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Publication Date
2007-04-01

Peer reviewed

Cross-sectional and Quasi-panel Explorations of the Connection between the Built Environment and Auto Ownership

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Abstract

Auto ownership is a critical mediating link in the connection between the built environment and travel behavior: the built environment presumably influences auto ownership, which in turn impacts travel behavior. However, the way in which individual elements of the built environment affect auto ownership choices is far from understood. Further, residential self-selection may confound the interaction between the built environment and auto ownership. And the absence of panel data impedes our understanding of the causal relationships. Using a survey of 1682 respondents in Northern California, this study applied ordered probit and static-score modeling techniques to investigate the causal link from the built environment to auto ownership in both cross-sectional and quasi-panel contexts. Through variable selection in cross-sectional analysis, we found that individuals' attitudes regarding residential neighborhood and travel are more strongly associated with their auto ownership decision than is the built environment *per se*. Specifically, when general preferences for various neighborhood traits were allowed to enter the model, they drove out from the model the (perceived) measure of the same trait for the neighborhood of current residence, a pattern suggesting that the observed correlation between neighborhood characteristics and auto ownership is primarily a result of self-selection. On the other hand, the quasi-panel results indicate that some built environment elements such as outdoor spaciousness and mixed land use are causes of auto ownership (remaining even after attitudes were allowed to enter the model), but their effects are marginal. In contrast, the strong influence of socio-demographics suggests that households' auto ownership decisions are fundamentally based on their mobility needs and purchasing power. Given the mixed findings, this study does not definitively confirm a causal relationship between the built environment and auto ownership. However, it provides encouraging evidence that land-use policies designed to reduce auto ownership and use will lead to a marginal reduction in auto ownership.

Key words: new urbanism, land use, auto ownership, travel behavior, panel model, residential self-selection

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1. Introduction

Auto ownership has a strong influence on travel behavior, as countless studies show. Most travel demand forecasting models, widely used in regional transportation planning, incorporate auto ownership as a key variable for predicting trip generation and mode split. Even though households without automobiles often rely on the automobiles of others for their daily travel, the correlation between auto ownership and travel by automobile is strong. According to the 2001 National Household Travel Survey (NHTS), households without a vehicle made 34.1% of their trips by auto, 19.1% by transit, and 43.5% by non-motorized modes; in contrast, households with one vehicle made 81.9% of their trips by automobile and households with 3 or more vehicles made 90.5% of their trips by automobile (Pucher and Renne, 2003). A study of cities in the U.S., Australia, Asia, and Europe found that the significant increase in vehicle travel between 1960 and 1990 was a direct result of increased incomes and greater automobile ownership (Cameron et al., 2004).

Auto ownership is a critical mediating link in the connection between the built environment and travel behavior: the built environment presumably influences auto ownership, which in turn impacts travel behavior (frequency, destination, mode, and trip chaining). As shown in Figure 1, travel decisions for an individual household are embedded in a choice hierarchy (Ben-Akiva and Atherton, 1977). As a medium-term decision, auto ownership is conditional on long-term decisions such as employment location and residential location. That is, households' auto ownership is likely to be impacted by their long-range decisions through the availability and attractiveness of alternative modes and various elements of the built environment. However, most studies on this connection assume that auto ownership is exogenous to individuals' activity/travel decisions, thereby inadequately evaluating the role auto ownership plays in the land use-transportation interaction (Badoe and Miller, 2000), and hence underestimating the total effects of land use on travel behavior. The argument that auto ownership is endogenous is supported by empirical evidence. For example, Schimek (1996) employed simultaneous equations to model individuals' residential choices and travel decisions, with auto ownership being an intermediating variable; and he found that the total effects of density on household vehicle miles traveled (VMT) and personal vehicle trips exceed the direct effects of density.

The connection between the built environment and auto ownership, however, has not been extensively studied. The available evidence suggests that households living in single-family dwellings, homogeneous and/or suburban types of neighborhoods, typically located farther away from employment sites, tend to own more vehicles (and use them more often) than households living in denser neighborhoods and/or closer to the central business district (e.g., Bagley and Mokhtarian, 2002; Cervero, 1996; Chu, 2002; Kitamura et al., 2001; Kockelman, 1997, Lerman, 1979; Sermons and Seredich, 2001). An overview of international cities found that higher urban density is consistently associated with lower auto ownership rate (Kenworthy and Laube, 1999). Similarly, case studies of Chicago, Los Angeles, and San Francisco concluded that automobile ownership was significantly correlated with neighborhood residential density, after accounting for average per capita income, average family size, and availability of public transit (Holtzclaw et al., 2000). However, the way in which individual elements of the built environment affect auto ownership choices is not well understood.

Further, residential self-selection may confound the interaction between the built environment and auto ownership (Boarnet and Crane, 2001). A study of urban form and auto ownership in Portland, Oregon found that as land use mix changes from homogeneous to diverse, the probability of owning an automobile decreases by 31 percentage points, after accounting for income and other factors (Hess and Ong, 2002). The authors concluded that traditional neighborhoods give households the "opportunity to express their preferences to avoid automobile ownership" (p. 35). In other words, the observed correlations between the built environment and auto ownership may be due in large part to the influence of preferences for auto ownership on residential location choice, rather than entirely to the influence of the built environment on auto ownership decisions, as illustrated in Figure 2. Accordingly, individuals' attitudes, especially travel attitudes and residential preferences, are likely to play a role in their auto ownership behavior. Some evidence also suggests that the accuracy of auto ownership choice models can be improved by incorporating attitudes towards auto ownership (Wu et al., 1999). The implication is that the effectiveness of influencing auto ownership and use through the built environment may be largely limited to the market share of individuals whose attitudes are favorable towards alternative modes and traditional neighborhoods. However, the absence of attitudinal factors in the literature and in the widely available data constrains our ability to address these complexities.

