Effect of the Built Environment on Motorized and Non-Motorized Trip Making: Substitutive, Complementary, or Synergistic?

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ABSTRACT

It has become well recognized that non-motorized transportation is beneficial to a community's health as well as its transportation system performance. In view of the limited public resources available for improving public health and/or transportation, the present study aims to (a) assess the expected impact of built environment improvements on the substitutive, complementary, or synergistic use of motorized and non-motorized modes; and (b) examine how the effects of built environment improvements differ for different population groups and for different travel purposes. The bivariate ordered probit models estimated in this study suggest that few built environment factors lead to the substitution of motorized mode use by non-motorized mode use. Rather, factors such as increased bikeway density and street network connectivity have the potential of promoting more non-motorized travel to supplement individuals' existing motorized trips. Meanwhile, the heterogeneity found in individuals' responsiveness to built environment factors indicates that built environment improvements need to be sensitive to the local residents' characteristics.

1. INTRODUCTION

The subject of non-motorized travel – that is, travel by non-motorized modes such as walk and bicycle – is gaining the attention of planning and transportation agencies around the world, primarily due to the adverse effects of auto dependency. In the U.S., for example, the sprawling land use patterns and the relatively low cost of operating motorized automobiles have contributed to deteriorating traffic and environmental problems. In 2002 alone, the total wasted fuel and time due to congestion in 85 urban areas was estimated to be $63.2 billion (Schrank and Lomax, 2004). Today, over 90 million Americans live in urban regions that are not in attainment of the National Ambient Air Quality Standards (NAAQS). To alleviate traffic congestion and reduce vehicular emissions, transportation agencies are seeking planning interventions that would support transportation alternatives, such as non-motorized modes, to the private automobile.

Meanwhile, non-motorized travel is also gaining the interest of researchers in the area of public health. In particular, recent studies have suggested that people's utilitarian non-motorized modes of travel have similar health benefits as recreational physical activity (see Sallis *et al.*, 2004 for a review of related studies). Thus, health agencies around the world are looking to 'active transport' (a term typically used in the health literature that is synonymous to non-motorized travel) as an important element of overall strategies to boost the levels of physical activity among individuals.

It has become clear from above that non-motorized transportation is beneficial both from a transportation system performance standpoint as well as a community's health. Hence, transportation and health professionals are beginning to join forces to create an environment to increase non-motorized transportation (Frank and Engelke, 2001; Saelens *et al.*, 2003; Sallis *et al.*, 2004). One of the potentially effective strategies is that of New Urbanism. The premise behind New Urbanism is that high density, mixed land use, and pedestrian/cyclist friendly neighborhoods will not only improve neighborhood vibrancy and social equity, but also inspire the greater use of non-motorized modes. However, the question of whether New Urbanist development would indeed alleviate the transportation and health problems that we face today remains a hot topic of debate. In particular, will the New Urbanist strategy of improving non-automobile travel options through the built environment (BE) lead to individuals replacing their driving by walking, bicycling, or taking transit (the substitutive effect)? Or, would people continue to drive just as much but, at the same time, make more walking or bicycling trips (the complementary effect)? Or, by potentially facilitating automobile use at the same time as accommodating non-automobile travel, would New Urbanism development backfire and induce more car trips as well as non-motorized trips (the synergistic effect)?

The true effects of the BE on the substitutive, complementary, or synergistic use of modes has important implications on the effectiveness of New Urbanism as a transportation and health improvement strategy. The substitutive effect represents a win-win situation where New Urbanist communities enjoy better transportation levels-of-service, better health, and enhanced quality of residential environments in general. The complementary effect, on the other hand, implies that New Urbanism would not be an effective travel demand management strategy, but could lead to improvement in general public health. The synergistic effect would suggest that, contrary to common perception, New Urbanism development would induce more demand for both motorized and non-motorized travel, possibly resulting in more auto trips than non-motorized ones. While this would be beneficial from the health perspective, it would be a counter-productive strategy for solving transportation problems. With limited public resources available for improving transportation and/or public health, it is crucial to assess the expected outcome of any BE improvements by differentiating among these three possible effects. Yet very few past empirical studies have accounted for and examined all three effects in a single analytical framework.

