

MODELING RESIDENTIAL SORTING EFFECTS TO UNDERSTAND THE IMPACT OF THE BUILT ENVIRONMENT ON COMMUTE MODE CHOICE

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ABSTRACT

This paper examines the significance of residential sorting or self selection effects in understanding the impacts of the built environment on travel choices. Land use and transportation system attributes are often treated as exogenous variables in models of travel behavior. Such models ignore the potential self selection processes that may be in play wherein households and individuals choose to locate in areas or built environments that are consistent with their lifestyle and transportation preferences, attitudes, and values. In this paper, a simultaneous model of residential location choice and commute mode choice that accounts for both observed and unobserved taste variations that may contribute to residential self selection is estimated on a survey sample extracted from the 2000 San Francisco Bay Area household travel survey. Model results show that both observed and unobserved residential self selection effects do exist; however, even after accounting for these effects, it is found that built environment attributes can indeed significantly impact commute mode choice behavior. The paper concludes with a discussion of the implications of the model findings for policy planning.

1. INTRODUCTION

The importance and the complexity of the land use - travel behavior relationship has been recognized for several decades in the transportation planning practice and research communities (see the next section for a brief review of the literature). The complexity of the land use - travel behavior association arises due to (1) the multitude of dimensions that define land use (for example, land use mix, urban form, street block density, and local network features) and travel behavior (such as auto ownership, mode choice, and overall travel demand), and (2) the possibility of multiple causal and/or pure associative relationships between the dimensions that define land use and travel behavior (see Bhat and Guo, 2005 for an extended discussion on the land use – travel behavior relationship).

In conventional transportation planning practice, a one-way causal flow in which the nature of the land use pattern affects travel behavior is often assumed. Assuming such a one-way causal relationship would mean that households and individuals first locate themselves in neighborhoods based on market forces such as housing affordability, crime statistics, and school quality. Their travel behavior is then shaped based on the neighborhood characteristics (or built environment attributes). The above reasoning would imply, for example, that land use patterns and neighborhood attributes can be modified in order to obtain a desired shift in travel mode shares. The fallacy in such a one-way cause-and-effect assumption, which implies a sequential nature of residential location and mode choice decisions (in that order), is that it ignores the associative nature of the decisions. That is, the relationship between residential location and travel mode choice decisions may be a mix of partial cause-and-effect linkage and partial associative correlation. In reality, households and individuals may locate themselves into neighborhoods that allow them to pursue their activities using modes that are compatible with their socio-demographics (*e.g.*, income), attitudes (*e.g.*, auto-disinclination), and travel preferences (*e.g.* preference for smaller commute time). If this is indeed the case, then urban land-use policies aimed at modifying neighborhood attributes for inducing mode shifts would alter the spatial residential location patterns more than the mode choice patterns. Such phenomenon is called residential self selection or residential sorting and calls for the treatment of residential location choice as an endogenous choice dimension that needs to be modeled simultaneously with the travel behavior dimension of interest. Ignoring the endogeneity of residential location choice or residential sorting effects (when present), can result in the identification of “spurious” causal effects of neighborhood attributes on travel behavior and lead to distorted policy implications. In order to correctly assess the impact of land-use patterns on mode choice, one must recognize and control for the associative correlations that may arise due to residential sorting. In the light of this discussion, the specific objectives of this study are to:

- Clearly understand the mechanism of the relationship between residential location patterns and commute mode choice.
- Assess the impact of built environment (BE) attributes on mode choice by controlling for residential sorting effects and disentangling the “spurious” and “true” causal effects of the neighborhood attributes on commute mode choice.

In order to accomplish the objectives, a comprehensive analysis of the effect of neighborhood attributes on commute mode choice is undertaken through a joint residential location choice and mode choice modeling effort. An extensive suite of neighborhood attributes or descriptors are used for the analysis of built environment effects as are a range of demographic variables in the mode choice model. In addition, a key aspect of the modeling framework employed in this paper is that both observed and unobserved heterogeneity (*i.e.*,

sensitivity variations due to household/individual observed demographics and unobserved factors) are accommodated in analyzing the effect of neighborhood attributes on residential choice and mode choice.

The econometric modeling methodology used in this paper is an extension of the general joint modeling methodology developed recently by Bhat and Guo (2005), in which they control for the endogeneity of residential location patterns (*i.e.*, self selection effects) to assess the impact of neighborhood attributes on car ownership. In that paper, car ownership is treated as an ordered discrete response choice variable. The modeling framework proposed in this paper is different in that the travel behavior variable of interest here (mode choice) is of an unordered discrete response nature.

The contribution of this paper is thus two-fold. First, the joint model can control for residential sorting effects to obtain the “true” effect of neighborhood attributes on mode choice. Such a joint model can predict the spatial residential relocation patterns as well as the travel behavior (mode choice in this case) changes that may be brought about in response to land-use policies. Second, from a methodological standpoint, the paper presents a methodology for simultaneously modeling the relationship between two unordered discrete choice variables, thus accommodating both causal as well as associative components of the relationship that may exist between them (residential location choice and commute mode choice in the current empirical context). This is one of the first studies that the authors are aware of in which two unordered discrete choice variables are modeled in a simultaneous equations framework.

The remainder of the paper is organized as follows. Following a brief review of the literature in the next section, the modeling methodology is presented in the third section. In the fourth section, a description of the data used in the study is presented. Model results are presented in the fifth section together with a discussion of the interpretation of the findings. Finally conclusions are presented in the sixth and final section.

