Walking, Bicycling, and Urban Landscapes: Evidence from the San Francisco Bay Area

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University of California Transportation Center
Working Paper

August 2003

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ABSTRACT

Car-dependent cities, some claim, contribute to obesity by discouraging walking and bicycling. This paper uses household activity data from the San Francisco region to study the links between urban environments and non-motorized travel. Factor analysis is used to represent the urban design and land-use diversity dimensions of built environments. Combining factor scores with control variables, like steep terrain, which gauge impediments to walking and cycling, discrete-choice models are estimated. Built-environment factors exerted far weaker, though not inconsequential, influences on walking and cycling than control variables. Stronger evidence on the importance of urban landscapes in shaping foot and bicycle travel is needed if the urban planning and public health professions are to forge an effective alliance against car-dependent sprawl.

INTRODUCTION

Urban planners and public health advocates alike decry sprawl for prodding Americans to drive their cars from anywhere to everywhere.[1,2] Car-dependent cities and suburbs, critics charge, spawn a sedentary lifestyle and associated health problems like obesity, adding as much as $76 billion annually to U.S. medical expenses by one estimate.[3] Eight-lane thoroughfares, serpentine roads, incomplete sidewalk networks, far-flung retail plazas, campus-style business parks, and other distinguishing traits of contemporary America are said to conspire against walking and bicycling. However, are their influences serious enough to warrant radical changes in how we design communities of the future?

Numerous studies have examined the effects of built environments on motorized travel, however far less attention has been given to impacts on walking and bicycling.[4,5] Probing effects on non-motorized transport (NMT) requires a different analytical approach. For one, walk and bicycle trips are usually shorter than those by car or public transit, requiring a finer analytical resolution. Geographic Information System (GIS) tools help in this regard, especially if one knows the longitudinal-latitudinal coordinates of trip origins and destinations. Additionally, choice models of motorized travel normally include comparative highway travel times of competing modes in their utility specifications.[6] This is because trip durations often vary substantially between the private car and public transit. For NMT, and especially walking, speeds tend to be so much slower than by car, train, or bus that travel-time differentials are meaningless. Because people of a similar age usually walk at comparable speeds and given that pedestrians perceive trip-making mainly in spatial terms, distance is a more suitable measure of impedance.[7]

As important to the question of model specification is the inclusion of factors that represent potential barriers to walking or cycling.[8] Besides distance, these include steep slopes, nightfall, precipitation, and less-secure environs. Failure to include such factors can compromise the internal and construct validity of the research. For example, curvilinear and cul-de-sac street layouts that discourage walking are particularly common in hilly terrain.[9] Ignoring topography means that associated variables, like road designs, that are included in a predictive model end up absorbing the influences of this omitted but relevant variable. Assigning health benefits to built environments necessitate a valid model specification that nets out impedance factors like the presence of a steep terrain.

In this study, the influences of urban designs, land-use diversity, and density patterns on the choice to walk or bicycle, vis-à-vis other factors, are examined using year-2000 data for the San Francisco Bay Area. The work builds upon other research that has applied the "3D" principle (density, diversity, and design) to associate travel choices with built environments.[10-12] The paper closes with discussions on the public health and urban planning implications of the research findings.

DATA AND METHODS

The chief data base used to carry out this research was the 2000 Bay Area Travel Survey (BATS) which contains up to two days of daily activity information for members of 15,066 randomly selected households in the nine-county San Francisco Bay Area.[13] Household activity surveys provide rich details on everyday activities of all household members, including travel and out-of-home activities. To narrow our investigation to trips that were potentially walkable or bikable, we limited the analysis to purposes that unlikely involved carrying significant amounts of items or goods, like groceries. Accordingly, records for the following out-of-home activities were selected: socialize/visit friends; meals/eating; personal services (e.g., banking); recreation/entertainment; volunteer/civic/ religious activities; and shopping away from home (under 15 minutes in duration). Because BATS did not reveal the exact nature of shopping, we imposed a 15-minute limit, as an upper bound, under the assumption this would correspond to a walkable convenience shop trip. One quarter of all sampled shop activities took fewer than 15 minutes and 94% of shop destinations reached by foot were below this benchmark. Also, only records for trips that did not begin at a workplace were selected; in most instances, trip origins corresponded to peoples' residences. A final refinement was the selection of trip records below 5 miles in length, a potentially walkable distance range that encompassed 88% and 96% of sampled bike and walk trips, respectively. These refinements yielded a sample frame of 7,889 trip records.