The scarcity of panel data further impedes our understanding of the causal relationship between the built environment and auto ownership. Cross-sectional analysis is sufficient to provide robust tests of the existence of a correlation between variables. However, both individuals' location choices and auto ownership choice are conditioned on their lifestyle choices with respect to family, employment, and leisure (Salomon and Ben-Akiva, 1983). Accordingly, this relationship could be largely spurious if some third variable – such as preferences – were a causal factor for both the built environment and auto ownership. A panel study showing that changes in built environment characteristics are associated with changes in auto ownership (while controlling for socio-demographic changes that might also be a factor) will offer more direct evidence of a causal link from the built environment to auto ownership than cross-sectional analysis can (Finkel, 1995).

The purpose of this paper is to investigate the causal relationship between the built environment and auto ownership using cross-sectional and quasi-panel data. The study addresses the following central questions: (1) What aspects of the built environment influence individuals' decisions on auto ownership? (2) Do changes in built environment characteristics lead to changes in auto ownership? (3) Does residential self-selection (as measured by attitudinal factors) impact individuals' auto ownership choices? (4) If there is an apparent influence of the built environment on auto ownership, does residential self-selection account for all of it? The next section describes the data, the variables and the modeling approaches used in this study. Section 3 presents the model results. The final section recapitulates the key findings and discusses policy implications of the results.

2. Methods

2.1 Survey and Data

The data used in this study came from a self-administered twelve-page survey mailed in two rounds in late 2003 to households in eight neighborhoods in Northern California. This section describes the survey sampling, design, pre-testing, and administration methodology, as well as providing a data summary. Survey content is presented in the next section.

The neighborhoods were selected to vary systematically on three dimensions: neighborhood type, size of the metropolitan area, and region of the state. Neighborhood type was differentiated as "traditional" for areas built mostly in the pre-World II era, and "suburban" for areas built more recently. Although this design was intended to provide ample variation across neighborhood types, and these discrete indicators of neighborhood type are useful for descriptive comparisons, they are too simplistic for more detailed analyses. For the models, we used a rich set of variables describing the neighborhoods along a variety of dimensions (see Section 2.2).

Using data from the U.S. Census, we screened potential neighborhoods to ensure that average income and other characteristics were near the average for the region. Four neighborhoods in the San Francisco Bay Area, including two in the Silicon Valley area and two in Santa Rosa, had been previously studied (Handy 1992). Two neighborhoods from Sacramento and two from Modesto were selected to contrast with Bay Area neighborhoods (Figure 3). 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, as shown in Figure 4 for Sacramento as an example.

[Insert Figure 3 here]
[Insert Figure 4 here]

For each neighborhood, we purchased two databases of residents from a commercial provider, New Neighbors Contact Service (www.nncs.com; this service maintains an overall database of names and addresses for residences throughout the U.S. constructed from a variety of public records. The database is largely used for commercial advertisement mailings): 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 neighborhood. The database of “nonmovers” consisted of a random sample of 500 residents not included in the “movers” list for each neighborhood.

Survey questions were developed from surveys used in previous research projects by the second and third authors and other researchers. The survey was pre-tested on UC Davis students and staff, then on a convenience sample of Davis residents. Participants were asked to first complete the survey, then to discuss the survey questions with the researchers, either in a group meeting or in one-on-one interviews. Based on these pretests, survey questions were modified and refined.

The survey was administered using a mail-out, mail-back approach. The initial survey was mailed out at the end of September 2003. Two weeks later, a reminder postcard was mailed to the entire sample using first-class mail. At the beginning of November, a second copy of the survey with a revised cover letter was sent to a shorter list that excluded incorrect addresses and individuals who had already responded to the survey. Two weeks later, a second reminder postcard was mailed to this list of residents. As an incentive to complete the survey, respondents were told they would be entered into a drawing to receive one of five $100 cash prizes; the winners were selected in December.

The original database consisted of 8000 addresses but only 6746 valid addresses. The number of responses totaled 1682 (688 movers), equivalent to a 24.9% response rate based on the valid addresses only. This is considered quite good for a survey of this length, since the response rate for a survey administered to the general population is typically 10-40% (Sommer and Sommer, 1997). A comparison of sample characteristics to population characteristics (based on the 2000 U.S. Census) shows that survey respondents tend to be older on average than residents of their neighborhood as a whole, and that households with children are underrepresented for most neighborhoods while home owners are overrepresented for all neighborhoods (Table 1). Median household income for survey respondents was higher than the census median for all but one neighborhood, a typical result for voluntary self-administered surveys. However, since the focus of our study is on explaining the relationships of other variables to auto ownership rather than on describing auto ownership per se, these differences are not expected to materially affect the results (Babbie, 1998). It is worth noting that 10.4% of “movers” had actually changed their residential locations more than a year earlier, and hence had been misclassified by the provider.

[Insert Table 1 here]

2.2 Variables

The dependent variables are household auto ownership and changes in auto ownership measured as number of vehicles. In the survey, respondents were asked to report their household vehicles available for daily use and recall the number of vehicles they had just before their residential relocation (only for movers). Table 2 presents an overview of auto ownership and changes in auto ownership. On average, households living in suburban neighborhoods own 0.14 (9%) more vehicles, but also have 21% more people in the household. In the cross-sectional analysis, four vehicles and five or more vehicles are recoded as three or more vehicles due to limited observations in these two categories.