2. LITERATURE REVIEW

There is a vast body of literature dedicated to the relationship between land use and travel behavior (see Bhat and Guo, 2005 for an extensive review of studies that examine the relationship between residential location and travel behavior, and for a discussion on the methods used in the past to accommodate residential sorting effects in travel behavior models). The intent of this section is not to provide a comprehensive literature review on the subject, but rather highlight some of the previous work germane to the topic addressed in this paper, *i.e.*, the relationship between residential location choice and mode choice.

Numerous studies in the past have examined the impact of neighborhood attributes on mode choice. Several of them (for example, Handy, 1996; Kockelman, 1997; Cervero and Kockelman, 1997; and Rajamani *et al.*, 2003) indicated a significant impact of neighborhood attributes in mode choice decisions. Other studies that reported a possibility of considerable mode shifts as a result of modifying built environment include Badoe and Miller (2000), Crane (2000), Ewing and Cervero (2001), Zhang (2004), Cervero and Wu (1997), Friedman *et al.* (1994), Frank and Pivo (1994), and Ewing *et al.* (1994); Zhang (2006) offers a comprehensive review of these studies. It should be noted, however, that not all studies have found or reported significant impacts of neighborhood attributes; for example, Crane and Crepeau (1998) and Hess (2001) found no evidence that land use affects travel mode choice patterns. Kitamura *et al.* (1997) examined the effects of land use, demographic, and attitudinal variables on the proportion and number of trips by various modes, and found that attitudinal and demographic variables have

a stronger influence, than that of land use attributes, on travel by each mode. Cervero (2002) studied mode choice behavior in Montgomery County, Maryland and found that the influences of urban design tend to be more modest than those of intensities and mixtures of land use on mode choice decisions.

There are a few studies that have attempted to account for residential self selection in specific travel mode choice contexts. For example, Boarnet and Sarmiento (1998) employed regressed (using instrumental variables) values of endogenous neighborhood attributes in order to estimate their “true” effect on non work auto trips. Their findings with the data from southern California region indicate a rather weak impact of built environment effects on non-work travel by auto mode, and clearly suggest that residential location choice and neighborhood attributes should be endogenously considered in models of travel behavior. Cervero and Duncan (2002) explored the issue of residential self selection by estimating a nested logit model for the joint choices of residing near a rail station and commuting by rail transit, using year-2000 travel data from San Francisco Bay area. Their analysis suggests that residential sorting due to transit-oriented lifestyle preferences accounts for about 40 percent of the rail-commute decision. Cervero and Duncan (2003), using data from San Francisco Bay area, found that neighborhood attributes had a weaker influence, in comparison with demographics, on the choice to walk/bike due to residential self selection. In other words, once one accounts for residential self-selection, the impact of neighborhood attributes is found to diminish and becomes smaller than the impact of socio-demographic attributes.

Zhang (2006) assessed the impact of land use on auto dependency (defined as the probability that auto is the only available travel mode) in a mode choice model, while recognizing the endogeneity involved in auto ownership, residential location, and travel mode choice through an instrumental variable approach. His analysis indicates that auto dependency is highly sensitive to street network connectivity and automobile availability. Schwanen and Mokhtarian (2005) found that though residential sorting plays a significant role in explaining commute mode choice, neighborhood characteristics have a non-negligible effect on commute mode choice even after controlling for such self selection effects.

In the context of residential self selection, the recent work by Bhat and Guo (2005) offers a comprehensive and general methodology to control for residential sorting effects. Specifically, they control for residential sorting due to observed socio-demographic and unobserved factors in an ordered response model of household car ownership. This study builds significantly upon their work by developing a joint model of residential location choice and mode choice that explicitly accommodates residential sorting effects and accounts for both observed and unobserved heterogeneity in residential self-selection. Detailed explanation of the methodology follows in the next section.

3. ECONOMETRIC MODELING FRAMEWORK

The mathematical formulation and intuitive appeal of the model structure and estimation are discussed in this section.

3.1 Mathematical Formulation

In the following presentation of the model structure, the index h is used for households ($h = 1, 2, \dots, H$), q_h for individual q ($q = 1, 2, \dots, Q$) from household h , i for the spatial unit of residential choice ($i = 1, 2, \dots, I$), and j for commute modes ($j = 1, 2, \dots, J$). The equation system for the joint residential choice and commute mode choice model is then written as follows:

$$u_{hi}^* = \gamma_h' x_i + \varepsilon_{hi}, \text{ spatial unit } i \text{ chosen if } u_{hi}^* > \max_{\substack{k=1,2,\dots,I \\ k \neq i}} u_{hk}^* \quad (1)$$

$$\mu_{q_n r j}^* = \alpha_{q_n j}' y_{q_n} + \beta_{q_n}' z_{q_n r j} + \delta_{hj}' x_r + \xi_{q_n r j}, \text{ mode } j \text{ chosen if } \mu_{q_n j}^* > \max_{\substack{m=1,2,\dots,J \\ m \neq j}} \mu_{q_n m}^*$$

The first equation above is the utility function for the choice of residence in which u_{hi}^* is the indirect utility that the household h derives from locating itself in spatial unit i , x_i is a vector of attributes corresponding to spatial unit i (x_i can potentially include non-built environment (non-BE) attributes such as racial composition, commute time, *etc.* and built environment (BE) attributes such as land-use mix, density, transit-accessibility, *etc.*), and γ_h is a household-specific coefficient vector capturing the sensitivity to attributes in vector x_i . γ_h is parameterized as follows: $\gamma_{hl} = (\gamma_l + \Lambda_l' w_{hl} + v_{hl} + \omega_{hl})$, where w_{hl} is a vector of observed household-specific factors affecting sensitivity to the l^{th} attribute in vector x_i , and v_{hl} and ω_{hl} are household-specific unobserved factors impacting household h 's sensitivity to the l^{th} attribute. v_{hl} includes only those household-specific unobserved factors that influence sensitivity to residential choice, while ω_{hl} includes only those household-specific unobserved factors that impact both residential choice and commute mode choice. Finally, ε_{hi} is an idiosyncratic error term assumed to be identically and independently extreme-value distributed across spatial alternatives i and households h .

