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Do changes in neighborhood characteristics lead to changes in travel behavior? A structural equations modeling approach

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Abstract Suburban sprawl has been widely criticized for its contribution to auto dependence. Numerous studies have found that residents in suburban neighborhoods drive more and walk less than their counterparts in traditional environments. However, most studies confirm only an association between the built environment and travel behavior, and have yet to establish the predominant underlying causal link: whether neighborhood design independently influences travel behavior or whether preferences for travel options affect residential choice. That is, residential self-selection may be at work. A few studies have recently addressed the influence of self-selection. However, our understanding of the causality issue is still immature. To address this issue, this study took into account individuals' self-selection by employing a quasi-longitudinal design and by controlling for residential preferences and travel attitudes. In particular, using data collected from 547 movers currently living in four traditional neighborhoods and four suburban neighborhoods in Northern California, we developed a structural equations model to investigate the relationships among changes in the built environment, changes in auto ownership, and changes in travel behavior. The results provide some encouragement that land-use policies designed to put residents closer to destinations and provide them with alternative transportation options will actually lead to less driving and more walking.

Keywords Longitudinal analysis · Smart growth · Built environment · Land use · Self-selection

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Introduction

A large number of studies have investigated the relationship between the built environment and travel behavior since the 1990s (as reviewed in Crane 2000; Ewing and Cervero 2001; Handy 1996). These studies have found that residents living in traditional neighborhoods (characterized as high density, high accessibility, mixed land uses, rectangular street network, and so on) drive less and walk more than those living in suburban neighborhoods (e.g., Cervero and Duncan 2003; Crane and Crepeau 1998). However, most of these studies confirm only an association between the built environment and travel behavior, and have yet to establish the predominant underlying causal link: whether the built environment independently influences travel behavior or whether preferences for land use patterns and travel options affect residential choice. If the latter direction is the dominant one, the observed relationship between the built environment and travel behavior may be attributable to residential self-selection. For example, those preferring walking may selectively live in walkable neighborhoods and thus walk more. If so, the ability to use the built environment to change individuals' travel patterns may be limited by the apparently sizable share of households who favor suburban types of development (Morrow-Jones et al. 2004), and land use and transportation policies aiming to reduce auto dependence may not have the expected effects.

The causality issue has recently become one of the key questions in the debate over the relationship between the built environment and travel behavior (Transportation Research Board & Institute of Medicine 2005). The purpose of this study is to explore this causal relationship by applying structural equations models to quasi-longitudinal data[1] collected from Northern California. In particular, this paper aims to address the following two questions: (1) Are changes in the built environment associated with changes in travel behavior, after taking multiple interactions into account and controlling for socio-demographics, attitudes, and preferences? (2) To what extent does residential self-selection explain individuals' travel behavior? The next section briefly reviews the literature addressing the residential self-selection problem. The ''Methodology'' section describes the data, variables and the modeling approaches used in this study. The following section presents the model results. The final section recapitulates the key findings.

Literature review

Several recent empirical studies have shed light on the causal relationships that underlie the correlations between the built environment and travel behavior (for a more complete review of methodologies and studies controlling for residential self-selection, see Cao et al. 2006a). With respect to single-equation cross-sectional studies, Kitamura et al. (1997) concluded that the variation in travel demand for their San Francisco Bay Area sample owed more to attitudinal factors than to land use characteristics. Cao et al. (2006b) investigated the influence of neighborhood characteristics and store characteristics on strolling and walking to the store, controlling for residential preferences. They confirmed the effect of residential self-selection. However, the built environment did have a separate

[1] Our data were collected at one point in time, but respondents were asked to retrospectively report a number of characteristics for a previous point in time as well as for the current time. So the data are different from longitudinal data, which are typically measured at two time points.

influence on pedestrian behavior beyond that effect. In three studies, Schwanen and Mokhtarian compared the trip frequency (2003), commute mode choice (2005a), and mode-specific distances traveled (2005b) of mismatched suburban and urban residents (those who preferred a more or less, respectively, dense/diverse neighborhood than the one they currently lived in) to their matched counterparts in both kinds of neighborhoods. In general, they found that while suburban residents' travel behavior was similar whether they were matched or mismatched, mismatched urban residents' behavior fell between that of matched urban and matched suburban residents – more auto-oriented than the former but less so than the latter. These findings suggest that suburban environments inhibit urban-style travel behavior to a greater extent than urban environments inhibit suburban-style travel behavior and support a built environment effect separate from self-selection. By contrast, Chatman (2005) found that effects of built environment characteristics showed little difference between those with strong and weak modal preferences and concluded that residential self-selection does not significantly explain travel behavior, at least for his data. In general, these studies accounted for the influence of attitudinal factors and hence presumably eliminated the rival hypothesis of a spurious relationship between the built environment and travel behavior. Accordingly, these studies offer stronger evidence for a causality inference than previous research does. However, they modeled only a single causal direction (from the built environment to travel behavior), which is too simplistic a representation of the interactions among the built environment, travel behavior, and attitudes.

Bagley and Mokhtarian (2002) employed a structural equations model (SEM) to investigate the relationships among those variables. They found that with respect to direct and total effects, attitudinal and lifestyle variables had the greatest impact on travel demand among all explanatory variables, while residential location type had little separate influence on travel behavior. These results lend strong support to the speculation that the observed relationships between the built environment and travel behavior are not direct causal links, but are primarily attributed to interactions of these variables with other variables. However, although allowing multiple directions of causality arguably constitutes a conceptual improvement over the single-equation approach, the use of cross-sectional data is still a practical drawback. Specifically, cross-sectional analysis is sufficient to establish evidence for association and nonspuriousness, but inadequate to infer the time precedence of a causal relationship.

By contrast, a longitudinal study showing that changes in built environment characteristics are associated with changes in travel behavior (while controlling for other confounding factors) will offer more direct evidence of a causal link from the built environment to travel behavior than cross-sectional analysis can (Finkel 1995). Further, focusing on changes controls for variables (both observed and unobserved) that do *not* change over time, thereby reducing a lot of the ''noise'' (due to unexplained variation, i.e., variation in dependent variables that is due to unobserved influences) in the observed relationships. A few studies have adopted a longitudinal (or quasi-longitudinal) design. In an evaluation of California Safe Route to School (SR2S) projects, Boarnet et al. (2005) examined the relationship between improvements in the walking and biking infrastructure and children's walking and bicycle travel to school, based on retrospective responses of 1,244 parents. Changes in this infrastructure (sidewalks, crossings, and traffic control) serve as a ''treatment'' for the children who passed the SR2S projects on their way to school (experimental group). The control group consists of those who did not pass the SR2S projects. Through *t*-tests, they found that 15.4% of the 486 children who passed the SR2S projects increased their walking or bicycle travel to school, while only 4.3% of the 376 children who did not pass the projects increased their non-motorized travel. However, memory biases and social desirability biases (given that the ''desirable'' answer was probably especially apparent to the treatment respondents) may be concerns of this study.

