestrian-oriented in their designs are associated with choosing shared-ride, transit, and non-motorized modes for non-work travel. Supplementing these factors were three variables that further embellished the model by revealing other elements of diversity and pedestrian-oriented design that reduce SOV trip-making. Notably, non-SOV travel increased with the spatial inter-mixing of land uses (reflected by the dissimilarity index). And while four-way intersections, as a proxy for gridded street patterns and controlled crossings, were associated with more non-SOV travel, separating buildings by front- and side-lot parking (and thus increasing setbacks and inconveniencing walkers) had the opposite effect. In fact, the model results suggest that, holding all else constant, someone heading to a shop within their neighborhood is, on average, 56% more likely to drive alone if all buildings are surrounded by front- and side-lot parking vs if all buildings have rear-lot parking.*

9.2.2. Non-personal vehicle model. When models were run for predicting the probability of choosing a non-personal vehicle mode for non-work trips, the built environment variables added even more incremental explanatory power. Table 11 shows that the *intensity* and *walking quality* factors emerged as particularly strong predictors of non-personal vehicle travel, and were supplemented by 'average sidewalk width' as an indicator of pedestrian capacity.

*Using the mean (or, for nominal variables, modal) values of all other explanatory variables in Table 10, the difference in probability was calculated as: $[(z+\exp(-0.7578))/((z+\exp(-0.7578))+1)] = 0.560$, where $z = \exp[(-0.0387)(1.78) + (-0.0288)(47.7) + (0.2222)(0.19) + (-0.2831)(0) + (-0.0086)(38.7) + (-2.5497)(1) + (-0.3927)(1) + (-0.0162)(4.76) + (0.1831)(0) + (0.1308)(-0.07) + (0.8131)(0.37) + (-0.7577)(0.40) + 4.6063)] = 0.805$.

Table 11. Models for predicting probability of traveling by a non-personal vehicle mode for non-work, home-based trips

Dependent variable: Non-work trip by non-personal vehicle (1 = yes, 0 = no)*	Base model		Built environment model	
	Coefficient	Probability	Coefficient	Probability
Explanatory variables				
No. of automobiles and vans in household per person over 4 years of age	−1.2506	0.000	−1.0199	0.000
Annual income per person (over 4 years of age) in household, in $1000	−0.0265	0.000	−0.0198	0.000
No. of children under 5 years of age in household	−0.1361	0.156	−0.2121	0.046
Possess a driver's license (1 = yes, 0 = no)	−1.1356	0.000	−1.2441	0.000
Employed, full-time or part-time, non-student (1 = yes, 0 = no)	−0.4003	0.001	−0.4205	0.000
Trip distance (Euclidean miles, centroid-to-centroid)	−0.1094	0.000	−0.1072	0.000
Proportion of non-residential parcels with paid off-street or abutting on-street parking	0.8120	0.000	0.7014	0.005
Intensity factor†	—	—	0.2162	0.049
Walking quality factor‡	—	—	0.4791	0.000
Average sidewalk width (feet)	—	—	0.0191	0.038
Constant	0.1287	0.404	0.9649	0.021
Summary statistics	Base model		Built environment model	
No. of cases	2850		2850	
Rho (pseudo-R squared)	0.1586		0.1802	
F statistic (probability) of model differences = 24.93 (0.000)				

*Non-personal vehicle represents travel by all means other than private automobile, truck, van, motorcycle, or taxi.
†See Table 7 for definition of intensity factor.
‡See Table 7 for definition of walking quality factor.

The same control variables as in the previous model were found to be significant; however, the traveler's gender and age did not enter as significant while the paid parking variable did. Partly because they have more limited access to personal vehicles, those without driver's licenses, young people, and those from poorer households rely more on public transportation for non-work trips and, as shown by Untermann (1984), are more likely to walk or cycle. The effects of having infants, toddlers, and pre-school children on non-work mode choice are particularly noteworthy, as revealed in Tables 10 and 11. Because parents often bring very young children along when shopping and heading to other non-work destinations, by definition they tend to make more multiple-occupant automobile trips (thus the positive sign on the non-SOV model). Yet these trips are normally by automobiles or vans (thus the negative sign on the non-personal vehicle model). The entry of these variables into the models underscores the importance of lifecycle factors, such as child dependency, in accounting for non-work mode choices. Both tables also show that vehicle usage generally increases with non-work trip distance, and Table 11 shows that paid parking within neighborhoods can encourage people to walk to shops and other non-work destinations.