The second equation in equation system (1) is the utility function for the choice of commute mode in which $\mu_{q_n r j}^*$ is the indirect utility that an individual q from household h (with the observed residential location at spatial unit r) associates with commute mode j . In the explanatory variables, y_{q_n} is a vector of attributes that includes non-spatial determinants of modal utilities such as individual and household level socio-demographics (for example, household and personal income, age, gender, *etc.*), $z_{q_n r j}$ is a vector of level-of-service (LOS) attributes faced by the individual q of household h between his/her observed residential location r and employment location by mode j (for example, travel time, travel cost, *etc.*), and x_r is a vector of attributes corresponding to the chosen residential spatial unit r (for example, BE attributes such as land-use mix, density, *etc.*, and household level non-BE attributes such as the total commute time of all commuters in the household with residential¹ location at spatial unit r). In the coefficient vectors, $\alpha_{q_n j}$ represents the impact of socio-demographics on the utility of mode j , β_{q_n} is a vector of response sensitivities² to the LOS attributes in $z_{q_n r j}$, and δ_{hj} is a household-specific³ coefficient vector capturing the impact of BE and non-BE attributes (in vector x_r) of chosen residential spatial unit r on the utility of mode j . The elements (indexed by l) of δ_{hj} are parameterized as follows: $\delta_{hjl} = (\delta_{jl} + \Delta'_{jl} s_{hl} + \eta_{hjl})$, where s_{hl} is a vector of observed

¹ This analysis assumes that the employment locations of the commuters are exogenous.

² The vector β_{q_n} may be parameterized to capture the variation in response sensitivities to level-of-service attributes due to observed and unobserved individual and household specific factors.

³ The impact of BE and non-BE attributes in the vector x_r can be household specific and/or person specific; the person specific nature of the attribute effects are ignored only in notation for the sake of brevity.

household-specific factors influencing the sensitivity to l^{th} attribute in x_r , Δ_{jl} is the corresponding vector of coefficients, and η_{hjl} is a term capturing the impact of household-specific unobserved factors on the sensitivity to l^{th} attribute in x_r . Finally, $\xi_{q_h j}$ is an error term that is partitioned into two components: $\sum_l (\pm \omega_{hjl}) x_{rl} + \zeta_{q_h j}$. The $\pm \omega_{hjl} x_{rl}$ terms are the common error components in residential choice and mode choice, while $\zeta_{q_h j}$ is an idiosyncratic term assumed to be identically and independently (IID)⁴ logistic distributed across individuals and modal alternatives.

3.2 Intuitive Discussion of Model Structure

The equation system (1) can be written as:

$$u_{hi}^* = \sum_l (\gamma_l + \Lambda_l' w_{hl} + v_{hl}) x_{il} + \left(\sum_l \omega_{hl} x_{il} + \varepsilon_{hi} \right) \quad (2)$$

$$\mu_{q_h rj}^* = \alpha_{q_h j}' y_{q_h} + \beta_{q_h}' z_{q_h rj} + \sum_l (\delta_{jl} + \Delta_{jl}' s_{hl} + \eta_{hjl}) x_{rl} + \left(\sum_l \pm \omega_{hjl} x_{rl} + \zeta_{q_h rj} \right)$$

In the above equation system, the self-selection of households into certain neighborhoods (that explains the endogeneity in the effect of neighborhood specific BE and non-BE attributes on commute mode choice) is captured by controlling for (1) observed and (2) unobserved factors that impact residential location and commute mode choice. The explanation is as follows.

First, the model formulation controls for the effect of systematic/observed socio-demographic differences among individuals in their mode choice decisions. Consider, for example, that households with high income stay away from high density neighborhoods. This can be reflected by including income as a variable in the w_{hl} vector in the residential choice equation. High income households are also likely to own more cars and the individuals belonging to those households are more likely to choose auto as their commute mode choice. The residential sorting based on income can then be controlled for when evaluating the effect of the BE attribute “density” on commute mode choice by including income as a variable in the in the y_{q_h} vector in the mode choice equation. Ignoring such residential sorting effects due to observed demographics can lead to an artificial inflation of the neighborhood attribute effects in mode choice decisions. Examples of studies that control for observed socio-demographic factors include Lund (2003), Kitamura *et al.* (1997), Schwanen and Mokhtarian (2004), Handy *et al.* (2005), and Khattak and Rodriguez (2005).

Second, the model formulation controls for unobserved attributes (such as attitudes/perceptions, and environmental considerations) that may influence both residential choice and commute mode choice. For example, households with individuals that are environment-conscious and auto disinclined may locate themselves into neighborhoods that are conducive to the use of non-motorized forms of transport so that they may walk or bike to work. Such common unobserved preferences are captured in the terms ω_{hl} and ω_{hjl} of the residential choice utility equations and the non-motorized modal utility equations, respectively. These common unobserved factors cause the endogeneity in the effect of corresponding BE and non-

⁴ The term $\xi_{q_h j}$ may be further partitioned to represent the non-IID nature of the error terms in modal utility equations.