Each trip record contained information on the purpose, mode, time-of-day, day-of-week, origin and destination longitudinal-latitudinal coordinates, and other features of the journey. Attributes of trip-makers (e.g., gender) and their households (e.g., vehicle availability) were obtained from the BATS personal and household data files and linked to each trip record. Data on built-environment and control variables were collected for year-2000 to match up with BATS travel records. Average slope (rise/run) was calculated based on the elevations of trip origins and destinations. Recorded times of trip departures and arrivals, matched against sunrise and sunset information for the Bay Area, produced a dummy variable on whether trips trip occurred during nightfall. Information on neighborhood crime rates and social conditions would have been a preferred measure of "safety and security", however the unavailability of geocoded data within a consistent 1-mile radius of trip origins and destinations precluded this. An admittedly less-than-ideal proxy for "neighborhood quality"– the proportion of households with annual incomes below $25,000 within a mile radius of trip origins and destinations – was used instead.

Data on neighborhood attributes, like median household incomes, were obtained from the 2000 Census. Information on employment by occupations (used to gauge land-use mixture) was acquired from the Association of Bay Area Governments (ABAG), stratified by census tract.[14]

For each trip record, density and land-use composition were imputed for 1-mile and 5-mile radii of origins and destinations using block-level data and GIS tools. Because many walk and bicycle trips are beyond 1-mile in length, we distinguished land-use attributes at both the origins and destinations of trips. Variables related to street and urban design characteristics within 1-mile radii of trip origins and destinations, like counts of 3-way intersections and lineal miles of local streets, were computed from 2000 Census TIGER (Topologically Integrated Geographic Encoding and Referencing) files. Numerous 3-way intersections equates to neighborhoods populated by T-intersections, curvilinear streets, and cul-de-sacs whereas areas with all 4-way intersections and small quadrilateral blocks have grid-iron, usually pedestrian-friendly, street patterns.[15,16]

We turned to discrete-choice logit modeling, of the following form, to estimate the probability Bay Area residents walked or bicycled:

$$P_{niod} = \exp(V_{niod})/[\Sigma_{j\in Cnod} \exp(V_{njod}], \quad \forall \; V_{niod} = f\,(I_{od}, PH_n, BE_o, BE_d) \qquad (1)$$

where:

P_{niod} = probability of person n choosing mode i for traveling between origin o and destination d;

C_{nod} = choice set of modes available to person n traveling between origin o and destination d

V_{niod} = utility function for person n traveling by mode i between origin o and destination d;

I_{od} = impedance vector for trips from origin o to destination d, including distance and slope;

PH_n = personal and household characteristics vector for trip-maker n (e.g, gender and vehicle availability);

BE_o = built environment vector for 1- or 5-mile radius of origin o, representing measures of land-use intensity, land-use mixture, land-use accessibility, and walking quality; and

BE_d = built environment vector for 1- or 5-mile radius of destination d, comparable to the vector for origin o.

Our operative hypothesis is that BE_o and BE_d are significant explainers of the decision of walk or ride a bike, controlling for I_{od} and PH_n. Because of high inter-correlations among variables in these vectors, we turned to factor analysis to express BE_o and BE_d.

FACTOR ANALYSIS

The core dimensions of built environments – density, diversity, design -- are not easily captured by a single variable. However, when multiple variables are used to express elements like street design and land-use mixture, multicollinearity problems often contaminate model estimation. As in several past studies of built environments and travel, we turned to factor analysis to resolve this problem.[10, 17-19] Using variables on street supply, intersection configurations, city block sizes, and housing/employment characteristics within 1-mile radii of trip origins and destinations, four interpretable factors that exhibited Thurstone's "deep structure" (with eigenvalues above 1) were extracted.[20] Principal components estimation and varimax rotation were used in deriving the results shown in Table 1. (Only factor loadings with values above 0.20, in absolute terms, are shown.) Together, these factors accounted for over two-thirds of the variance among the 18 variables listed in the table.