More than two-thirds of movers in both types of neighborhoods kept their auto ownership unchanged after residential relocation. Many who changed auto ownership, of course, did so for reasons unrelated to their new neighborhoods. Only 49 (7.4% of) movers explicitly responded that they changed auto ownership owing to the characteristics of their current residential neighborhood, and 49 movers considered getting another vehicle or getting rid of a vehicle for the same reason. For 59 (60%) of those 98 cases, the actual or considered changes were in the expected direction (e.g. they increased vehicle ownership after a move to a suburban area), but the remaining 40% were counter to the expected direction. Overall, there was no significant difference in the distribution of responses between those moving to traditional neighborhoods and those moving to suburbs (neither for the 98 alone, nor for the entire sample of movers), and so the descriptive statistics suggest that the apparent overt impact of a change in built environment on a change in auto ownership is relatively minor. However, the multivariate static score model may modify this conclusion after confounding factors are controlled for.

[Insert Table 2 here]

The explanatory variables are classified into four groups: neighborhood characteristics, neighborhood preferences, travel attitudes, and socio-demographics. Although variables related to travel behavior were measured in the survey, they are not used in this study. In the near term, travel behavior is conditional on auto ownership (Ben-Akiva and Atherton, 1977), and the observed influence of travel behavior on auto ownership is likely to be a proxy for the influence of travel-related attitudes, which is directly taken into account in this study. The remainder of this section will present the four groups of variables in turn.

- Neighborhood characteristics and neighborhood preferences

Respondents were asked to indicate how true 34 characteristics are for their current and previous (only for movers) neighborhood, on a four-point scale from 1 ("not at all true") to 4 ("entirely true"). 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/if they were looking for a new place to live were measured on a four-point scale from 1 ("not at all important") to 4 ("extremely important"). The comparison of individuals' perceived neighborhood characteristics for their current residence and their neighborhood characteristic preferences indicates how well their current neighborhoods meet their preferences. Since some of these characteristics measure similar dimensions of the built environment and are highly correlated, we conducted a factor analysis to identify underlying constructs of perceived and preferred neighborhood characteristics. Finally, these items were reduced to six factors (some items were dropped due to their poor conceptual interpretability): accessibility, physical activity options, safety, socializing, attractiveness, and outdoor spaciousness (Table 3).

[Insert Table 3 here]

Following the survey, objective measures of land use mix and 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, and take-out), and leisure (health club, bookstore, bar, theater, and video rental). Land use mix refers to the relative proximity of different land uses, such as homes, stores, offices, parks, and other uses, within a given area (Handy et al., 2002). In this study, land use mix indicators were measured as the number of different types of businesses within specified distances. Further, according to Hansen (1959), spatial accessibility is a gravity function of opportunities at the destination and travel costs (such as travel time and travel distance) from origins to destinations. Accessibility indicators used here were simplified to the number of establishments (opportunities) of each business type within specified distances and the distance to the nearest establishment of each type. 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.

Commute distance, a measure of proximity of employment and residential locations, was also measured in the survey. In contrast to most non-work activities, the commute is a necessary and spatially constrained trip for workers. Therefore, commute distance has the potential to influence workers' auto ownership.

- Travel attitude

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 1 ("strongly disagree") to 5 ("strongly agree"). Factor analysis was then used to extract the fundamental dimensions spanned by these 32 items, for reasons similar to those for neighborhood characteristics. As shown in Table 4, six underlying dimensions were identified: pro-bike/walk, pro-transit, pro-travel, travel minimizing, car dependent, and safety of car.

[Insert Table 4 here]

- Socio-demographics

Finally, the survey also contained a list of socio-demographic variables that may help to explain auto ownership decisions. 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 for movers (one year ago for non-movers) and currently.

2. 3 Analysis methods

The multinomial logit (MNL) model is commonly used in auto ownership modeling at the disaggregate level (e.g., Purvis, 1994). The MNL model is a random utility model of individual choice among a set of alternatives, and requires an assumption of independence of irrelevant alternatives (IIA) (Ben-Akiva and Lerman, 1985). Accordingly, the MNL model treats auto ownership as an unordered categorical response.

Recently, several studies have employed ordered-response techniques to model auto ownership (Bhat and Pulugurta, 1998; Chu, 2002; Hess and Ong, 2002; Kitamura et al., 2001). In contrast to the MNL model, ordered-response models consider auto ownership level as an ordinal scale (Y = 0, 1, 2,…j,…, J). It assumes an underlying latent continuous variable, Y*, representing a household's propensity to own cars (Daykin and Moffatt, 2002). Y* is expressed in the following form:

$$Y^* = \beta' X + e, \tag{1}$$

where X is a vector of explanatory variables, β is a vector of parameters, and e is the unobserved error term. The relationship between the latent Y* and the observed Y is:

$$Y = j \text{ if } \mu_{j-1} < Y^* \leq \mu_j,\ \mathrm{j} = 0, 1, 2, ..., \mathrm{J}, \tag{2}$$

where the μ_js are cut points or threshold parameters, defined as $\mu_{-1} = -\infty$, $\mu_J = +\infty$, and $\mu_{j-1} < \mu_j$ for all j. In the context of the ordered probit model, $e \sim N[0, \sigma_e^2]$, and we have the following probabilities:

$$P(Y = j) = P(\mu_{j-1} < Y^* \leq \mu_j) = \Phi(\frac{\mu_j - \beta' X}{\sigma_e}) - \Phi(\frac{\mu_{j-1} - \beta' X}{\sigma_e}). \tag{3}$$

where Φ denotes the standard normal CDF.

It is worth noting that Bhat and Pulugurta (1998) found MNL models to be superior to ordered models in terms of predictive adjusted likelihood ratio index, average probability of correct prediction, and non-nested hypothesis test. However, the IIA assumption cannot reflect the ordered nature of household auto ownership. The ordered probit model is adopted in this study due to its parsimonious model structure although oversimplification may also be a concern.