BE attributes in the commute mode choice model, and give rise to correlation in the error components across the residential location and mode choice models leading to the joint nature of the model structure. The ‘ \pm ’ in front of the $\omega_{hjl}x_{rl}$ terms in the mode choice equation indicates that the impact of common unobserved factors in moderating the influence of the characteristics represented by x_{rl} across the residential choice and mode choice equations may be in the same or opposite directions, respectively (called as positive or negative correlation, respectively). If the sign is ‘+’, it implies that the unobserved factors that increase (decrease) the individuals’ (households) preference to the characteristic represented by x_{rl} in residential location choice decisions also increase (decrease) their preference to commute mode j , while a ‘-’ sign implies that the unobserved factors that increase (decrease) the individuals’ preference to the characteristic captured by x_{rl} in residential location choice decisions decrease (increase) their preference to commute mode j . If the x_{rl} measures are defined in the context of promoting smart growth and neo-urbanism concepts (such as high density and increased land use diversity) to promote non-motorized travel to work, then there may be an expectation that the appropriate sign in front of the $\omega_{hjl}x_{rl}$ term in non-motorized modal utility equations should be positive. Through the model formulation adopted in this paper, it is possible to test which one of the two signs is appropriate. A positive sign suggests that households who have an intrinsic preference for neo-urbanist neighborhoods also have a higher preference for non-motorized modes of transport (due to unobserved attributes such as auto-disinclination). Ignoring these $\omega_{hjl}x_{rl}$ terms while estimating the mode choice utility equations leads to an artificial inflation of the positive sign on the corresponding neo-urbanist BE attributes (*i.e.*, an artificial inflation of the positive sign on the δ_{jl} terms in the non-motorized modal utility equations). If x_{rl} represents an attribute such as total commute time of all individuals in the household, the anticipated sign in front of the $\omega_{hjl}x_{rl}$ term in auto modal utility equations could be either positive or negative. A negative sign indicates that the unobserved factors (such as attitudes/perceptions towards traveling and spending time on the road) that increase (decrease) individuals’ sensitivity to total commute time in residential location decisions also increase (decrease) their preference for the relatively faster auto modes. On the other hand, a positive sign indicates the presence of unobserved factors affecting residential location choice that contribute to individuals/households increasing their total commute time and therefore becoming more auto-oriented in their commute mode choice. For example, one may consider such factors as crime, school quality, aesthetic appeal of neighborhood, neighborhood amenities, and perceptions of the prestige associated with living in a certain neighborhood. Although individuals/households would like to minimize their total commute time index, simply doing so may result in their locating in less-desirable residential neighborhoods. These unobserved factors then lead to individuals/households living in neighborhoods that increase their total commute time index and make them more auto-oriented.

Overall, the model formulation explicitly considers residential sorting effects that may be traced to observed socio-demographics, and unobserved attitudinal variables and personal lifestyle preferences.

3.3 Model Estimation

The parameters to be estimated in the equation system (2) include the α and β vectors, the γ_l , δ_l , Λ_l , and Δ_l vectors, and the variances of v_{hl} ($= \sigma_{vl}^2$), η_{hjl} ($= \sigma_{\eta l}^2$), and ω_{hl} ($= \sigma_{\omega l}^2$) for those

BE and non-BE attributes with random taste heterogeneity. It is to be noted that the random taste heterogeneity to a particular attribute l may occur only in residential choice, only in some of the modal utilities, independently in residential choice and mode choice, or as combinations of the above patterns with a common effect on both residential choice and mode choice. Also, there may not be any random heterogeneity for some or all of the attributes in either of the residential choice and mode choice models.

Let Ω represent a vector that includes all the parameters to be estimated, and let $\Omega_{-\sigma}$ represent a vector of all parameters except the variance terms. Also, let c_h be a vector that stacks the v_{hl} , η_{hjl} , and ω_{hl} terms across all BE and non-BE attributes and let Σ be a corresponding vector of standard errors. Define $a_{hi} = 1$ if household h resides in spatial unit i and 0 otherwise. Similarly, define $b_{q_h,j} = 1$ if an individual q_h chooses the commute mode j and 0 otherwise. Then, the likelihood function for a given value of $\Omega_{-\sigma}$ and c_h may be written for an individual q_h as:

$$L_{q_h}(\Omega_{-\sigma}) | c_h = \left[\frac{\exp(\gamma'_h x_i)}{\sum_k \exp(\gamma'_h x_k)} \right]^{a_{hi}} \left[\frac{\exp(\alpha'_{q_h,j} y_{q_h} + \beta'_{q_h} z_{q_h,rj} + \delta'_{hj} x_r)}{\sum_k \exp(\alpha'_{q_h,j} y_{q_h} + \beta'_{q_h} z_{q_h,rj} + \delta'_{hj} x_r)} \right]^{b_{q_h,j}} \quad (3)$$

Finally, the unconditional likelihood function can be computed for individual q_h as:

$$L_{q_h}(\Omega) = \int_{c_h} (L_{q_h}(\Omega_{-\sigma}) | c_h) dF(c_h | \Sigma), \quad (4)$$

where F is the multidimensional cumulative normal distribution. The log-likelihood function can be written as: $L(\Omega) = \sum_{q_h} \ln L_{q_h}(\Omega)$. Simulation techniques are applied to approximate the multidimensional integral in Equation (4), and maximize the resulting simulated log-likelihood function. Specifically, the scrambled Halton sequence (see Bhat, 2003) is used to draw realizations of c_h from its population normal distribution. In the current paper, 125 realizations of c_h were used to obtain stable estimation results.