The first two factors pertain to street and city-block characteristics -- one factor for the trip origin, the other for the destination. We call these "Pedestrian/Bike Friendly" factors since positive signs on loadings reflect urban design characteristics that are conducive to walking and bicycling. The block-size/intersection attributes of trip origins had the highest commonality among factors (eigenvalue of 3.86), accounting for 21.5% of total variance. Factor loadings reveal that areas with large city blocks are not pedestrian/bicycle friendly environs. Neither are neighborhoods with large shares of 3-way intersections and dead-ends, signs of non-grid street patterns. On the other hand, areas dotted with 4-way intersections (denoting grid-iron street patterns) as well as intersections with 5 or more converging streets (suggesting even higher levels of connectivity) were positively associated with the walking-biking friendly factor.

The third and forth factors reflect land-use diversity of trip origins and destinations. Neighborhoods with heterogeneous mixes of single-family and multi-family housing as well as jobs spread across the retail-service, office, and manufacturing-trade-other sectors scored high on these factors (based on the 0-1 entropy index, wherein 1 represents maximal heterogeneity). So did areas with a balance of employed-residents and jobs within 1-mile radii (based on the 0-1 balance index, wherein 1 represents perfect balance). Indices reflecting a balance of retail-service activities relative to employed-residents within 1-mile radii of origins and destinations also scored high on the diversity factor. These indices are considered to be particularly relevant since they reflect the relative availability of retail shops and consumer services within 1-mile (and thus plausibly walkable) radii of origins and destinations. Lastly, indices denoting the degree to which neighborhoods are residential in character loaded negatively onto the diversity factor. This accounts for the fact that bedroom communities are usually not land-use-rich settings whereas areas with higher shares of non-residential activities often are.

We note that other extracted factors (not shown in Table 1 because of low eigenvalues) captured some aspects of land-use intensity, such as population and employment densities, however loadings on these factors were fairly small and not always interpretable. To a significant extent, density attributes of neighborhoods are captured in what we are calling the design and diversity factors – i.e., neighborhoods with small blocks, grid street patterns, and mixed uses also tend to be fairly dense.

RESULTS

Walking Choice Model

Walking constituted 12.5% of surveyed BATS trips that were 5 miles or less in distance for the trip purposes studied. Far more common was travel by automobile, van, or motorcycle, comprising 82.6% of the total. Even for trips under a mile, the car dominated, making up 60.7% of the total (compared to 34.3% for walking).

The best-fitting walking choice model, shown in Table 2, presents the estimated coefficients that appear in the variables of each vector in Equation 1. The coefficients reflects the direction in which each variable influences the walking choice – positive values denote that a variable increases the probability of walking while negatives indicate the opposite. Table 2 reveals that control variables had appreciably stronger predictive powers than built-environment factors in explaining whether Bay Area residents traveling under 5 miles walked or not. Trip purpose weighed in heavily, with social and recreation/entertainment activities, in particular, increasing the likelihood that people walked. Weekends also favored walking. Personal attributes likewise mattered. Predictably, those with physical disabilities and numerous cars in the household were less likely to walk. More surprising was the ethno-racial dimension. Even after controlling for a socio-economic factor like vehicle ownership levels, African-Americans were more likely to walk than were whites or Asian-Americans. [This is consistent with 2000 Census results showing higher shares of African-Americans (3.2%) walked to work than the typical American worker (2.9%);[21] for all trip purposes, African-Americans averaged 82% more walk trips in 1995 than whites.[22]] Further, males tended to walk more than females, all else being equal.

Five impedance factors entered the model, reflecting walking disutilities. Even within a 5-mile distance band, the likelihood of walking eroded steadily with trip length. Steep terrain, rain, and nightfall also deterred walking. The model further suggests that pedestrians tended to shy away from lower-income settings, presumably because of safety concerns.