We use a different approach for modeling changes in auto ownership for movers. As discussed in Section 2, our data contain measurements of variables for each mover at time t and t-1. Thus, a causal model can be constructed and estimated based on quasi-panel data (differing from true panel data in that previous values of variables were not directly measured at time t-1 but recalled). A variety of alternative specifications of the causal effect are available, modeling Y or ΔY as a function of X_{t-1}, X_t, ΔX, or some combination of these variables (Finkel, 1995). Based on Finkel's discussion, a static-score model incorporating the influence of the lagged endogenous variable (Y_{t-1}) is applied in this study. Specifically, the changes in auto ownership are expressed as a function of prior auto ownership, and prior and current values of explanatory variables as well as the changes between them:

$$\Delta Y = Y_t - Y_{t-1} = \alpha_1' X_t + \alpha_2' X_{t-1} + \alpha_3'(X_t - X_{t-1}) + \gamma' Y_{t-1} + e . \tag{4}$$

In reality, however, the inclusion of all three X terms on the right-hand side is over-specified and hence will result in collinearity. Therefore, on a variable-by-variable basis, at most two of the three measurements for each explanatory variable were included simultaneously when we calibrated the model using ordinary least squares (since ΔY could take on the nine integer values from –4 to 4, with several of those values containing few observations, we chose to treat the dependent variable for this model as quasi-continuous, and use the robust OLS approach).

3. Results

3.1 Auto ownership

Using the software package Limdep 8.0, we developed two ordered probit models for auto ownership: Model 1, without attitudinal factors in the model specification, and Model 2, including attitudes. As shown in Table 5, ρ^2 for Model 2 is larger than that for Model 1. Since neither model is a constrained version of the other, the non-nested hypothesis test was used to evaluate the performance of the two models (Ben-Akiva and Lerman, 1985). Specifically, if Model 1 (containing K_1 parameters) is the true model, the probability of finding a Model 2 (with K_2 parameters) having an adjusted ρ^2 z units greater is not larger than $\Phi\left\{-\left[-2z\,LL(C) + (K_2 - K_1)\right]^{1/2}\right\}$ asymptotically, where Φ is the standard normal cumulative distribution function and LL(C) is the log-likelihood evaluated for a model with only a constant term and the threshold parameters (Bhat and Pulugurta, 1998). Thus, if that probability is small for Model 2, we reject the null hypothesis that Model 1 is correct. The test result indicates that Model 2 is significantly better than Model 1. Therefore, incorporating attitudes in the model significantly improves the model.

[Insert Table 5 here]

As shown in Model 1, household size, the number of household members within driving age (16-85), and the number of workers in the household each increase the propensity to own more vehicles. This indicates, not surprisingly, that household mobility needs are important in the auto ownership decision-making process, but it is interesting that three different measures of household size are simultaneously (highly) significant. The relative magnitudes of the three coefficients show that among them, the largest marginal impact on latent ownership propensity arises from simply being of driving age, with smaller additional incremental impacts for each worker and non-driver in the household.

The model also shows that individuals who are lower-income have a lower latent propensity for vehicle ownership, as expected. Those having constraints on driving have a lower propensity for vehicle ownership, while individuals who are limited or prevented from using transit have a higher one. Home renters have a lower propensity for vehicle ownership. This is plausible since in this dataset home renters are more likely than owners to be lower income, and to live with fewer household members, but it is interesting that the variable appears in addition to those others. This suggests that there is something beyond the raw socio-demographic traits for which being a renter is a marker – perhaps indicating a lifestyle in transition, or a philosophy of accumulating fewer material possessions (cars as well as homes). Female respondents tend to have lower vehicle ownership propensities. In this dataset, being female is associated with households having lower income, a smaller number of workers, and a smaller number of driving-age members. Therefore, gender is likely to be a proxy for these and related household characteristics and offers additional explanatory power to the model.

Individuals' perceptions of their neighborhood characteristics have associations with their auto ownership decisions. Outdoor spaciousness, in the form of large yards and off-street parking, typical characteristics of suburban neighborhoods, are related to higher propensities. Conversely, the number of business types within 400 meters of residence negatively affects auto ownership, which suggests that mixed land uses make it easier for residents to own fewer vehicles.

However, the effects of the spaciousness factor and land use mix indicator on auto ownership are marginal. Among the variables significant in the model, they are the least important according to the standardized coefficients. In contrast, socio-demographics show a strong influence on auto ownership. This pattern suggests that auto ownership is heavily determined by socio-demographic characteristics, especially household structure and income.

When residential preferences and travel attitudes are taken into account, as shown in Model 2, the perceived spaciousness and land use mix indicator become insignificant (specifically, the p-values for these two variables, if retained, would be 0.215 and 0.351, respectively); instead, preferences for spaciousness and accessibility enter the model, with the expected signs. Therefore, the effects of actual (perceived) neighborhood characteristics on auto ownership are likely to be proxies for the preferences for those neighborhood characteristics. This result lends credible support to the speculation that residential self-selection explains correlations between the built environment and auto ownership. Travel attitudes also influence auto ownership. Those who think their daily activities are dependent on vehicles and have safety concerns regarding the use of alternative modes have a higher ownership propensity.

A comparison of standardized parameter estimates shows that socio-demographic characteristics are the most important determinants of auto ownership propensity even after incorporating attitudinal factors in the model. Each attitudinal factor alone has only a marginal effect on the decisions of auto ownership. However, the extensive presence of residential preferences and travel attitudes in the model implies that attitudes may collectively play an important role in individuals' auto ownership behavior.