4. DATA

The primary data source used in the analysis is the 2000 San Francisco Bay Area Travel Survey (BATS), designed and administered by MORPACE International, Inc. for the Bay Area Metropolitan Transportation Commission (see MORPACE International Inc., 2002 for details on survey design, sampling, and administration procedures). In addition to the activity survey, six other data sets associated with the San Francisco Bay area were used in the current analysis: land-use/demographic coverage data, zone-to-zone travel level-of-service (LOS) data, a GIS layer of bicycle facilities, the Census 2000 Tiger files, census demographic data, and Public Use Microdata Sample (PUMS) data. Bhat and Guo (2005) offer a detailed explanation of the various data sources and how they were used to construct an integrated and comprehensive land use – travel behavior – level of service database that can be used to study land use – travel behavior relationships.

The geographic area of study in this research is the Alameda County in the San Francisco bay area with 233 transport analysis zones. The residential choice of households and commute mode choice of individuals within this county constitute the focus of analysis for this paper.

After extracting the Alameda County households from the survey sample and merging the various secondary data sources, the final sample for analysis comprised 1,878 individuals from 1,447 households. The household and person characteristics of the estimation sample are provided in Tables 1 and 2.

The average household size is about 2.5 persons per household with nearly a quarter of the households reporting household sizes of four or more persons. Nearly one-third of the households report having an individual less than 18 years of age in the household. The median household income is rather high with about 50 percent of the households falling into the fourth and highest income quartile. On average, households reported a little over two cars per household with less than two percent of the households having zero cars. On average, the ratio of vehicles to licensed drivers is greater than one, generally indicating a high level of auto availability. A little over one-third of the households have zero bicycles; at the same time, about one-quarter of the households have three or more bicycles. About 70 percent of the households own the home in which they reside, generally indicating a rather high level of home ownership within the survey sample used in this paper. With respect to the type of residential location, about one quarter live in potentially higher density CBD and urban environments while 70 percent live in potentially lower density suburban locations. A very small percentage lives in rural locations.

Table 2 presents person characteristics for the estimation sample used in this paper. The person sample includes only commuters who are employed outside the home. The average age of the sample persons is 43 years and more than 50 percent of the persons are male. More than 85 percent of the individuals are employed full time. The degree of work flexibility is quite high with about 60 percent of the individuals indicating that they have at least some (moderate) flexibility with respect to their work arrangement. A vast majority (98 percent) is licensed to drive and commute by auto; more than 80 percent drive alone to work. Less than one percent use transit, about 11 percent carpool to work either as a driver or passenger, and about 6.5 percent use non-motorized modes (bike/walk) to commute to work.

Table 3 offers a description of the land use characteristics associated with the Alameda county sample used for model estimation. About 65 percent of the 233 zones are suburban locations and another 30 percent are urban locations. The percent of zones that are CBD or rural in nature is quite small at about 3 percent each. As expected, the number of zones accessible by transit is greatest for CBD and urban locations and lowest for rural locations. Consistent with land use definitions, household density, employment density, shopping accessibility, and employment accessibility are greatest for CBD and urban locations and lowest for rural locations. On the other hand, the recreational accessibility is greatest for rural locations. Similarly, the street block density, bikeway density, and land use mix show a decreasing trend with the highest values associated with CBD and urban locations and lower values associated with suburban and rural locations. Bhat and Guo (2005) offer a detailed explanation and definition of these variables that define land use characteristics associated with various zones.

Table 4 offers a summary of home-to-work level of service characteristics for the estimation sample used in this paper. As expected, the average travel times for the auto modes are about 20-25 minutes and the auto mode is the fastest among all modes. The average travel time is about six hours for the walk mode, more than one hour for the bicycle mode, and about 45 minutes for the transit mode. On average, the drive alone mode and the transit mode are nearly equal in cost while the auto-shared ride mode is considerably less expensive. The walk and bike modes are assumed to have zero cost associated with them.

All of these variables and attributes are merged with the travel survey sample data to form a comprehensive land use – travel behavior – network level of service database suitable for analyzing the relationships between residential location choice and commute mode choice.

5. MODEL ESTIMATION RESULTS

This section provides a description of the model estimation results. The model system is estimated as a joint choice model including both residential location choice and commute mode choice dimensions. All 233 zones are considered to be alternatives in the residential location choice set. The commute mode choice set definition accounts for modal availability at the individual/household level. A household must own an automobile and an individual must have a driver's license for the auto drive (drive alone and drive with passenger) modes to be available in the choice set. The auto-passenger mode choice is available to all individuals as are the bike and walk modes. The transit mode is included in the choice set based on transit availability as specified in the network level of service files.

Table 5 presents estimation results for the residential location choice model. In general, the results are found to be plausible and consistent with expectations. Both the number of households in a zone and the density of households in a zone positively affect residential location choice. However, it is found that seniors are less likely to locate in zones of high density as evidenced by the negative coefficient associated with the interaction term. As expected high employment density zones are less likely to be chosen for residential location, except for lower income households who may be compelled to choose lower cost housing in such locations. Also, households desiring to live in single family detached housing units are more likely to locate in zones with a higher fraction of such a housing stock. The land use mix measure is negatively associated with residential location choice; this suggests that households are more prone to live in zones that are rather homogeneous in nature. This finding may also be an artifact of both zoning policies and zone definition strategies. Zoning policies may often dictate that land uses be segregated and traffic analysis zones themselves are often defined based on homogeneity of land uses. As a result, the likelihood of a household being located in a mixed land use zone is potentially going to be small simply because such zones are few and far between. Rather surprisingly (but consistent with the findings in Bhat and Guo, 2005), the fraction of residential land area is negatively associated with residential location choice. A higher recreational accessibility is associated with a greater likelihood of locating residence in a particular zone.