Using the Puget Sound Transportation Panel data, Krizek (2003) applied linear regression models to test whether changes in travel behavior could be attributed to changes in neighborhood accessibility, controlling for changes in socio-demographic characteristics, workplace accessibility, and regional accessibility. He found that changes in neighborhood accessibility were statistically significant in all models of travel behavior. This finding suggests that when households' neighborhood accessibility changes, their travel behavior also changes, all else being equal. The author pointed out, however, that the results should be interpreted with caution, as the changes in both neighborhood accessibility and travel behavior may be the result of changes in attitudinal predispositions toward the residential environment and travel choices. Alternatively, the results could reflect moves to residential environments that better match pre-existing travel preferences, thereby better enabling an expression of those preferences (and therefore still representing a self-selection effect).

Meurs and Haaijer (2001) investigated the extent to which changes in residential environment characteristics led to changes in travel patterns, using Dutch Time Use Study data from 1990 and 1999. For the dynamic analysis, the respondents were divided into two segments: movers and non-movers. Regression analyses were conducted on both segments, in which changes in the number of trips by various modes were regressed against changes in residential environment and personal characteristics. For the people who moved, changes in residential environment characteristics influenced travel behavior, and changes in employment and auto ownership as well as other socio-demographic factors greatly influenced changes in auto trip frequency. For the people who did not move, the observed effects of spatial changes (which were relatively minor and incremental, such as an extra garage, the installation of traffic calming measures, and the provision of a bike path) were limited, as they expected.

Similarly, Handy and her colleagues classified their Northern California respondents into movers and non-movers, based on whether they moved within the last year. Handy et al. (2005, 2006) developed three ordered probit models to investigate the unidirectional causal link from the built environment to travel behavior. After accounting for the influence of current attitudes and changes in socio-demographics, they found that changes in neighborhood characteristics consistently affected changes in these behaviors. However, these analyses are still not definitive, nor do they clarify the nature of the causal relationship. First, the built environment is, at least partially, endogenous to travel behavior in these two studies. Although they took into account individuals' self-selection of the built environment by employing a quasi-longitudinal design and by controlling for residential preferences and travel attitudes, they did not model the influence of attitudinal factors on the choice of the built environment. Second, they treated auto ownership as exogenous in the relationship between the built environment and driving behavior, but it was actually endogenous. Cao et al. (2007) and Handy et al. (2005) showed that changes in the built environment influence changes in auto ownership, which in turn affect changes in driving. In other words, auto ownership is a mediating link connecting the built environment and travel behavior. The same data are analyzed here using the structural equations modeling approach, which explicitly permits multiple directions of causality simultaneously, allowing the dependent variable of one equation to be an explanatory variable in another equation in the system. These more sophisticated models will help to establish the strength and direction of the relationships among changes in the built environment, changes in travel behavior, changes in auto ownership, and other factors.

Methodology

Data and variables

This paper uses data collected from residents living in four ‘‘traditional’’ neighborhoods and four ‘‘suburban’’ neighborhoods in Northern California. The neighborhoods were selected to vary systematically on neighborhood type, size of the metropolitan area, and region of the state. The neighborhoods chosen as ‘‘traditional’’ included Mountain View (Downtown), Sacramento (Midtown), Santa Rosa (Junior College area), and Modesto (Central). The neighborhoods chosen as suburban were Sunnyvale (I-280 area), Sacramento (Natomas area), Santa Rosa (Rincon Valley area), and Modesto (suburban area). The four traditional neighborhoods differ in visible ways from the four suburban neighborhoods—the layout of the street network, the age and style of the houses, and the location and design of commercial centers (see Handy et al. 2004 for details).

For each neighborhood, we purchased two databases of residents from a commercial provider, New Neighbors Contact Service (www.nncs.com): a database of ‘‘movers’’ and a database of ‘‘nonmovers.’’ The ‘‘movers’’ included all current residents of the neighborhood who had moved within the previous year. From this database, we drew a random sample of 500 residents for each of the eight neighborhoods. The database of ‘‘nonmovers’’ consisted of a random sample of 500 residents not included in the ‘‘movers’’ list for each neighborhood. The survey was administered in October and November 2003, using a mail-out, mail-back approach. This approach resulted in 1682 responses, a 24.9% response rate based on the valid addresses only. Since the survey did not measure changes in auto ownership for non-movers due to a survey design flaw, only those who had moved within the previous year (N = 547) were analyzed in this study. Table 1 presents sample characteristics of these movers. Compared to movers currently living in traditional neighborhoods, those moving to suburban neighborhoods have a greater tendency to be homeowners, have children, live in a larger household, be older, and own more vehicles. Further, the sample contains more female movers than male movers.

The variables used in this study can be classified into five groups: travel behavior, neighborhood characteristics, neighborhood preferences, travel attitudes, and sociodemographics.

Travel behavior

Changes in travel behavior were measured using a series of general indicators. Because it is difficult for individuals to accurately recall the specifics of their travel behavior from as long as one year ago, respondents were asked to indicate how their travel differs now, from before they moved. In particular, a series of questions asked respondents about use of different modes compared to previously, on a five-point scale from ‘‘a lot less now’’ to ‘‘a lot more now.’’ Thus, to maximize recall *accuracy*, we consciously sacrificed measurement *precision*.