The only built-environment factor significant at the 5% probability level was land-use diversity at the trip origin (which in most instances corresponded to a 1-mile radius of a person's residence). Balanced, mixed-use environs with retail services significantly induced walking, *ceteris paribus*. Similarly, land-use diversity at the destination generally encouraged walking, however this relationship was statistically weak. On the other hand, pedestrian/bike friendly designs at neither the origin nor destination had much bearing on mode choice. Evidently, the micro-design elements of neighborhoods examined in this study, likely intersection configurations and block sizes, exerted fairly inconsequential influences on walking. Only slightly more important, though still statistically insignificant, was employment density within a mile of one's residence (reflected by the isochronic measure of job accessibility).

These results are consistent with those of past studies suggesting that density (as reflected by the employment accessibility variable) and land-use diversity exert stronger pressures than urban design on the decision to walk.[5,10,12] This is even after introducing far more control variables that account for walking impedances than in the case of past studies. The findings also align with earlier studies that show travel choice depends as much, if not more, on the degree of land-use mixing as urban densities.[5,23] Perhaps most notably, these results parallel other research findings that show land-use factors exert fairly modest influences on travel behavior in comparison to the demographic characteristics of trip-makers and impedances factors like distance and travel time.[4]

Bicycle Choice Model

Only 1.5% of BATS trips 5 or fewer miles (for the sub-sampled non-work trip purposes) were by bicycle. (For trips beyond 5 miles, the share was nearly identical.) For recreation/entertainment trips of 5 miles or less, bicycling captured a higher market share, 2.3% of all journeys. Bicycling is generally more popular in the Bay Area than in other parts of the United States. In 1995, just 0.9% of U.S. trips were by bike.[24]

The binomial choice mode for bicycle trips, shown in Table 3, produced results that were fairly similar to those of the walk choice model, although built-environment factors emerged as generally stronger predictors. The influences of control variables were akin to those of the walk choice model with a few exceptions: weekend and shop trips were more weakly related to biking; the only reasonably significant ethno-racial variable was "African-Americans"; slope was less and nightfall was more of a deterrent to biking; rainfall generally did not dissuade people from cycling; and, predictably, the likelihood of biking increased with the number of bicycles in one's household (just as studies show that driving increases with car ownership). This relationship is likely circular – i.e., a desire to cycle no doubt increases bicycle ownership.

Among built environment features, the urban design and land-use diversity factors were positively associated with the decision to ride a bicycle. Although the relationships were not significant at the 5% probability level, design had a far stronger influence on bicycling than walking choice. Block size, grid-iron streets, and other design attributes were slightly more important to the decision to bike at the destination than the origin. Mixed land uses and balances of residences, jobs, and retail-services also worked in favor of cycling, though only to a notable degree at the origin of trips. The influence of density was less straightforward. Having appreciable retail and service activities within a mile radius of one's origin generally encouraged a person to cycle. This isochronic metric of retail-service density captured the availability of nearby convenience retail outlets. Within a larger 5-mile radius of a trip origin, higher overall employment densities (as reflected by the "employment accessibility" variable) deterred bicycle travel.

Presumably this is because dense employment settings, like urban job centers and edge cities, often create numerous roadway conflict points and safety hazards for cyclists.

DISCUSSIONS

Past research on how urban landscapes shape travel behavior can be faulted on a number of grounds, though none more so than questionable construct and internal validity of research designs. Many factors conspire against walking and cycling in contemporary urban American of which car-dependent landscapes is just one. Unless factors like weather conditions or topography are controlled for, our understanding of how built environments influence travel will remain murky.

Our research reveals that urban landscapes in the San Francisco Bay Area generally have a modest and sometimes statistically insignificant effect on walking and cycling. Although well-connected streets, small city blocks, mixed land uses, and close proximity to retail activities were shown to induce NMT, various exogenous factors, like topography, darkness, and rainfall, had far stronger influences. Other control variables, such as demographic characteristics of trip-makers, were also far stronger predictors of walking and cycling choice than built-environment factors. From a public-policy standpoint, this suggests that a greater public-health benefit might accrue from designing walkable neighborhoods that appeal to the niche-market characteristics of different demographic groups versus micro-designing places in hopes of swaying travel behavior. That is, pedestrian-friendly places suited to the taste preferences of socio-demographic groups might induce more physical activity over the long run through the process of residential self-selection than overt efforts to create compact, mixed-use, gridded-street neighborhoods all over suburbia. Market responsive planning and zoning would help in this regard.