9.2.3. Non-personal vehicle choice for personal-business trips. In general, results were similar when mode choice models were run for non-work trips stratified by specific purpose (e.g. shopping, personal business, and social–recreation). The most significant stratified mode choice model was for personal business trips. Table 12 shows the *intensity* and *walking quality* factors added nearly 10 percentage points to the predictive abilities of the base model, a highly significant jump. Thus, within-neighborhood trips (e.g. controlling for distance) to a bank or a dentist for personal services are more likely to be by transit, foot, or bicycle in dense, activity-rich, and pedestrian-friendly environments. One might surmise that, since personal business trips are less likely to require goods and purchases to be hauled, they are potentially less wedded to the use of personal vehicles (unlike, say, shopping) in a conducive built environment.

9.3. Work mode choice

While research by Handy (1993) and Ewing *et al.* (1994) suggests shopping and other non-work trips might be most strongly influenced by mixed land uses, other studies (Cervero, 1991, 1996;

Table 12. Models for predicting probability of traveling by a non-personal vehicle mode for personal business, home-based trips

Dependent variable: Personal business trip by non-personal vehicle (1 = yes, 0 = no)*

	Base model		Built environment model	
	Coefficient	Probability	Coefficient	Probability
Explanatory variables				
No. of automobiles and vans in household per person over 4 years of age	−1.4731	0.000	−0.9127	0.033
No. of children under 5 years of age in household	−0.9617	0.073	−0.8576	0.077
Possess a driver's license (1 = yes, 0 = no)	−1.8992	0.000	−2.2854	0.000
Male (1 = yes, 0 = no)	−0.5559	0.079	−0.6311	0.072
Employed, full-time or part-time, non-student (1 = yes, 0 = no)	−0.8943	0.000	−1.0070	0.018
Trip distance (Euclidean miles, centroid-to-centroid)	−0.6660	0.000	−0.8344	0.000
Intensity factor†	—	—	1.3430	0.000
Walking quality factor‡	—	—	0.3242	0.078
Constant	2.2064	0.000	2.4999	0.000
Summary statistics	Base model		Built environment model	
No. of cases	509		509	
Rho (pseudo-R squared)	0.3089		0.4003	
F statistic (probability) of model differences = 38.08 (0.000)				

*Non-personal vehicle represents travel by all means other than private automobile, truck, van, motorcycle, or taxi.
†See Table 7 for definition of intensity factor.
‡See Table 7 for definition of walking quality factor.

Frank and Pivo, 1994) have shown the presence of retail activities can also be a significant inducement to non-auto commuting, both by workers and residents. These studies have suggested that the presence of convenience and grocery stores near residences encourages transit commuting by allowing workers to shop while en route from transit stops to their homes in the evening.

As shown in Table 13, our research results were consistent with this proposition. Notably, controlling for factors like trip distance and transit service intensities, pedestrian-friendly environments and the presence of convenience stores within a quarter mile of residences appears to induce commute trips via transit and non-motorized modes. In fact, the model suggests that the probability of commuting by a non-personal vehicle mode is nearly three-quarters higher in a neighborhood where everyone lives within a quarter mile of a convenience store vs one where no one lives this close, holding constant factors like transit service intensity, commute distance, gender, and the like.* Importantly, these model results suggest that plentiful neighborhood retail shops and pedestrian-oriented designs, and not residential densities, are significant factors in encouraging people to commute by transit and non-motorized modes. Experiences from the Bay Area also suggest that diversity and design within residential neighborhoods appear capable of yielding transportation benefits not only for non-work travel, but for work trips as well.

10. CONCLUSION

Our research findings lend some degree of credibility to the claims of new urbanists and others that compact, mixed-use, pedestrian-friendly designs can 'degenerate' vehicle trips, reduce VMT per capita, and encourage non-motorized travel. As with any cross-sectional statistical analysis and in light of the methodological limitations inherent in this line of research, the results must be interpreted as being associative rather than causal. Overall, our research suggests that the effects of the Bay Area's built environment on travel demand were modest to moderate at best. This finding is best summarized by elasticities between different indicators of travel demand and measures of the three dimensions of the built environment, as shown in Table 14. Elasticities fell in the range of 0.063 to 0.592, in absolute terms. Once other variables, like vehicle-ownership rates, were

*Using the mean (or, for nominal variables, modal) values of all other explanatory variables in Table 13, the differential was calculated as: $[(z+\exp(0.9815))/((z+\exp(0.9185))+1)]=0.729$, where $z=\exp[(-1.1823)(1.78)+(-0.2601)(0.19)+(-1.8751)(1)+(-0.7853)(0)(-0.2966)(9.78)+(0.7047)(0.57)+(1.8656)(0.06)+(0.3422)(0)+(0.9815)(0.41)+2.0078)$ $=0.0174$.