Table 1 Sample characteristics

	Traditional				Suburban			
	Mountain View	SR Junior College	MD Central	SC Midtown	Sunnyvale	SR Rincon Valley	MD Suburban	SC Natomas
Number	89	79	54	99	78	54	42	52
Percent females	54	61	74	60	48	60	60	51
Average auto ownership	1.78	1.51	1.59	1.43	1.68	1.54	1.74	1.62
Age	36.6	39.0	41.2	35.6	38.4	49.4	42.7	39.4
Average HH size	2.06	1.92	2.31	1.64	2.71	2.06	2.26	2.40
Percent of HHs w/kids	29	28	59	5	88	43	52	54
Percent home owners	31	36	57	18	38	48	71	71
Mean HH income ($k)	93.3	59.6	63.9	61.7	88.0	54.4	56.9	60.9
Median HH income ($k)	110	55.0	55.0	60.0	100	50.0	57.5	60.0

Notes. SR = Santa Rosa, MD = Modesto, SC = Sacramento, HH = household

Neighborhood characteristics and neighborhood preferences

Respondents were asked to indicate how true 34 characteristics are for their current and previous neighborhoods, on a four-point scale from ‘‘not at all true’’ (1) to ‘‘entirely true’’ (4). The characteristics of these neighborhoods as perceived by survey respondents reflect fundamental differences in neighborhood design. Also the importance of these items to respondents when they were looking for a new place to live was measured on a four-point scale from ‘‘not at all important’’ (1) to ‘‘extremely important’’ (4). We conducted a factor analysis to identify underlying constructs of perceived and preferred neighborhood characteristics. Finally, these items were reduced to six factors: accessibility, physical activity options, safety, socializing, attractiveness, and outdoor spaciousness (Table 2). Changes in the built environment were measured by taking the difference in perceived characteristics between the current and previous neighborhoods.

Following the survey, objective measures of accessibility were estimated for each respondent, based on distance along the street network from home to a variety of destinations classified as institutional (bank, church, library, and post office), maintenance (grocery store and pharmacy), eating-out (bakery, pizza, ice cream, fast food, and take-out), and leisure (health club, bookstore, bar, theater, and video rental). Commercial establishments were identified using on-line yellow pages, and ArcGIS was used to calculate network distances between addresses for survey respondents and commercial establishments. Accessibility measures included the number of different types of businesses within specified distances, the distance to the nearest establishment of each type, and the number of establishments of each business type within specified distances. Note that all these measures should be viewed generally as indicators of accessibility. It is those

Table 2 Key variables loading on the neighborhood characteristic and travel attitude factors that are significant in the final model

Factor	Statement
Perceived and preferred neighborhood characteristics	
Accessibility	Easy access to a regional shopping mall (0.854); easy access to downtown (0.830); other amenities such as a pool or a community center available nearby (0.667); shopping areas within walking distance (0.652); easy access to the freeway (0.528); good public transit service (bus or rail) (0.437)
Physical activity options	Good bicycle routes beyond the neighborhood (0.882); sidewalks throughout the neighborhood (0.707); parks and open spaces nearby (0.637); good public transit service (bus or rail) (0.353)
Safety	Quiet neighborhood (0.780); low crime rate within neighborhood (0.759); low level of car traffic on neighborhood streets (0.752); safe neighborhood for walking (0.741); safe neighborhood for kids to play outdoors (0.634); good street lighting (0.751)
Socializing	Diverse neighbors in terms of ethnicity, race, and age (0.789); lots of people out and about within the neighborhood (0.785); lots of interaction among neighbors (0.614); economic level of neighbors similar to my level (0.476)
Attractiveness	Attractive appearance of neighborhood (0.780); high level of upkeep in neighborhood (0.723); variety in housing styles (0.680); big street trees (0.451)
Outdoor spaciousness	Large back yards (0.876); large front yards (0.858); lots of off-street parking (garages or driveways) (0.562); big street trees (0.404)
Travel attitudes	
Pro-bike/walk	I like riding a bike (0.880); I prefer to bike rather than drive whenever possible (0.865); biking can sometimes be easier for me than driving (0.818); I prefer to walk rather than drive whenever possible (0.461); I like walking (0.400); walking can sometimes be easier for me than driving (0.339)
Travel minimizing	Fuel efficiency is an important factor for me in choosing a vehicle (0.679); I prefer to organize my errands so that I make as few trips as possible (0.617); I often use the telephone or the Internet to avoid having to travel somewhere (0.514); the price of gasoline affects the choices I make about my daily travel (0.513); I try to limit my driving to help improve air quality (0.458); vehicles should be taxed on the basis of the amount of pollution they produce (0.426); when I need to buy something, I usually prefer to get it at the closest store possible (0.332)
Safety of car	Traveling by car is safer overall than riding a bicycle (0.489); traveling by car is safer overall than walking (0.753); traveling by car is safer overall than taking transit (0.633); the region needs to build more highways to reduce traffic congestion (0.444); the price of gasoline affects the choices I make about my daily travel (0.357)
Car dependent	I need a car to do many of the things I like to do (0.612); getting to work without a car is a hassle (0.524); we could manage pretty well with one fewer car than we have (or with no car) (−0.418); traveling by car is safer overall than riding a bicycle (0.402); I like driving (0.356)

Note. The numbers in parentheses are the pattern matrix loadings for the obliquely rotated factors
Source: Handy et al. (2004)

general characteristics of a neighborhood that might be expected to influence personal travel choice, rather than the specific land use types themselves.

Travel attitudes

To measure attitudes regarding travel, the survey asked respondents whether they agreed or disagreed with a series of 32 statements on a 5-point scale from ‘‘strongly disagree’’ (1) to ''strongly agree'' (5). Through factor analysis, six underlying dimensions were identified: pro-bike/walk, pro-transit, pro-travel, travel minimizing, car dependent, and safety of car. The four factors found significant in the models of this paper are shown in Table 2.

Socio-demographics

Finally, the survey contained a list of socio-demographic variables. These variables include gender, age, employment status, educational background, household income, household size, the number of children in the household, mobility constraints, residential tenure, and so on. Some changeable socio-demographics such as household structure and income were measured before residential relocation and currently.

Modeling approach

An SEM approach was employed in this study. Although SEMs can include latent endogenous variables, the present application is restricted to the case where all endogenous variables are observed. Using the matrix notation in Mueller (1996), an SEM for observed (mean-centered) variables can be defined as having the following form:

$$\mathbf{Y} = \mathbf{BY} + \mathbf{\Gamma X} + \boldsymbol{\zeta},$$

where

$\mathbf{Y}$ = ($N_Y \times 1$) column vector of endogenous variables (N_Y = number of endogenous variables),
$\mathbf{X}$ = ($N_X \times 1$) column vector of exogenous variables (N_X = number of exogenous variables),
$\mathbf{B}$ = ($N_Y \times N_Y$) matrix of coefficients representing the direct effects of endogenous variables on other endogenous variables,
$\mathbf{\Gamma}$ = ($N_Y \times N_X$) matrix of coefficients representing the direct effects of exogenous variables on endogenous variables, and,
$\boldsymbol{\zeta}$ = ($N_Y \times 1$) column vector of errors.