3.2 Changes in auto ownership

Because we wanted to isolate the effects (if any) of changes in the built environment on changes in auto ownership, we estimated the quasi-panel model for movers only. In contrast to the previous case, here the addition of attitudinal variables did not affect the inclusion of any of the other variables in the model, so we present only the single final model, including attitudes, in Table 6. Among various categories of determinants of auto ownership, socio-demographic characteristics are the most important because of their extensive presence in the model and their large standardized coefficients. In particular, vehicle ownership increases with both household income before moving and the change in income itself, and with both the current number of driving-age members and the change in that number. The presence of both level and change variables for these two traits (income and number of driving-age members) indicates a non-linear effect on auto ownership change: the change in number of vehicles is greater at higher levels of those variables than it is at lower levels. Older people and individuals with personal constraints on driving tend to reduce their number of vehicles. Ultimately, these findings reinforce the argument that socio-demographics are fundamental determinants of auto ownership, and that the built environment works at best as a facilitator or a constraint.

[Insert Table 6 here]

As shown in Table 6, changes in perceived spaciousness are positively related to changes in auto ownership. In addition, individuals living in diverse land use areas tend to reduce their auto ownership, presumably because they are more likely to be able to conduct their daily activities with one fewer vehicle. Since the changes in auto ownership were measured after residential relocation, we can more confidently conclude that there is a causal effect from built environment characteristics to auto ownership. However, these effects are marginal in terms of the size of standardized coefficients.

Residential preference and travel attitudes also affect changes in auto ownership. Those preferring large yards and off-street parking tend to reduce their auto ownership (significant at the 0.1 level), probably because they have owned a larger number of vehicles before moving. And car-dependent individuals tend to increase their auto ownership. However, the effects of these two variables on changes in auto ownership are less important (without them, the R^2 of the model drops only slightly, from 0.548 to 0.536). Compared to Model 2 of Table 5, the relative absence of attitudinal factors indicates that this panel model is effective at controlling for some individual permanent effects resulting from unchanging explanatory variables. Of course, those unchanging variables can include not just attitudes, but other characteristics both measured, such as gender (note that gender is significant to the level of auto ownership in Table 5, but not to the change in number of autos in Table 6), and unmeasured, such as lifestyle indicators.

It is worth noting that the lagged endogenous variable, auto ownership before residential relocation, shoulders a large proportion of explanatory power for the variation in changes in auto ownership. Particularly, removing this variable from the model reduces R^2 from 0.548 to 0.195. Logically enough, the more vehicles households own, the more inclined they are to reduce the number of vehicles and the fewer vehicles, the more inclined to increase.

4. Conclusions

Communities throughout the US are turning to compact development, neotraditional design, and smart growth in the hope of reducing auto dependence. As an intermediating bridge, auto ownership plays an important role in the interactions between the built environment and travel behavior: auto ownership influences travel behavior and the built environment may influence auto ownership. Simply treating auto ownership as an exogenous socio-demographic trait in practice may result in endogeneity bias and hence threaten the validity of parameter estimates of models that link the built environment and travel behavior. However, the connection between the built environment and auto ownership has not received much attention from researchers and planners. This paper describes an effort to investigate their causal link by applying cross-sectional and quasi-panel analyses.

This study has several limitations. First, perceived measurements may not be good indicators of objective measurements due to individuals' variation. On the other hand, theory suggests that perceptions and beliefs should affect behavior more directly than reality. Even proponents of utility maximizing theory acknowledge the role of perceptions in the decision-making process (McFadden, 2002). Second, the assumption that attitudes remained stable before and after the move should be tested with a true panel, providing data on their attitudes in real time, across multiple waves including residential relocations. In the present study, it is possible that changes in the built environment are confounded with unmeasured changes in attitude. That is, perhaps it is in fact changes in tastes that prompted a change in the built environment, and it is those preference changes rather than the built environment changes per se that are influencing auto ownership in the static-score model. Third, the static-score model assumes that there is no autocorrelation between Y_t and Y_{t-1}, no autocorrelation between X_t and X_{t-1}, and no causal link between X_{t-1} and Y_{t-1}. Further research should relax these assumptions using a panel path analysis.

Our results, however, contribute to answering the four questions posed in the Introduction. With respect to question 1, we first find dominant influences of socio-demographics on auto ownership, suggesting that households' auto ownership decisions are primarily dependent on their mobility needs and purchasing power. The persistence of ownership may be a further factor, since a vehicle, once acquired, is not readily discarded. Given the relatively low operating costs of vehicles, we cannot expect that changes in the built environment will greatly change individuals' auto ownership.

Built environment elements do affect household auto ownership levels, but the effects are marginal. First, a cross-sectional model confirms that neighborhood characteristics have some association with auto ownership, controlling for socio-demographics. Specifically, perceived spaciousness is positively associated with auto ownership propensity, while the number of business types within 400 meters of the residence is negatively related to that propensity. Therefore, it appears that more space and homogeneous land uses tend to increase auto ownership. However, the inclusion of preference factors pushes those neighborhood characteristics out of the model, suggesting that attitudes are more strongly associated with auto ownership than are built environment elements per se. Further, the displacement of neighborhood perception by preferences for the same aspect provides evidence for the argument that the observed correlation between the built environment and auto ownership is a consequence of residential self-selection (question 3).

In contrast, the results of the panel model indicate the existence of a causal relationship between changes in the built environment and changes in auto ownership (question 2), even after accounting for attitudes: increases in perceived spaciousness (such as large yards and off-street parking) are associated with increases in auto ownership, and current access to local businesses is related to decreases in auto ownership. According to the former association, this study demonstrates that changes in the outdoor spaciousness of one's neighborhood will lead to changes in auto ownership. This effect is moderate in terms of its standardized coefficient, but the significance of these two variables suggests that residential self-selection does not account for all influences of the built environment on auto ownership (question 4). Therefore, this study provides encouraging evidence that land use policies designed to reduce auto ownership and auto use (especially, limited space and mixed land use) will lead to a marginal reduction in auto ownership.