Table 13. Models for predicting probability of traveling by a non-personal vehicle mode for work, home-based trips

Dependent variable: Work trip by non-personal vehicle (1 = yes, 0 = no)*	Base model		Built environment model	
	Coefficient	Probability	Coefficient	Probability
Explanatory variables				
No. of automobiles and vans in household per person over 4 years of age	−1.2706	0.000	−1.1823	0.000
No. of children under 5 years of age in household	−0.3285	0.086	−0.2601	0.164
Possess a driver's license (1 = yes, 0 = no)	−1.8469	0.000	−1.8751	0.000
Male (1 = yes, 0 = no)	−0.7751	0.000	−0.7853	0.000
Trip distance (Euclidean miles, centroid-to-centroid)	−0.3049	0.000	−0.2966	0.000
Proportion of non-residential parcels with paid off-street or abutting on-street parking	1.2373	0.000	0.7047	0.155
Transit service intensity†	2.3045	0.078	1.8656	0.098
Walking quality factor‡	—	—	0.3422	0.051
Proportion of residential area within 1/4 mile of a convenience retail store	—	—	0.9815	0.046
Constant	2.3380	0.000	2.0078	0.021
Summary statistics	Base model		Built environment model	
No. of cases	1544		1544	
Rho (pseudo-R squared)	0.3487		0.3601	
F statistic (probability) of model differences = 13.66 (0.000)				

*Non-personal vehicle represents travel by all means other than private automobile, truck, van, motorcycle, or taxi.
†Transit service intensity = total route miles of revenue service over the 8–9 am peak period within the tract (or along its borders), divided by developed active area (in acres) of tract, measured as: $\{60\,[\sum_i (M_i/H_i)]\}/A_i\}$, where M = route miles of revenue service within or bordering tract, from 8–9 am, H = average headways of bus routes within tract, A = developed active area, in acres (e.g. excluding public parks, vacant land, cemeteries, public infrastructure space, etc.), and i = origin (residential zone).
‡See Table 7 for definition of walking quality factor.

controlled, the intensity factor was found to have a fairly marginal impact on travel demand, consistent with the arguments by Ewing (1994). Densities exerted the strongest influence on personal business trips. Additionally, residential neighborhoods that were spatially accessible to commercial activities, reflected by the accessibility index variable, tended to average appreciably less VMT per household. Table 14 further shows that diversity also had a modest impact on travel demand, though where it was significant, its influences were a bit stronger than that of density. Consistent with the findings of Frank and Pivo (1994) and Cervero (1996), having retail activities within neighborhoods was most closely associated with mode choice for work trips. Lastly, the dimension of walking quality was generally moderately associated with travel demand. Importantly, its influences on mode choice for non-work trips, controlling for trip distance, was stronger than that of density. Moreover, several specific design elements of the built environment seemed to be particularly relevant to non-work trip-making. Notably, neighborhoods with high shares of four-way intersections, as a proxy for grid-iron street patterns, and limited on-street parking abutting commercial establishments tended to average less single-occupant vehicular travel for non-work purposes.

Furthermore, based on our factor analysis results, our findings suggest that the somewhat obtuse concept of 'built environment' can be defined along distinct dimensions, and that these dimensions, both individually and collectively, are associated with how Bay Area residents travel, though often only moderately so and in ways that are still not fully understood. Higher densities, diverse land uses, and pedestrian-friendly designs, we believe, must co-exist to a certain degree if meaningful transportation benefits are to accrue. Having nice sidewalks, attractive landscaping, and other pedestrian amenities in a low-density, residential-only neighborhood is unlikely to prompt many residents to walk to shops and stores. However, the synergy of the 3Ds in combination is likely to yield more appreciable impacts.