The two coefficient matrices $\mathbf{B}$ and $\mathbf{\Gamma}$ determine the structure of an SEM. In addition, a covariance matrix $\mathbf{\Phi}$ ($N_X \times N_X$) for exogenous variables $\mathbf{X}$ and a covariance matrix $\mathbf{\Psi}$ ($N_Y \times N_Y$) for error terms $\boldsymbol{\zeta}$ can be specified. The $\mathbf{B}$, $\mathbf{\Gamma}$, $\mathbf{\Phi}$, and $\mathbf{\Psi}$ matrices together establish an SEM for observed variables. To estimate an SEM, $\mathbf{\Sigma}$, the model-implied covariance matrix of observed variables $\mathbf{X}$ and $\mathbf{Y}$, will be reproduced in terms of specific functions of unknown model parameters (namely, the $\mathbf{B}$, $\mathbf{\Gamma}$, $\mathbf{\Phi}$, and $\mathbf{\Psi}$ matrices). If specific values for the unknown parameters are inserted in these functions, a model-implied (reproduced) covariance matrix is obtained, and then the difference between this matrix and the observed (sample) covariance matrix $\mathbf{S}$ is calculated based on some criterion. A structural equations modeling program fits the specified model to the data by repeatedly inserting better and better estimates of these parameters until the difference between the reproduced and observed covariance matrices is minimized in terms of some criterion. In view of the nature of the estimation process, the SEM is commonly referred to as covariance structure analysis. The goodness-of-fit of an SEM relies on how well its model-implied covariance matrix $\mathbf{\Sigma}$ conforms to its observed covariance matrix $\mathbf{S}$ (Raykov and Marcoulides 2000).

In the step of model specification, we addressed two fundamental issues. First, changes in travel behavior, changes in the built environment, and changes in auto ownership were selected as endogenous variables, based on the findings of Handy et al. (2005, 2006) and Cao et al. (2007) as well as previous studies. Second, we set the presumed directions of influences. The directionalities of the presumed causal effects are important in a longitudinal study. As an example, changes in travel behavior after a move are likely to be a result of changes in built environment characteristics, but the reverse direction is less plausible according to the temporal nature of influences. For endogenous variables, our assumed directions of influences are as follows: changes in the built environment affect both changes in auto ownership and changes in travel behavior, and the latter two changes are allowed to influence each other. Further, we assumed that changes in all endogenous variables are additionally influenced by changes in socio-demographics and by current attitudes. Since the base values of (as well as the changes in) changeable explanatory variables influence dependent variables (Krizek 2003), we allow current or previous measures of these variables (as well as change measures) to enter the model.

What general inferences could be made from our model, with respect to the influences of attitudes (AT, whether travel attitudes or neighborhood preferences) and changes in the built environment (ΔBE) on changes in travel behavior (ΔTB)? If all three links AT $\rightarrow$ ΔBE, AT $\rightarrow$ ΔTB, and ΔBE $\rightarrow$ ΔTB are significant, we conclude that both self-selection and the built environment separately help determine travel behavior (similar comments can be made with respect to socio-demographic characteristics as well as attitudes, but we continue to focus on attitudes in this work): if two people with different attitudes end up in the same neighborhood for whatever reasons, the one with a stronger walk predisposition will presumably tend to walk more, although the built environment can still facilitate or constrain the walking behavior of both people, and similarly for driving. If we find only AT $\rightarrow$ ΔBE and AT $\rightarrow$ ΔTB, but not ΔBE $\rightarrow$ ΔTB, we conclude that the BE has no true effect on TB—that the observed relationship between them is accounted for by the antecedent influence of AT on both. However, if we find AT $\rightarrow$ ΔBE and ΔBE $\rightarrow$ ΔTB but not AT $\rightarrow$ ΔTB, the implications are somewhat more nuanced. In that case attitudes have no *separate* impact on travel behavior: if two people with different attitudes ended up in the same residential area for different reasons, they would not, on average, travel differently from each other (or else we would see a significant AT $\rightarrow$ ΔTB relationship in addition to the ΔBE $\rightarrow$ ΔTB one). It would not be appropriate to say that attitudes are irrelevant in that case, because they do affect the likelihood that the individual will end up in a neighborhood where people tend to travel in a certain way (i.e., they have an *indirect* effect on travel behavior, through their effect on the built environment). But it does mean that to the extent that individuals with certain propensities are motivated to move to a neighborhood that counteracts those propensities, their travel behavior would tend to fall into line with the prevailing patterns of their neighborhood, attitudes notwithstanding.

The maximum likelihood estimation (MLE) approach, commonly used in practice, was chosen to develop the SEMs. Using AMOS 5.0, we first estimated an SEM studying the relationships among changes in driving, changes in the built environment, and changes in auto ownership, which is presented in the ‘‘Driving behavior’’ section. We then present a model incorporating both walking and driving behavior in the ‘‘Driving and walking behavior’’ section. Since the number of exogenous variables far exceeds the number of endogenous variables in these two SEMs, model identification is not a problem.

Model results

Driving behavior

Our previous work showed that changes in driving behavior are influenced by changes in accessibility, and that changes in auto ownership are affected by changes in outdoor spaciousness (Handy et al. 2005; Cao et al. 2007). Therefore, changes in accessibility and outdoor spaciousness were chosen as endogenous variables capturing changes in the built environment. Accordingly, we specified our conceptual model, as shown in Fig. 1. We allowed the error terms of all equations for endogenous variables to be correlated.

Multivariate normality examination and goodness-of-fit

The validity of MLE theoretically depends on whether the SEM meets the assumption of multivariate normality of its variables. When this assumption holds, estimates of the variances of parameters are consistent. A review of the literature reveals that meeting this condition is a problem in many studies. Bentler and Dudgeon (1996, p. 566) stated that ''in practice [for structural equation models], the normality assumption will often be incorrect.'' Micceri (1989) reviewed numerous data sets that were used in journal articles and found that a majority of the conclusions were based on data that were nonnormally distributed.