The total drive commute time for the household serves as a surrogate measure of the overall location of the household *vis-à-vis* the work locations of the commuters in the household (assuming work locations are exogenous). Thus, this variable may be treated as an overall commute time index for the household. As expected, households attempt to locate such that this commute time index is reduced as evidenced by the negative coefficient associated with this variable. The total drive commute cost variable is found to be significant for households in the lowest quartile suggesting that lower income households are more sensitive to commuting costs than other households.

Within the context of the commute time index, the standard deviation of its random coefficient specific to the residential location model is highly significant with a test statistic value of 11.82, indicating significant population heterogeneity in the sensitivity to commute time index in residential location decisions. It is also found that there are common unobserved factors affecting both residential location choice and auto mode (all auto modes) choice in the context of

commute time index; the corresponding error components are found to be negatively correlated. The standard error of this negative error correlation is found to be marginally significant with a test statistic value of 1.53. The presence of this correlation suggests that it is very important to model residential location choice and mode choice in a simultaneous equations framework because there are unobserved factors related to commute time that affect both of these choice dimensions simultaneously. In this particular instance, the interpretation of the negative sign on the correlation is as follows. The unobserved factors that increase (decrease) the sensitivity of individuals/households to total commute time index in residential location decisions, also make them more (less) oriented towards the relatively faster auto modes. For example, one may consider such factors as individuals' attitudes/perceptions towards traveling and spending time on the road that could contribute to higher (lower) sensitivity to total commute time index in residential location decisions, as well as higher (lower) preference to auto modes. Not accounting for such endogeneity could potentially lead to biased estimation of the impact of total commute time index in the commute mode choice model.

The remaining variables offer plausible interpretations consistent with expectations. Among the network level of service measures, street block density, bicycle facility density, and transit availability are desirable attributes with respect to residential location choice. However, as expected, households with higher vehicle availability are likely to be those located in suburban zones with lower street block density. This is supported by the negative coefficient associated with the interaction term between street block density and household vehicle availability. Similarly, the positive coefficient associated with the interaction term between bicycle facility density and bicycle ownership indicates that households with higher bicycle ownership are likely to be located in zones with higher bicycle density. Although transit availability is itself positively influencing residential location choice, transit stop access time negatively impacts residential location choice. This finding is not surprising in that while most zones are served by transit, most households are living in suburban locations where the access time to a stop is likely to be greater.

The demographic, housing cost, and ethnic composition variables all indicate that there is a natural self-selection process that occurs in the housing market. Similar income groups, similar ethnic groups, and households of similar size tend to cluster together. The median housing value has a negative impact on residential location choice suggesting that, as housing prices increase, the likelihood of locating in a zone decreases.

Results of the mode choice model estimation are presented in Table 6. All of the results are plausible and consistent with expectations. Relative to the auto mode, all other modes are less preferred as evidenced by the negative alternative specific constants. Higher vehicle availability is associated with auto mode usage while higher bicycle ownership is positively associated with bicycle mode usage. Higher household sizes are associated with the use of shared-ride modes consistent with the greater opportunity and/or need for sharing a ride when there are multiple individuals in a household. Both travel time and travel cost have negative coefficients, with an added negative effect in the absence of work arrangement flexibility. Presumably, sensitivity to travel time becomes more pronounced in the absence of work flexibility.

The total drive commute time for the household serves as a surrogate for the location of the household *vis-à-vis* the work locations of the workers in the household. The positive coefficient here is consistent with the notion that as households locate themselves such that their overall distance to the workplace increases, then the likelihood of becoming auto-oriented with

respect to commute mode choice increases as well. The standard error of the negative error correlation term in the context of the total drive commute time index variable is suggestive of the influence of common unobserved factors that affect residential location choice and choice of auto modes. The interpretation and explanation of this finding was presented earlier in the context of the description of the results of Table 5.

Higher population and employment density contribute positively to bicycle and walk mode usage while a higher degree of land use mix contributes positively to transit usage. Similarly, a higher street block density and bicycle facility presence contribute positively to the use of non-motorized modes of transportation. It is to be noted here that the current model specification allows for the process of households *self selecting* themselves into neighborhoods with street block density (and bicycle facility density) compatible with their vehicle availability (and bicycle ownership). The control for such residential sorting is achieved by including vehicle availability and bicycle ownership variables in the mode choice model. These findings are consistent with those in the literature and suggest that, even when controlling for residential sorting effects, the built environment attributes (street block density and bicycle facility presence in this case) have non-negligible effects on commute mode choice.

Log-likelihood ratio tests were performed to assess the significance and contribution of observed factors and unobserved residential sorting (joint correlation) effects. The log-likelihood value at convergence for the final joint model is -9384.7. The corresponding value for the model with no allowance for unobserved variations in sensitivity to the built environment and commute attributes is -9430.94. Then, the likelihood ratio test for testing the presence of unobserved variations in sensitivity is 92.47, which is larger than the critical chi-square value with 2 degrees of freedom at any reasonable level of significance (the 2 degrees of freedom correspond to the standard deviations on the drive commute time coefficient in the residential location model, and on the common error component, related to drive commute time coefficient, between the residential location and mode choice models). Further, the log-likelihood value corresponding to equal probability for each of the 233 zonal alternatives in the residential location model and sample shares in the car ownership model (corresponding to the presence of only the threshold parameters) is -11494.3. Therefore, the likelihood ratio index for testing the presence of exogenous variable effects and unobserved taste variations is 4219, which is substantially larger than the critical chi-squared value with 38 degrees of freedom at any level of significance. Overall, these test results indicate that residential sorting effects are significant as are observed and unobserved taste variations in explaining commute mode choice behavior.