Besides these general findings, several additional insights were gained through this research. One, neighborhood characteristics were generally a stronger predictor of mode choice for non-work trips than for commute trips. Nonetheless, the presence of convenience shops and retail outlets within neighborhoods was associated with commuting via transit and non-motorized

Table 14. Elasticities between measures of the built environment and travel demand, using mid-point (mean and mode) values for explanatory variables

Built environment	Travel demand					
	Person vehicle miles traveled per household for*		Probability of travel by			
			Non-SOV for:†	Non-personal vehicle for:†		
	All trips	Non-work	Non-work trips	Non-work	Pers. bus.	Work
Density‡						
Intensity factor§	—	−0.063¶	0.098	0.084	0.113	—
Accessibility index	−0.274	—	—	—	—	—
Diversity‡						
Land use mixing	—	—	0.111	—	—	—
Vertical mixing	—	−0.141	—	—	—	—
Population within 1/4mile of store	—	—	—	—	—	0.365
Design‡						
Walking quality factor§	—	—	0.085	0.183	0.174	0.119
Four-way intersections	—	−0.592	0.501	—	—	—
Quadrilaterals	0.185	0.463	—	—	—	—
Sidewalk width	—	—	—	0.087	—	—
Front and side parking	—	—	−0.505	−0.121	—	—

*Elasticities computed as: $\beta\ (x/y)$, where: β = estimated coefficient; x = mean of explanatory (built environment) variable; y = mean of dependent (travel demand) variable.

†Elasticities computed as: $\beta(x)(1-\pi)$, where: β = estimated coefficient; x = mean of explanatory (built environment) variable; π = mean estimated probability.

‡See Tables 3 and 8–13 for definitions of variables, and Table 7 for definition of factors.

§Since factor scores are standardized, with means equal to zero, mid-point (i.e. mean-value) elasticities cannot be calculated. Instead, the elasticities for factors were estimated as the proportion point change in probability estimates for the dependent (travel demand) variables given a 1 standard deviation increase in a factor score, setting all other explanatory variables in the models at their mean (or for nominal variables, modal) values, as shown in footnotes (pp. 214 and 216) of this article.

¶For the reason explained in note § above, the elasticity of personal vehicle miles traveled per household as a function of the intensity factor was calculated for values of the dependent variable and intensity factor one standard deviation above the mean (i.e. $y = 50.4$, $x = 1$).

modes. Second, factor analysis proved to be a useful approach for combining colinear variables to reveal the relative contributions of different attributes of the built environment in explaining travel demand. Trying to measure the unique travel effects of any one element of the built environment is often fruitless because of the high multicolinearity and statistical interaction of built environment variables. Third, the dissimilarity index of spatial mixing proved to be a more powerful predictor and measure of diversity than the entropy index of land-use heterogeneity. Fourth, despite very time-consuming field work, relatively few land-use and urban design variables entered the predictive models. Most micro-elements of a neighborhood, like sidewalk widths and presence of street trees, had little bearing on travel demand once more basic explainers, like land-use diversity and demographic attributes, were accounted for. The lack of significant predictive powers among many design variables was also likely attributable, in part, to less variation relative to control variables. As noted, while control variables like income, age, and trip lengths varied across tens of thousands of trips and over 8000 households, there were only 50 possible data values for the built environment variables (i.e. one for each of the 50 case neighborhoods). The much smaller cross-observation variation among built environment variables undoubtedly placed these variables at a predictive disadvantage.

It would have been desirable to investigate whether the built environment had a significant impact on specific non-work travel choices, such as walk trips. The presence of neighborhood convenience stores and tree-lined sidewalks, for instance, could be expected to induce some within-neighborhood shop trips to be made by foot. They would likely have little influence on transit patronage, however. Thus, lumping walk, bicycle, and transit trips together as 'non-personal-vehicle' travel might have diluted the analysis by losing some of the precision on mode choice. The problem encountered in attempting to model mode choice for walk trips alone, however, was the shortage of cases. For the 50 sampled neighborhoods, there were only 340 walk trips out of some 3000 recorded trips; several neighborhoods had no recorded walk trips. Gauging how the built environment affects the choice of any particular non-automobile mode, be it walking or transit, would require a very generous budget to collect detailed land-use and design data across numerous tracts and to obtain many more travel diaries within each tract than are normally available from regional surveys. Based on the somewhat encouraging findings from our study, we believe such research refinements would be worthwhile pursuing. In that the admittedly tenuous link between transportation and land use has come under assault from many quarters in recent times, research that enriches our understanding of how different elements of the built environment combine to shape travel behavior under different conditions is more imperative now than ever.

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