To test for departures from normality, we reviewed the Mardia statistic (a measure of multivariate kurtosis) of the SEM with variables in their original form. That statistic was equal to 66.53, with a critical ratio of 28.99 (a critical ratio above 1.96 signifies departure from multivariate normality with 95% confidence). Given this significant failure, modifications were in order. In particular, we transformed (taking the natural log of) some variables that had high kurtosis values, and removed one marginally significant variable (change in the number of children under 5) having an extremely high kurtosis value. The Mardia statistic of the re-estimated model was reduced to 15.88, with a critical ratio of 7.31. To make our data conform to the multivariate normality distribution, we also tried to remove some extreme observations but discarded this approach because it did not produce satisfactory results (refer to Cao 2006 for details).

Although our SEM still deviates from the multivariate normality assumption, the influence of non-normal data is reduced when using MLE with a larger sample size (Anderson and Amemiya 1988; Lei and Lomax 2005). What constitutes a large sample size? First, Stevens (1996) suggested that the ratio between the sample size and the number of observed variables should not be less than 15. In our model, the sample size is considered to be quite large since this ratio is 547/17 > 32, more than twice the recommended

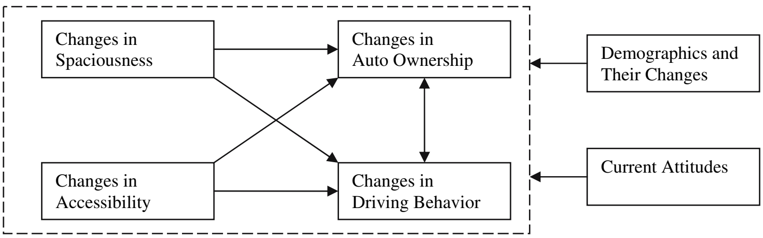

Fig. 1 Conceptual structural model: driving

Table 3 Measures of fit for the structural equations model: driving ($N = 547$)

Degrees of freedom	35
χ^2: measures discrepancy between the sample and model-implied covariance matrices; the smaller the better[a].	78.80
χ^2/d.f.: a ''relative chi-square value'' corrected for degrees of freedom; values of 3 or less indicate a good fit, and values as high as 5 represent an adequate fit.	2.25
Goodness-of-Fit Index (GFI): the relative proportion of variance and covariance in the sample covariance matrix explained by the model-implied covariance matrix, with values closer to 1 being better.	0.98
Normed Fit Index (NFI): proportion of worst (independence) model χ^2 explained by the model of interest; varies between 0 and 1, with values larger than 0.90 indicating a well-fitting model.	0.91
Comparative Fit Index (CFI): assumes a noncentral χ^2 distribution for the worst (independence) model discrepancy; varies between 0 and 1, with values closer to 1 indicating a good fit.	0.94
Incremental Fit Index (IFI): the incremental improvement of the model of interest over the worst (independence) model; values closer to 1 indicate a good fit.	0.95
Root Mean Square Error of Approximation (RMSEA): measures the estimated discrepancy between the model-implied and true population covariance matrix, corrected for degrees of freedom; values less than 0.05 indicate a good fit, and values as high as 0.08 represent a reasonable fit.	0.048

[a] The chi-squared statistic increases with the sample size, and so it is not a good measure of goodness-of-fit (GOF). However, as the basis for other GOF measures, it is always reported anyway (Byrne 2001).

threshold. Second, when the sample size is larger than 500 and the degrees of freedom of an SEM are over 30, we can achieve a relatively high power (over 0.95) for hypothesis testing, even in the presence of non-normality (MacCallum et al. 1996). Therefore, the possible non-normality of the data after the transformations does not seem to be a serious problem in our case.

Given the substantial improvement of the Mardia statistic after transformation over that of the original model, the large sample size, and generally good measures of fit (Table 3), this SEM is chosen as the final model.

Discussion

The final model consists of four endogenous variables: changes in outdoor spaciousness, changes in accessibility, changes in auto ownership, and changes in driving. The error terms for changes in outdoor spaciousness and changes in accessibility are negatively correlated at the 0.05 level, indicating that unobserved factors influence these two variables in opposite ways (as would be expected, since the variables themselves are negatively correlated).

Table 4 presents the matrix of standardized direct effects and total effects,[2] which largely follow expectations. Changes in outdoor spaciousness are positively associated with a preference for spaciousness and with changes in the number of driving-age members in the household, but negatively related to a preference for accessibility and to the current measure for age. Changes in accessibility are exclusively determined by attitudinal factors: individuals preferring high-accessibility neighborhoods are more likely to move to

[2] Total effects include direct effects and indirect effects. For example, if the variable X influences the variable Y2 without any mediating variables, this influence (X → Y2) represents a direct effect from X to Y2; by contrast, if X influences Y2 through Y1, this influence (X → Y1 → Y2) represents an indirect effect from X to Y2. Standardized effects, as in single-equation regression, are based on the coefficients of a model in which all variables have been standardized to remove scale dependence.

Table 4 Standardized direct and total effects: driving model

Variables	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving
Endogenous variables				
Changes in spaciousness	—	—	0.158 (0.158)	0 (0.016)
Changes in accessibility	—	—		−0.206 (−0.206)
Changes in automobiles[a]	—	—	—	0.099 (0.099)
Changes in driving	—	—	—	—
Exogenous variables				
Socio-demographics				
Changes in income[a]			0.130 (0.130)	0.087 (0.100)
Changes in # of driving-age members[a]	0.112 (0.112)		0.294 (0.312)	0 (0.031)
Current education				−0.079 (−0.079)[b]
Ln (1 + current # of kids < 18)				0.096 (0.096)
Current age	−0.128 (−0.128)		−0.123 (−0.143)	−0.104 (−0.118)
Neighborhood characteristics				
Current socializing	—	—		−0.087 (−0.087)
Current dist. to nearest fast food (km)	—	—	0.076 (0.076)[b]	0 (0.008)
Current # of leisure businesses w/in 1600 m	—	—		−0.080 (−0.080)[b]
Travel attitudes				
Travel minimizing		0.138 (0.138)		0 (−0.028)
Safety of car		−0.103 (−0.103)		0 (0.021)
Car dependent				0.108 (0.108)
Residential preferences				
Accessibility	−0.140 (−0.140)	0.130 (0.130)	0 (−0.022)	0 (−0.029)
Outdoor spaciousness	0.221 (0.221)		−0.099 (−0.064)	0 (−0.006)
Squared multiple correlations	0.093	0.056	0.189	0.131