While individuals' attitudes and the built environment both influence auto ownership decisions, it is possible that the built environment also plays an additional indirect role by influencing these attitudes over time. Living in a suburban-style development, for example, may foster the formation of an auto-oriented lifestyle along with attitudes that favor the car. Conversely, it is possible that attitudes that favor the car can be altered over time through the implementation of neighborhood design strategies that increase the attractiveness of alternatives to driving. Without changes to suburban-style development, attitudes towards auto dependence and auto-oriented development are unlikely to change, for this generation or the next. Although we cannot test these possibilities with the data used in this study, our results point to the importance of additional research that will help us to better understand the complex interactions between attitudes, the built environment, and auto ownership.

Acknowledgements

The data collection was funded by the California Department of Transportation, with additional funding from the University of California Transportation Center and the Robert Wood Johnson Foundation. Advice from three anonymous referees was helpful in improving this paper.

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Table 1. Sample Characteristics vs. Population Characteristics

	Traditional				Suburban			
	Mountain View	SR Junior College	MD Central	SC Midtown	Sunnyvale	SR Rincon Valley	MD Suburban	SC Natomas
Sample Characteristics								
Number	228	215	184	271	217	165	220	182
Percent of females	47.3	54.3	56.3	58.2	46.9	50.9	50.9	54.9
Average auto ownership	1.80	1.63	1.59	1.50	1.79	1.66	1.88	1.68
Age	43.3	47.0	51.3	43.4	47.1	54.7	53.2	45.6
Average HH size	2.08	2.03	2.13	1.78	2.58	2.19	2.41	2.35
Percent of HHs w/kids	21.1	18.6	21.7	8.9	42.4	24.8	25.5	31.9
Percent of home owners	51.1	57.8	75.6	47.0	61.1	68.7	81.0	82.4
Median HH income (k$)	98.7	55.5	45.5	64.2	95.0	49.5	55.5	55.3
Population Characteristics								
Population	5,493	9,886	13,295	7,259	14,973	13,617	19,045	13,295
Age	36.1	36.3	36.5	42.7	35.9	38.3	38.1	31.7
Average HH size	2.08	2.21	2.46	1.79	2.66	2.48	2.51	2.57
Percent of HHs w/kids	19.3	20.3	32.9	12.4	35.3	35.4	34.2	41.7
Percent of home owners	34.3	31.2	58.8	34.3	53.2	63.5	61.4	55.2
Median HH income (k$)	74.3	40.2	42.5	43.8	88.4	49.6	40.2	46.2

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

Table 2. An Overview of Auto Ownership and Changes in Auto Ownership

	Category	Traditional	Suburban
Observations		898	784
	0	4.8%	3.6%
	1	42.8%	36.7%
Auto ownership [a]	2	40.8%	44.8%
	3	9.0%	10.8%
	4	2.0%	3.2%
	5+	0.6%	0.9%
	Average [b]	1.62	1.76
Observations		292	386
	Decrease	19.4%	18.8%
Changes in auto ownership	Constant	67.6%	68.8%
(Movers only)	Increase	13.0%	12.4%
	Total	386	292

a. Differences between neighborhood types significant at the 0.05 level (χ^2 test).
b. Differences between neighborhood types significant at the 0.01 level (t test).

Table 3. Pattern Matrix for Neighborhood Characteristic Factors

Variable	Factor Label					
	Accessibility	**Physical Activity Options**	**Safety**	**Socializing**	**Attractiveness**	**Outdoor Spaciousness**
Cronbach's α	0.804	0.705	0.846	0.652	0.720	0.737
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	0.353				
Good bicycle routes beyond the neighborhood		0.882				
Sidewalks throughout the neighborhood		0.707				
Parks and open spaces nearby		0.637				
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			
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		
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	0.404
Large back yards						0.876
Large front yards						0.858
Lots of off-street parking (garages or driveways)						0.562

a. Extraction method: principal component analysis; Rotation method: oblimin with Kaiser Normalization.
b. The extraction of the accessibility and physical activity options factors is independent of the extraction of the other factors.
c. Factor loadings lower in magnitude than 0.33 are suppressed.
d. Reliability tests (computations of Cronbach's α) are based on the highly loading (>0.33) variables.

Table 4. Pattern Matrix for Travel Attitude Factors

Variable	Factor Label					
	Pro-Bike/Walk	**Pro-Travel**	**Travel Minimizing**	**Pro-Transit**	**Safety of Car**	**Car Dependent**
Cronbach's α	0.819	0.600	0.568	0.692	0.544	0.522
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			0.363		
Walking can sometimes be easier for me than driving	0.339			0.344		
The trip to/from work is a useful transition between home and work		0.683				
Travel time is generally wasted time		-0.681				
I use my trip to/from work productively		0.616				
The only good thing about traveling is arriving at your destination		-0.563				
I like driving		0.479				0.356
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		0.357	
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			
I like taking transit				0.778		
I prefer to take transit rather than drive whenever possible				0.771		
Public transit can sometimes be easier for me than driving				0.757		
Traveling by car is safer overall than riding a bicycle				0.338	0.489	0.402
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	
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

a. Extraction method: principal component analysis; Rotation method: oblimin with Kaiser Normalization.
b. Factor loadings lower in magnitude than 0.33 are suppressed.
c. Reliability tests (computations of Cronbach's α) are based on the highly loading (>0.33) variables.