Among the built-environment factors that entered the models, land-use diversity in and around one's neighborhood (e.g., the presence of neighborhood retail) was the strongest predictor of walking. Bicycling, on the other hand, was equally influenced by density, diversity, and design, especially at the origin (i.e., residential-end) of a trip. Because of the stronger statistical fits, our results hint that built environments exert bigger impacts in and around one's residential neighborhood than destination. The evidence is suggestive though hardly compelling.

Might these results be generalizable beyond the Bay Area? We suspect so. Although factors like a hilly topography and Mediterranean climate are unique to the San Francisco region, given that these and other factors were controlled for in this study, the marginal impacts of built-environment elements, we suspect, are likely similar in other settings.

We do not rule out that the absence of strong statistical relationships in this study could reflect the use of imperfect variables to capture the myriad features of built environments. While GIS tools enable physical attributes of neighborhood streets and blocks to be defined, other micro-design attributes of built environments, like the presence of landscaping or street furniture, were not examined due to data limitations. Other research suggests such features generally exert minor influences on mode choice.[5,10, 25,26] Still, statistical analyses like ours should be supplemented by micro-level analyses, including qualitative case studies and quasi-experimental comparisons, that account for possible influences of street-scale design elements.[27,28]

While their motives are different, urban planners and public health officials form a potentially powerful alliance in the fight against car-dependent sprawl and the promotion of healthy cityscapes. More research is needed, however, that clarifies the potential environmental benefits – whether cleaner air or healthier citizens – of altering urban landscapes if this alliance is to gain legitimacy.

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Table 1 - Factor Analysis Loadings and Summary. Only loadings > |.20| shown.

	Pedestrian/ Bike Friendly Design Factor, Origin	Pedestrian/Bike Friendly Design Factor, Destination	Land-Use Diversity Factor, Origin	Land-Use Diversity Factor, Destination
Square meters per block within 1 mile, average; origin	-.480			
Square meters per block within 1 mile, average; destination		-.327		
3-way intersections, prop. of total intersections within 1 mile; origin	-.942			
3-way intersections, prop. of total intersections within 1 mile; destination		-.952		
4-way intersections, prop. of total intersections within 1 mile; origin	.933			
4-way intersections, prop. of total intersections within 1 mile; destination		.943		
5 or more-way intersections, prop. of total intersections within 1 mile; origin	.690			
5 or more-way intersections, prop. of total intersections within 1 mile; destination		.677		
Dead-ends as prop. of total intersections within 1 mile; origin	-.890			
Dead-ends as prop. of total intersections within 1 mile; destination		-.873		
Mixed use entropy (within 1 mile) = $-1*\{[\Sigma_i (p_i) (\ln p_i)]/\ln k\}$, at origin, where: p = prop. of total land uses; k = category of land use (single family housing units, multi-family housing units, retail service employment, office employment, manufacturing-trade-other employment); ln = natural logarithm			.826	
Mixed use entropy (within 1 mile) = $-1*\{[\Sigma_i (p_i) (\ln p_i)]/\ln k\}$, at destination, where: p = prop. of total land uses; k = category of land use (single family housing units, multi-family housing units, retail service employment, office employment, manufacturing-trade-other employment); ln = natural logarithm.				.828
Employed-residents to jobs balance index (within 1 mile of origin) = (1 - (((ABS(ER-JOBS))/(ER+JOBS))), where: ABS = absolute value; ER = no. of employed residents; JOBS = no. of workers			.871	

Employed-residents to jobs balance index (within 1 mile of destination) = (1 - (((ABS(ER-JOBS))/(ER+JOBS))), where: ABS = absolute value; ER = no. of employed residents; JOBS = no. of workers				.802
Employed-residents to retail-services balance index (within 1 mile of origin) = (1 - (((ABS(ER-RS))/(ER+RS))), where: ABS = absolute value; ER = no. of employed residents; RS = no. of retail and service jobs			.884	
Employed-residents to retail-services balance index (within 1 mile of destination) = (1 - (((ABS(ER-RS)) /(ER+RS))), where: ABS = absolute value; ER = no. of employed residents; RS = no. of retail and service jobs				.873
"Residential-ness" index = housing units as prop. of total employment and housing units; origin				-.879
"Residential-ness" index = housing units as prop. of total employment and housing units; destination				-.773
Summary Statistics: Eigenvalue Percent of variance Cumulative percent of variance captured by factors = 68.34%	 3.86 21.47	 3.51 19.50	 2.54 14.11	 2.39 13.27