Notes. Data were automatically standardized when the model was estimated. The numbers in parentheses are total effects. The dashes are constraints imposed according to the hypothesized model. A blank cell indicates that this variable was found to be insignificant in the model and hence constrained to have a zero coefficient

[a] These variables are log-transformed to improve multivariate normality. Because they are centered around zero, the logarithm transformation is problematic (since the natural logarithm function is undefined for zero and negative numbers). To address this problem, these variables (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \text{Ln}\ (X + 1)$; if $X < 0$, $X_{new} = -\text{Ln}\ (-X + 1)$. This transformation retains the symmetry and sign properties of the original X; for example, the values −2, −1, 0, 1, 2 are transformed to −ln 3, −ln 2, ln1 = 0, ln 2, ln 3

[b] Significant at the 0.1 level; all other parameters are significant at the 0.05 level

neighborhoods with higher accessibility; so are those having a tendency to minimize their daily travel; but people who value the safety nature of cars are more likely to move to lower-accessibility neighborhoods.

Changes in incomes and changes in the number of driving-age members in the household have positive associations with changes in auto ownership, while older people are more likely to reduce their auto holdings after a move. Preference for outdoor spaciousness has a negative association with changes in auto ownership. Since those who prefer outdoor spaciousness have a slight tendency to have already owned a larger number of autos before they moved (the correlation is 0.09, statistically significant at the 0.05 level), they are less likely to increase their auto ownership levels. So this association is plausible. In addition, changes in auto ownership are positively associated with two built environment measurements: changes in outdoor spaciousness and distance to the nearest fast food, a general indicator of (lower) accessibility (i.e., the greater the distance to such a commercial establishment, the lower the accessibility of the current neighborhood, and the greater the increase in auto ownership). These associations hold even after residential preference is controlled for, suggesting that the built environment has a direct causal influence on auto ownership.

Changes in driving are negatively affected by current measures for age and education, and positively impacted by current number of children under 18 years old in the household. In addition to changes in household income, a larger increase in auto ownership leads to a larger increase in driving. It is worth noting that in the model representing the initially assumed bi-directional associations between changes in auto ownership and changes in driving behavior (Fig. 1), both coefficients are empirically insignificant. Since auto ownership is a mid-term choice while travel behavior is a near-term choice (Ben-Akiva and Atherton 1977), we constrained the link from changes in driving behavior to changes in auto ownership to be structurally zero, yielding the model of Table 4 in which the influence of changes in auto ownership on changes in driving is significant. Only one travel attitude factor (car dependent) directly influences changes in driving although others have an indirect influence. Further, three built environment measurements are negatively associated with changes in driving: changes in accessibility, the level of the socializing factor and the number of leisure businesses within 1600 meters in the current neighborhood—an indicator of (higher) accessibility. This finding suggests that there is a causal link from the built environment to driving behavior.

With respect to the influence of residential self-selection on travel behavior, the model provides some clear-cut evidence in the case of some socio-demographic variables. For example, an increase in the number of driving-age household members leads to an increase in both spaciousness and auto ownership, and the latter two change variables are associated. In the case of the attitudinal variables, our results fall mainly into the third category described in the ''Modeling approach'' section: attitudes directly influence the change in built environment (AT $\rightarrow$ ΔBE), but not the change in driving behavior (not AT $\rightarrow$ ΔTB) (although there are some nuances: spaciousness preference affects auto ownership as well as change in spaciousness; the car dependent attitude does affect driving behavior directly, but not the built environment). This finding suggests both clear self-selection effects through the impact of attitudes on the choice of residential environment but also clear built environment effects on travel behavior, given the absence of a direct link between attitudes and changes in travel behavior.

There are some interesting results when we examine the total effects of the explanatory variables (Table 4). First, although changes in outdoor spaciousness do not have a direct influence on changes in driving behavior, moving to a more spacious environment does encourage driving through its influence on auto ownership. So does the distance to the nearest fast food establishment. Second, some attitudinal factors and socio-demographics have additional influences on driving behavior through their effects on changes in the built environment and changes in auto ownership.

Moreover, a comparison of standardized total effects shows that the influence of built environment variables, including the indirect influence of socio-demographics and attitudes through their impacts on the built environment, appears similar to that of socio-demographics. Among variables tested, changes in perceived accessibility have the largest effect, indicating that this variable is the most important predictor among those tested here. Further, if we increase the three built environment variables having negative coefficients by one standard deviation and decrease the two built environment variables having positive signs by one standard deviation simultaneously (as might be the case with a move from a suburban to a traditional neighborhood, since the former three variables and the latter two variables might tend to vary together but in opposite ways), on average our indicator of driving behavior will be reduced by 0.397 standard deviations (=0.206 + 0.087 + 0.080 + 0.016 + 0.008). In other words, roughly speaking, the overall marginal effects of built environment variables on driving behavior are 0.397.

Driving and walking behavior

In addition to the driving behavior variable that was the focus of the analysis in the preceding subsection, it is also of interest to examine the relationships affecting walking behavior. Accordingly, we further incorporated changes in walking behavior into the conceptual model shown in Fig. 1. Although we constrain the association between changes in driving and changes in walking to be zero since their relationship is expected to be spurious (due to the simultaneous influence of the built environment and auto ownership on each separately), joint relationships among other variables are of interest, and produce a superior model when considered together than in a separate model of walking behavior only.

A previously estimated single-equation model for changes in walking showed that this variable is influenced by four change variables of the built environment: attractiveness, physical activity options, safety, and socializing (Handy et al. 2006). For the sake of parsimony, we chose only changes in attractiveness (having the largest standardized coefficient among the four change variables) as an endogenous variable, in addition to the two-built environment variables already included in Fig. 1. Figure 2 illustrates the new conceptual model tested in this section. As before, we allowed the error terms of all equations for endogenous variables to be correlated.