Table 5. The Ordered Probit Models for Auto Ownership

	Model 1: Excluding Attitudes			Model 2: Including Attitudes		
	β	**Std. β [a]**	**p-value**	**β**	**Std. β [a]**	**p-value**
Constant	0.685	2.492	<0.001	0.653	2.538	<0.001
Socio-demographics						
Female	-0.207	-0.103	<0.001	-0.195	-0.100	0.002
HH income (k$)	0.00844	0.305	<0.001	-0.00817	0.295	<0.001
HH size	0.0828	0.0982	0.014	0.0786	0.0932	0.023
Number of HH members within driving age (16-85)	0.588	0.450	<0.001	0.617	0.472	<0.001
Number of workers in the HH	0.147	0.125	<0.001	0.136	0.115	0.001
Driving disability	-1.360	-0.167	<0.001	-1.192	-0.147	<0.001
Transit disability	0.473	0.0705	0.010	0.323	0.0482	0.085
Residential tenure (rent=1,own=0)	-0.254	-0.122	<0.001	-0.269	-0.129	<0.001
Neighborhood Characteristics						
Outdoor spaciousness	0.0699	0.0649	0.044			
Number of business types within 400 meters	-0.0246	-0.0572	0.081			
Neighborhood Preferences						
Accessibility	-		-	-0.102	-0.0954	0.004
Outdoor spaciousness	-		-	0.08711	0.0800	0.015
Travel Attitudes						
Car dependent	-		-	0.0977	0.0967	0.002
Safety of car	-		-	0.0980	0.0974	0.004
μ_1	2.240	2.240	<0.001	2.290	2.290	<0.001
μ_2	3.940	3.940	<0.001	4.000	4.000	<0.001
Number of observations		1495			1495	
Degrees of freedom (K)		10			12	
Log-likelihood at constant (LL(C))		-1639.722			-1639.722	
Log-likelihood at convergence (LL(β))		-1305.571			-1292.060	
ρ^2 (1-LL(β)/LL(C))		0.204			0.212	
Adjusted ρ^2 (1-[LL(β)-K]/LL(C))		0.198			0.205	
Non-nested test result [b]			Φ (-5.002) = 0.000000284			

a. Dependent variable was not standardized.

b. The statistic is $\Phi\left\{-\left[-2z\,LL(C)+(K_2-K_1)\right]^{1/2}\right\}$, where z = [adjusted ρ^2 (Model 2) - adjusted ρ^2 (Model 1)].

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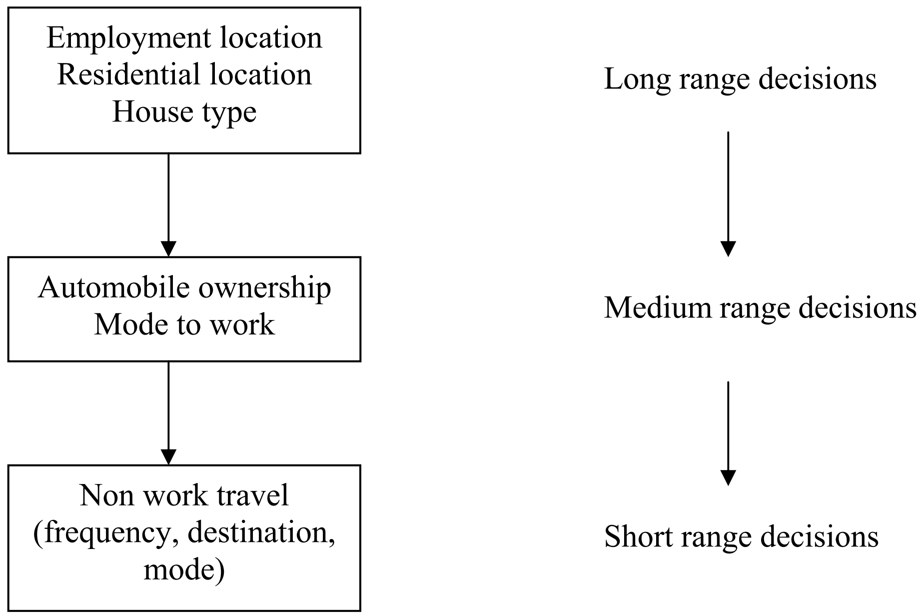
Table 6. The Static-Score Model for Changes in Auto Ownership (Movers only)

Variable	Category	β	Std. β	p-value
Constant		0.536		<0.001
Changes (ΔX)				
Household income (k$)	Socio-demographic	0.00400	0.114	<0.001
Number of household members within driving age (16-85)	Socio-demographic	0.0809	0.0863	0.008
Outdoor spaciousness	Neighborhood perception	0.0497	0.0875	0.002
Measurement at t (X_t)				
Number of household members within driving age (16-85)	Socio-demographic	0.341	0.291	<0.001
Age	Socio-demographic	-0.00689	-0.113	<0.001
Driving disability	Socio-demographic	-0.384	-0.0677	0.019
Number of business types within 400 meters	Neighborhood characteristic	-0.0180	-0.0581	0.042
Outdoor spaciousness	Neighborhood preference	-0.0488	-0.0544	0.062
Car dependent	Travel attitude	0.0499	0.0614	0.034
Measurement at t-1 (X_{t-1})				
Household income (k$)	Socio-demographic	0.00250	0.107	0.001
Lagged endogenous variable (Y_{t-1})				
Number of autos	Lagged endogenous variable	-0.654	-0.687	<0.001
Number of observations			614	
R^2			0.548	
Adjusted R^2			0.540	

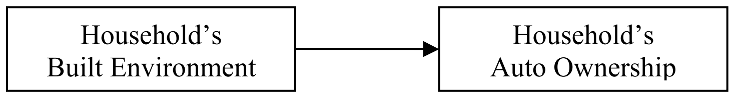
Figure 1. Household's Choice Hierarchy



Source: Ben-Akiva and Atherton (1977)