6. SUMMARY AND CONCLUSIONS

This paper addresses the key role of residential sorting effects in studying the impact of built environment attributes on travel mode choice. In the current land use – transportation planning context where the merits of altering the structure of the built environment to bring about changes in travel behavior are being debated, this study makes an important contribution to the field by presenting a joint model of residential location choice and commute mode choice that accounts for both observed and unobserved self-selection processes.

In previous studies of land use – travel behavior relationships, the residential location choice dimension is treated as exogenous and travel characteristics are often assumed to be affected by the attributes of the residential location. These studies often ignore the residential self-selection process that may be taking place in the housing market. Households/individuals may be locating in certain neighborhoods due to their lifestyle preferences, attitudes, values, and

other unobserved factors. In the presence of such residential sorting effects, one may erroneously overestimate the impacts of built environment attributes on travel choices. In reality, individuals and households may simply be locating in neighborhoods that offer attributes consistent with their intrinsic preferences, attitudes, and values. More recent work in the field has recognized this important concept and begun to attempt to account for residential sorting effects in evaluating the impacts of the built environment on travel behavior.

This paper presents a rigorous econometric methodological framework for simultaneously modeling residential location choice and commute mode choice, two endogenous unordered discrete choice variables, while accounting for both observed and unobserved heterogeneity in the choice processes. The model system is estimated on a sample of households and individuals residing in Alameda County who responded to the activity-based household travel survey conducted in the San Francisco Bay Area in 2000.

The model estimation results offer some key conclusions that shed additional light on the debate surrounding the land use – travel behavior relationship. First, it is found that there are significant observed factors contributing to residential self selection. It is found that households self select their residential location based on demographic characteristics such as auto and bicycle ownership, income, household size, and race. Second, and more importantly, the common error component on the total drive commute time variable supports the endogenous treatment of residential location choice in a simultaneous equations modeling framework. The negative error correlation associated with this variable suggests that there are unobserved factors that may increase (decrease) the sensitivity of households and individuals to overall commute time in their residential location decisions and also make them more (less) auto-oriented in their commute mode choice decisions. Third, and perhaps most importantly, the built environment attributes such as accessibility, density, and land use mix have significant impacts on commute mode choice even after controlling for residential sorting effects and unobserved taste variations that contribute to such effects.

From a policy perspective, the results suggest that built environment attributes are not truly exogenous in travel choice decisions made by individuals. Households and individuals are locating themselves in built (transportation) environments that are consistent with their lifestyle preferences, attitudes, and values. In other words, households and individuals are making residential location and travel choice decisions jointly as part of an overall lifestyle package. Nevertheless, the findings in this paper suggest that modifying the built environment can bring about changes in mode choice behavior as evidenced by the significance of these attributes in the commute mode choice model even after controlling for residential sorting effects.

Future research directions arise from three limitations of the current study. First, several policy scenario simulations or an elasticity analysis would have provided further insights regarding the benefits obtained by accounting for residential sorting effects in a simultaneous equations modeling framework. Second, commonly used traffic analysis zones are treated as potential spatial residential locations; in reality, decision makers may have a different spatial unit in mind when making residential location decisions. Third, mode choice data limitations prevented the use of a rich mode choice model specification that included attitudinal attributes. Besides expanding on these limitations, a simultaneous analysis of residential location, auto and bicycle ownership, and commute mode choice decisions, within the rigorous methodological framework proposed in this paper may be of interest to the research community.

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Table 1. Household Characteristics in Alameda County Sample (1447 households)

Characteristic	Sample Shares
Household Size	2.53
1	22.8%
2	36.2%
3	16.3%
≥4	24.7%
Presence of Kids	
age <18 years	32.6%
Household Income	\$83,510
Low (in quartile 1 and 2)	18.1%
Medium (in quartile 3)	30.9%
High (in quartile 4)	51.0%
Vehicle ownership	2.14
0	1.7%
1	26.5%
2	43.2%
3	18.9%
≥4	9.7%
#vehicles/#licenses	1.13
Bicycle ownership	1.6
0	34.1%
1	21.1%
2	20.1%
≥3	24.7%
Household Tenure	
Own house	69.8%
Housing Type	
Single Detached House	69.4%
Duplex/Apartment	28.2%
Other	2.4%
Residential Location	
CBD	1.3
Urban	24.7
Suburban	71.6
Rural	2.4

Table 2. Person Characteristics in Alameda County Sample (1878 Persons)

Characteristic	Sample Shares
Age (in years)	42.96
18-29	17.1%
30-65	79.6%
≥ 66	3.3%
Gender	
Male	56.3%
Employment Stats	
Full-time	86.2%
Part-time	13.8%
Work Flexibility	
Not Flexible	40.7%
Moderately Flexible	30.2%
Flexible	29.1%
Driver's License	
Licensed	97.9%
Commute Mode Share	
Auto - Drive Alone	82.1%
Auto - Drive with Passenger	4.7%
Auto – Passenger	6.0%
Walk	3.8%
Bike	2.8%
Transit	0.7%

Table 3. Land-use Characteristics in the Alameda County Sample (233 Zones)