Multivariate normality examination and goodness-of-fit

We first estimated an SEM with the endogenous variables in their original form. The Mardia statistic was equal to 83.89, with a critical ratio of 25.71. Again, we transformed some variables. After re-estimating the previous model with the newly transformed variables, the Mardia statistic was reduced to 51.41. The bottom of Table 5 lists goodness-of-fit measures for the re-estimated model. Generally, these measures are inferior to those for the model discussed in the ‘‘Driving behavior’’ section. We tried several approaches (such as removing some observations and removing an equation) to improve the Mardia statistic and measures of fit, but none of them produced satisfactory results. Given that this model offers insightful practical interpretations, however, we accepted it as our final model.

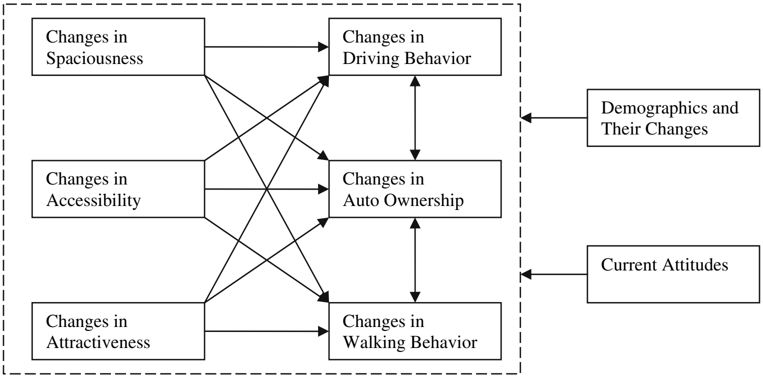

Fig. 2 Conceptual structural model: driving & walking

Discussion

The final model consists of structural equations for six endogenous variables: changes in attractiveness, changes in outdoor spaciousness, changes in accessibility, changes in auto ownership, changes in driving, and changes in walking. Table 6 presents the statistically significant correlations among the error terms in these equations. A positive correlation between error terms for two variables indicates that unobserved variables affect the two variables in the same direction; a negative sign shows that unobserved variables affect the two variables in opposite ways.

It may seem that the high and positive correlation between unobserved influences on changes in spaciousness and changes in attractiveness is counterintuitive. In general, one might assume that attractiveness is a trait more strongly associated with traditional neighborhoods, while suburban neighborhoods have more space. Therefore, unobserved variables could be expected to affect joint choices of attractiveness and spaciousness in opposite ways. In this dataset, however, changes in spaciousness are positively correlated with changes in attractiveness (correlation: 0.304). Further, there is no significant difference in perceived outdoor spaciousness between traditional and suburban neighborhoods. And although individuals living in traditional neighborhoods on average perceive attractiveness to be higher than do suburban residents, about a fifth (21.5%) of residents in traditional neighborhoods perceive attractiveness to be lower than the median level of attractiveness perceived by suburban residents, while a similar proportion (19.5%) of suburban residents perceive attractiveness to be higher than the median level perceived by those in traditional neighborhoods. So, for example, a move from an urban area perceived to be somewhat blighted to a lower-density area may generate increases in both perceived attractiveness and spaciousness, or a move from a well-maintained traditional neighborhood to a new suburban subdivision with small lots and bland houses might decrease both perceived attractiveness and spaciousness.

The matrix of standardized direct and total effects is shown in Table 5. Compared to the driving behavior SEM, the explanatory variables in the equations for changes in outdoor spaciousness, changes in accessibility, and changes in auto ownership remain significant in this SEM, but the number of leisure businesses within 1600 meters became insignificant and hence was dropped out of the equation for changes in driving. It is worth noting that the influence of changes in walking on changes in auto ownership was found to be

Table 5 Standardized direct and total effects: driving & walking model

Variables	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles[a]	Changes in driving	Changes in walking
Endogenous Variables						
Changes in attractiveness	—	—	—			0.213 (0.213)
Changes in spaciousness	—	—	—	0.157 (0.157)	0 (0.016)	
Changes in accessibility	—	—	—		−0.213 (−0.213)	
Changes in automobiles[a]	—	—	—	—	0.099 (0.099)	—
Exogenous Variables						
Socio-demographics						
Changes in # of kids (≤5)[a]	−0.086 (−0.086)					0.092 (0.073)
Changes in # of driving-age members[a]		0.118 (0.118)		0.294 (0.312)	0 (0.031)	
Changes in income[a]				0.130 (0.130)	0.008 (0.093)[b]	
Ln (1 + current # of kids < 18)					0.114 (0.114)	
Current age	−0.125 (−0.125)	−0.129 (−0.129)		−0.123 (−0.143)	−0.101 (−0.115)	0 (−0.026)
Currently working						−0.075 (−0.075)
Current education					−0.081 (−0.081)	
Neighborhood characteristics						
Changes in physical activity options	—	—	—			0.137 (0.137)
Changes in safety	—	—	—			0.128 (0.128)
Changes in socializing	—	—	—			0.164 (0.164)
Current socializing	—	—	—		−0.094 (−0.094)	
Current # of business types w/in 400 m	—	—	—			0.096 (0.096)
Current dist. to nearest fast food	—	—	—	0.076 (0.060)[b]	0 (0.008)	

Table 5 continued

Variables	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles[a]	Changes in driving	Changes in walking
Residential preferences						
Accessibility		−0.118 (−0.118)	0.143 (0.143)	0 (−0.019)	0 (−0.032)	
Outdoor spaciousness		0.212 (0.212)		−0.099 (−0.066)	0 (−0.006)	
Attractiveness	0.210 (0.210)					0 (0.045)
Travel attitudes						
Safety of car			−0.098 (−0.098)		0 (0.028)	−0.127 (−0.127)
Travel minimizing			0.127 (0.127)		0 (−0.027)	
Car dependent					0.113 (0.113)	
Pro-bike/walk						0.103 (0.103)
Squared multiple correlations	0.064	0.087	0.055	0.189	0.125	0.200

Goodness of fit measures: d.f. = 98; χ^2 = 345; χ^2/d.f. = 3.52; GFI = 0.96; NFI = 0.84; CFI = 0.87; IFI = 0.88; RMSEA = 0.068

Notes: Data were automatically standardized when the model was estimated. The numbers in parentheses are total effects

[a] These variables (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \mathrm{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\mathrm{Ln}(-X + 1)$

[b] Significant at the 0.1 level; all other parameters are significant at the 0.05 level

Table 6 Correlations of the error terms in the driving and walking model

	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles	Changes in driving	Changes in walking
Changes in attractiveness	1					
Changes in spaciousness	0.637 (0.000)	1				
Changes in accessibility	0.265 (0.000)	−0.173 (0.012)	1			
Changes in automobiles				1		
Changes in driving					1	
Changes in walking					−0.236 (0.000)	1

Note. The numbers in parentheses are *p*-values

insignificant in the model and hence was constrained to be empirically zero, while the influence of changes in driving on changes in auto ownership was constrained to be structurally zero for the same reason as that discussed in the ‘‘Driving behavior’’ section.