Table 2 - Walk Choice Model for Predicting Probability Trip Made by Walking

	Coefficient	Stand. Error	Probability
Constraints/Deterrents			
Trip distance (miles)	-1.970	0.074	.000
Slope (rise/run)	-4.109	2.090	.049
Rainfall day of trip (inches, 24 hours)	-0.729	0.330	.027
Dark (1=yes, 0=no) (before sunrise or after sunset)	-0.158	0.112	.159
Low income neighborhood (proportion of households within 1 mile of origin and destination with annual incomes < $25,000)	-0.766	0.523	.143
Personal/Household Attributes			
Disability (1=yes, 0=no)	-0.480	0.275	.081
Gender (1=male, 0=female)	0.161	0.083	.051
African-American (1=yes, 0=no)	0.788	0.278	.005
Asian-American (1=yes, 0=no)	-0.286	0.192	.136
White (1=yes, 0=no)	-0.310	0.118	.008
No. of vehicles in household	-0.695	0.050	.000
Trip Characteristics			
Weekend trip (1=yes, 0=no)	0.246	0.100	.013
Recreation/Entertainment purpose (1=yes, 0=no)	0.809	0.120	.000
Eat/Meal purpose (1=yes, 0=no)	0.688	0.127	.000
Social purpose (1=yes, 0=no)	0.886	0.144	.000
Shop purpose (1=yes, 0=no)	0.623	0.165	.000
Built Environment Characteristics			
Employment accessibility: no. of jobs (in 10,000s) within1 mile of origin	.068	0.042	.104
Pedestrian/Bike friendly design factor, origin	.037	0.048	.441
Pedestrian/Bike friendly design factor, destination	.035	0.047	.465
Land-use diversity factor, origin	.098	0.042	.021
Land-use diversity factor, destination	.023	0.042	.590
Constant	1.217	0.198	.000
Summary Statistics: No. of cases = 7,836 X^2 = 2,010.5 (prob. = .000) Rho-squared: 1 - *L (1)/L (0)* = .429			

Table 3 - Bicycle Choice Model for Predicting Probability Trip Made by Bicycle

	Coefficient	Stand. Error	Probability
Constraints/Deterrents			
Trip distance (miles)	-0.291	0.084	.001
Slope (rise/run)	-7.796	5.930	.187
Dark (1=yes, 0=no) (before sunrise or after sunset)	-0.721	0.314	.022
Low income neighborhood (proportion of households within 1 mile of origin and destination with annual incomes < $25,000)	-1.657	1.221	.175
Personal/Household Attributes			
Gender (1=male, 0=female)	0.588	0.194	.002
African-American (1=yes, 0=no)	0.854	0.472	.071
No. of vehicles in household	-0.629	0.120	.000
No. of bicycles in household	0.345	0.037	.000
Trip Characteristics			
Weekend trip (1=yes, 0=no)	0.226	0.219	.301
Recreation/Entertainment purpose (1=yes, 0=no)	0.602	0.225	.001
Social purpose (1=yes, 0=no)	0.861	0.281	.002
Shop purpose (1=yes, 0=no)	0.443	0.389	.256
Built Environment Characteristics			
Employment accessibility: no. jobs (in 10,000s) within 5 miles of origin	-0.017	0.011	.106
Retail-service density: no. retail-service jobs per net commercial acre within 1 mile of origin	0.005	0.003	.114
Pedestrian/Bike friendly design factor, origin	.234	0.151	.122
Pedestrian/Bike friendly design factor, destination	.193	0.113	.088
Land-use diversity factor, origin	.156	0.098	.112
Land-use diversity factor, destination	.056	0.099	.570
Constant	-3.773	0.392	.000
Summary Statistics: No. of cases = 7,836 X^2 = 152.8 (prob. = .000) Rho-squared: 1 - *L (1)/L (0)* = .131			