Characteristic	Average value by Area type				
	CBD (2.8%)	Urban (30.2%)	Suburban (64.2%)	Rural (2.8%)	Overall
Number of destination zones (out of 1099) accessible by transit	774.50	671.20	551.85	272.50	586.35
Household density (Number of households per acre)	8.86	8.13	3.48	0.60	4.95
Employment density in zone (Number of jobs per acre)	107.63	38.91	19.91	21.68	28.15
Shopping accessibility	33.67	25.14	22.12	18.68	23.26
Recreational accessibility	5.85	6.43	7.75	8.15	7.31
Employment accessibility	10.14	7.10	6.41	5.64	6.70
Street block density (no. blocks per square mile)	243.47	172.03	78.70	24.67	110.01
Bikeway density (miles per square mile)	7.67	4.88	3.59	0.52	4.01
Land-use mix index for zone (range: 0-1)	0.53	0.43	0.40	0.21	0.41

Table 4. Home-to-Work Level-of-Service Characteristics (1878 persons and 1447 households)

Characteristic	Sample Average	Standard Deviation
Travel Times (in minutes for 1878 persons)		
Auto - Drive alone	19.67	15.10
Auto - Shared ride	24.02	12.59
Walk	293.21	346.50
Bike	73.30	86.62
Transit	47.98	36.12
Travel Costs (in dollars for 1878 persons)		
Auto - Drive alone	1.16	1.06
Auto - Shared ride	0.30	0.25
Transit	1.23	0.99

Note: Walk and bike times are calculated assuming speeds of 12mph and 3mph, respectively. Walk and Bike costs are assumed to be zero.

TABLE 5. Estimation Results of the Residential Location Choice Model

Variables	Parameter	t-statistic
Zonal size and density measures (including demographic interactions)		
Logarithm of number of households in zone ($\times 10^{-1}$)	9.803	15.02
Household density (#households per acre $\times 10^{-1}$)	0.351	3.70
interacted with presence of seniors in household	-0.652	-1.93
Employment density (#employment per acre $\times 10^{-1}$)	-0.211	-2.89
interacted with household income in the lowest quartile	0.196	2.38
Zonal land-use structure variables (including demographic interactions)		
Fraction of residential land area	-0.813	-5.70
Fraction of single family housing interacted with household living in single family detached housing	2.298	13.03
Land-use mix	-0.305	-2.07
Regional accessibility measures (including demographic interactions)		
Recreation accessibility $\times 10^{-2}$ (by auto mode)	0.425	6.35
Commute-related variables (including demographic interactions)		
Total drive commute time of all commuters in household (minutes $\times 10^{-2}$)	-11.472	-24.28
Standard deviation of the error term in residential location model	5.809	11.82
Standard deviation of the error term common to residential location and mode choice models (negative correlation between the error terms)	0.859	1.53
Total drive commute cost of all commuters in household (dollars $\times 10^{-1}$)	0	fixed
interacted with household income in the lowest quartile	-4.600	-2.47
Local transportation network measures (including demographic interactions)		
Street block density (number of block per square mile $\times 10^{-2}$)	0.163	1.47
interacted with number of vehicles per number of licenses in household	-3.526	-3.34
Bicycle facility density (miles per square mile $\times 10^{-1}$)	0.251	2.54
interacted with number of bicycles in the household	0.864	2.34
Transit availability in zone	0.570	2.71
Transit access time to stop (minutes $\times 10^{-1}$)	-0.425	-5.25
Zonal demographics and housing cost (including demographic interactions)		
Absolute difference between zonal median income and household income ($\$ \times 10^{-5}$)	-2.077	-11.59
Absolute difference between zonal average household size and household size	-0.349	-5.05
Average of median housing value ($\$ \times 10^{-5}$)	-0.182	-7.01
Zonal ethnic composition measure		
Fraction of Caucasian population interacted with Caucasian dummy variable	2.836	13.82
Fraction of African-American population interacted with African-American dummy variable	2.736	5.18
Fraction of Hispanic population interacted with Hispanic dummy variable	2.199	4.47

TABLE 6. Estimation Results of the Mode Choice Model

Variables	Parameter	t-statistic
Alternative specific constants		
Auto – Drive alone	0	fixed
Auto – Drive with passenger	-3.418	-16.88
Auto – Passenger	-1.397	-3.00
Walk	-1.020	-1.64
Bike	-3.021	-5.20
Transit	-3.825	-4.23
Socio-demographics		
Number of vehicles per number of licenses – Drive modes	1.918	4.32
Number of bicycles – Bike mode	0.419	7.70
Household size – Passenger and drive passenger modes	0.170	3.04
Individual level level-of-service variables (including demographic interactions)		
Travel time (in minutes)	-0.011	-1.57
interacted with inflexible work schedule	-0.008	-1.55
Travel cost (in dollars)	-0.144	-1.82
Household level commute-related variables		
Total drive commute time of all workers (minutes x 10 ⁻¹) – Auto modes	1.336	1.60
Standard deviation of the error term common to residential location and mode choice models – Auto modes (negative correlation)	0.859	1.53
Zonal size and density measures (including demographic interactions)		
Population density (#households per acre x 10 ⁻¹) – Non auto modes	0.019	2.25
Employment density (#employment per acre x 10 ⁻¹) – Non auto modes	0.004	2.16
interacted with household income in lowest quartile –Non auto modes	0.268	1.39
Zonal land-use structure variables		
Land-use mix – Transit mode	2.418	1.60
Local transportation network measures (including demographic interactions)		
Street block density (#blocks/square mile x 10 ⁻¹) – Non motorized modes	0.367	2.64
Total length of bikeways within one mile radius (meters x 10 ⁻⁵) – Bike mode	1.267	1.22