Changes in attractiveness are influenced by three variables. Attractiveness preference positively influences changes in attractiveness, as expected. The moves of older people tend to result in larger decreases in attractiveness. And increases in the number of children under 5 years old are negatively associated with changes in attractiveness, consistent with the stereotypical move from the traditional to suburban neighborhood with the expansion of the household, assuming that suburban environments are less attractive on average. These two results suggest that the need to move for other reasons sometimes necessitates a compromise on aesthetics for these segments of the population.

Individuals experiencing an increase in the number of children under 5 years old tend to have a larger increase in walking trips, while the converse is true for those currently working. A pro-walk/bike attitude is positively associated with changes in walking, but the safety of car factor has a negative association with changes in walking. After controlling for socio-demographics and attitudes, various measurements for changes in the built environment—attractiveness, safety, physical activity options, and socializing—have positive influences on changes in walking. Further, the current number of business types within 400 meters (again, a general indicator of higher accessibility) is positively associated with changes in walking. These results show that the built environment has a causal influence on walking behavior.

For changes in driving behavior, this SEM dropped current number of leisure businesses, which was marginally significant in the driving behavior SEM. With respect to parameter estimates, current number of children under 18 years old has the largest difference (0.114 vs 0.096). For other variables, this SEM yields parameter estimates quite similar to the SEM considering only driving behavior.

As before, the influence of built environment variables is equivalent to or even larger than that of socio-demographics. Changes in attractiveness have the largest effect, indicating that this variable is the most important predictor among those tested here. Further, if we decrease changes in safety by one standard deviation and increase the other four built environment variables by one standard deviation at the same time (as might be the case with a move from a suburban to a traditional neighborhood), on average our walking behavior indicator will increase by 0.482 standard deviations (=0.137 + 0.164 + 0.213 + 0.096−0.128). In other words, roughly speaking, the overall marginal effects of built environment variables on walking behavior are 0.482. Note that the marginal effects on walking behavior are larger than the marginal effects on driving, as would be expected when the built environment is measured at a neighborhood scale (Handy et al. 2006).

It is also of interest to compare the SEM results to those that can be obtained from single-equation regression. We found that the latter yielded parameter estimates, as well as p-values, similar to the SEM direct effects (refer to Cao 2006 for details). Therefore, although SEM is a more advanced modeling technique, the ordinary least squares (OLS) parameter estimates for changes in travel behavior can still be meaningful. Two cautions are in order, however. One is that it is easy to overlook indirect effects when estimating a single equation, so that statistically and practically significant relationships might be excluded if their path of influence were not fully understood. The second is that the similarities between SEM and OLS seen here may be specific to the relatively simple, ''recursive'' structure of the conceptual model we ultimately adopted, and do not necessarily generalize to more complex, and especially ''non-recursive'' structures.

Conclusions

As part of an ongoing analysis of the causal relationship between the built environment and travel behavior, this study employed a structural equations modeling approach to explore the relationships among changes in the built environment, changes in auto ownership, and changes in travel behavior.

In this study, we addressed residential self-selection in several ways. First, we controlled for socio-demographics, residential preferences, and travel attitudes, and hence presumably eliminated the rival hypotheses resulting from these third-party variables. Second, we accounted for the dynamic nature of the influences through the use of quasi-longitudinal data. Further, we captured multiple causal relationships among the built environment, auto ownership, and travel behavior by estimating several interconnected equations simultaneously. The latter two approaches (the dynamic SEM) represent a quantum improvement over prior work in terms of methodology. Therefore, this study yields more robust results than previous research. However, there are still limitations in our application of the SEM, given the limitations of our data. First, this study lacks a control group of non-movers because we did not measure changes in auto ownership for non-movers. Second, because it is not feasible to retrospectively measure attitudes, we have data on current attitudes only, and thus our models only control for current attitudes rather than changes in attitudes. So we cannot rule out the competing hypothesis that an attitude change preceded and (partly) prompted the residential location change. To the extent that is true, the attitude change is confounded with the change in built environment and may account for some of the apparent effect of the built environment seen here. Further, since our data do not have attitudes over time, we cannot examine feedback loops from the built environment to attitudes toward travel and residence. That is, we are less able to understand how the built environment affects the formulation and change of these attitudes. This understanding is critical for planners and policy makers to manage individuals' travel behavior through land use policies over the long term. Therefore, future work should use a true panel design so that we can capture changes in attitudes, as well as more precise measures of travel behavior than the retrospective qualitative (ordinal) measures available in this study.

Nevertheless, this study offers some insightful results. First, we found that residential self-selection has significant direct and indirect impacts on travel behavior. Specifically, in both SEMs presented here, neighborhood preferences and/or travel-related attitudes (as well as socio-demographic variables) (1) exert direct influences on the choice of residential neighborhood, which then influences travel behavior, and (2) exert direct influences on auto ownership, driving behavior, and/or walking behavior even after built environment influences are accounted for.

Second, we found that changes in the built environment have a statistically significant association with changes in travel behavior, controlling for current attitudes and changes in socio-demographics, and taking multiple interactions into account. Specifically, our models point to increases in accessibility as the most important factor in reducing driving. Further, enhancements to some qualities of the built environment might increase walking: attractiveness (appearance, level of upkeep, variety in housing styles, big street trees), physical activity options (bike routes, sidewalks, parks, public transit), safety (quiet, low crime, low traffic, safe for walking, safe for kids to play, street lighting), and socializing (diverse neighbors, people out and about, interaction among neighbors, similar economic levels). These results suggest that there is a causal connection from the built environment to driving and walking behavior.

Further, based on standardized coefficients, we found that the effects of built environment variables on travel behavior are similar to or larger than those of socio-demographics, suggesting that the influence of the built environment is not only statistically significant but also practically important. Overall, this study provides some encouragement that land-use policies designed to put residents closer to destinations and provide them with viable alternative transportation options will actually lead to less driving and more walking.

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