Figure 2. The Connection between Built Environment and Auto Ownership

Commonly Assumed Causality



More Likely Causality

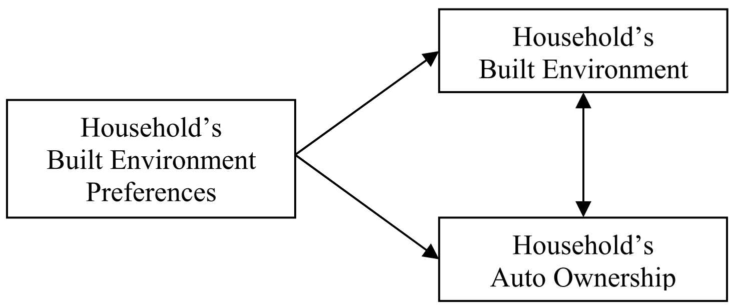


Figure 3. Geography of Neighborhoods

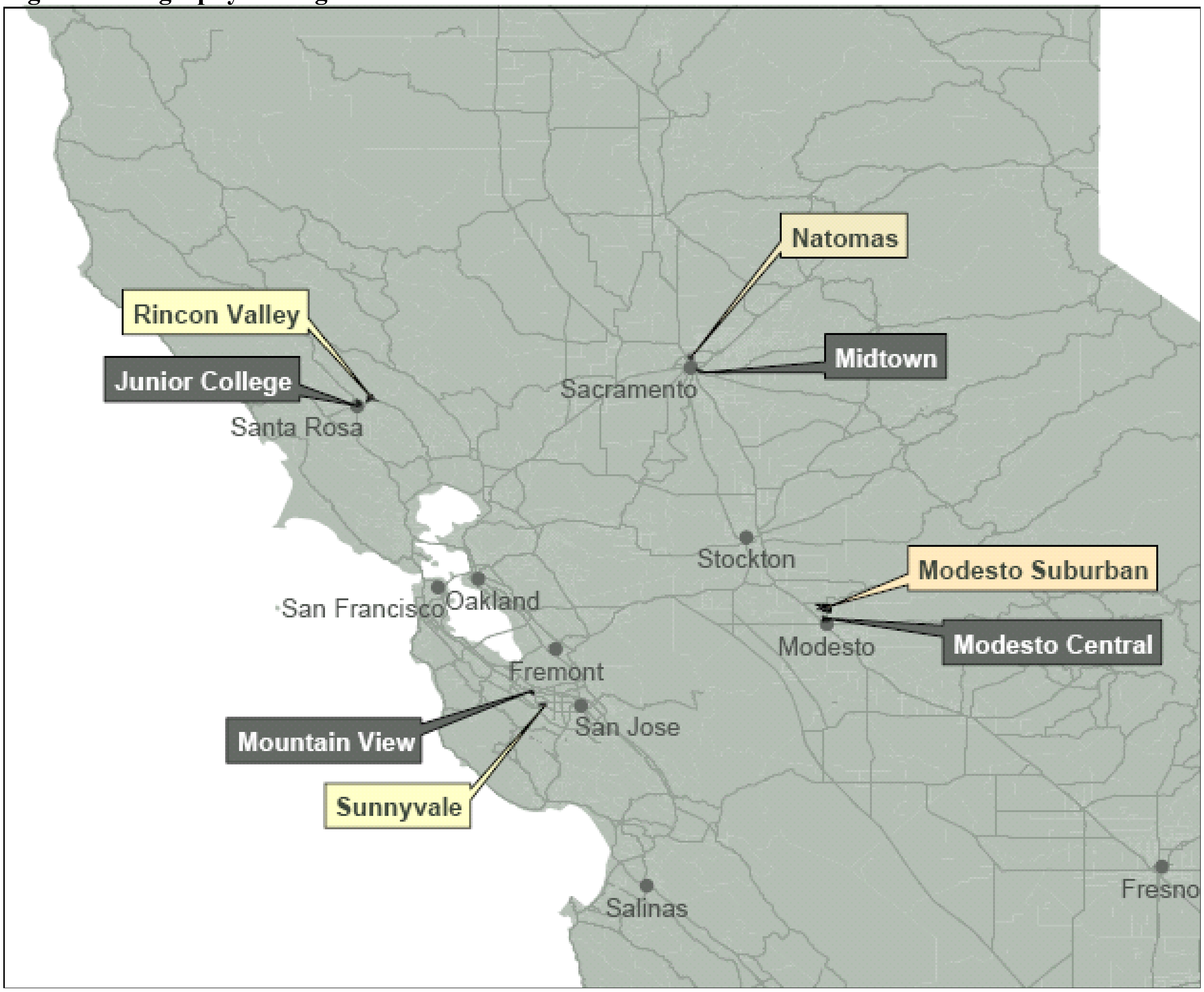
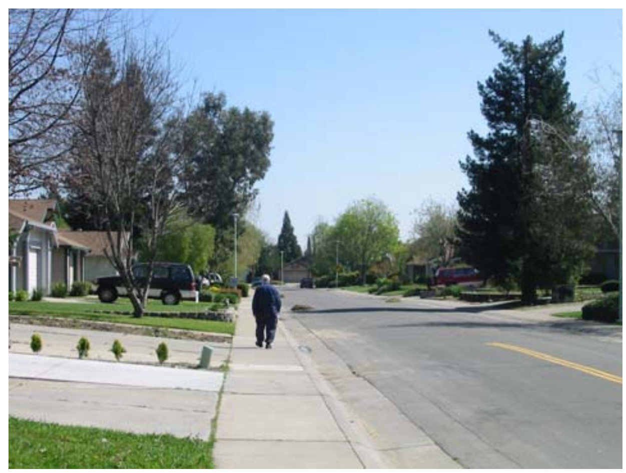


Figure 4. Comparison of Traditional and Suburban Neighborhoods (Sacramento)

Sacramento – Traditional | Sacramento - Suburban

Street network

Houses



Commercial centers