The current study sets out to address the questions regarding the alternative effects of New Urbanist development on motorized versus non-motorized mode use. Specifically, our objectives are: (a) To determine if, and how much, different aspects of the BE affect the substitutive, complementary, or synergistic relationship between motorized and non-motorized mode use, and (b) To assess whether, and how, the effects of the BE differ for different population groups and for different travel purposes. These objectives are achieved by jointly analyzing motorized and non-motorized mode use frequencies, while systematically considering interaction terms of BE and socio-demographic factors. Separate models are estimated for trips of non-work maintenance and discretionary purposes. These trips together constitute about three quarters of urban trips and represent an increasingly large proportion of peak period trips

(Federal Highway Administration, 1995). They are generally more flexible than work trips and may therefore be influenced by urban form to a greater degree than work trips are (Rajamani *et al.*, 2003).

The remainder of the paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 describes the research design, including the data sources used for this study, the formation of the sample for analysis, the suite of BE measures considered in the analysis, the characteristics of the final sample, and the modeling framework employed to address our research questions. Section 4 reports the model estimation results. The final section concludes the paper with a discussion of the implications for policy making and directions for further research.

2. RELATED PAST RESEARCH

The search for effective urban development patterns to reduce driving and promote alternative mode use has led to an abundant body of literature devoted to investigating the connection between the BE and mode use, and the BE and trip generation (for a review of this literature see Badoe and Miller, 2000; Crane, 2000; Boarnet and Crane, 2001; Ewing and Cervero, 2001; Frank and Engelke, 2001; and Badland and Schofield, 2005). Many of the past studies employ an aggregate analysis approach of relating observed aggregate (zone level) travel data to aggregate land use variables, such as residential density, topography of towns, and/or area size (for example, Nelson and Allen, 1997, and Dill and Carr, 2003). The aggregate approach is particularly useful for evaluating factors that may influence differences in travel dependencies in different regions (Replogle, 1997). Yet it does not consider the demographic and urban form diversity within each aggregate spatial unit and, therefore, provides little behavioral insights.

The alternative, disaggregate, approach of modeling travel behavior of individual travelers has been used in more recent studies. By using statistical methods, such as regression models and discrete choice models, the disaggregate approach focuses on the tradeoffs that people make among various factors influencing travel behavior. The approach also allows the analyst to examine and quantify the interaction among the influencing factors. In the next three sections, we discuss earlier disaggregate models of mode choice (Section 2.1), trip generation

(Section 2.2), and joint mode choice and trip generation (Section 2.3) that are relevant to our current paper.

2.1. Mode Choice Studies

Several disaggregate models have been formulated to examine why individuals choose to travel by non-motorized modes as opposed to other modes. For example, Cevero (1996) developed three binomial mode choice models (one for each of private auto, mass transit, and walking/bicycling modes) for commute trips. He found that the presence of low density housing (single-family detached, single-family attached and low-rise multi-family buildings) in the immediate vicinity (300 feet) of one's residence and the presence of grocery or drug stores beyond 300 feet but within 1 mile deter walk and bicycle commuting. On the other hand, the presence of high density housing (mid- and high-rise multi-family buildings) and the presence of commercial and other non-residential buildings within 300 feet encourage walking or bicycling to work.

Rajamani *et al.* (2003) developed a multinomial logit mode choice model for non-work activity travel that considered the drive alone, shared ride, transit, walk, and bicycle modes. Among the individual socio-demographic variables, ethnicity was the single most important determinant of the likelihood to walk. The authors also found that mixed land use leads to considerable substitution between the motorized modes and the walk mode. Lower density and cul-de-sacs increase the resistance to walking as compared to other modes. The share of walking is also very sensitive to walk time. Improved accessibility by walk/bicycle modes increases the walk/bicycle share for recreational trips.

Rodriguez and Joo (2004) also developed a multinomial mode choice model to examine BE variable effects. Of the individual characteristics considered in the model, age did not have a significant impact on mode choice, while students, males, and individuals with lower number of vehicles at home have a higher propensity to walk relative to non-students, females, and individuals with more vehicles in their households, respectively. Of the physical environment variables, flat terrain and presence of sidewalks significantly increased the odds of walking or bicycling. Surprisingly, land use (residential density) and presence of walking and bicycling paths were found to be statistically insignificant.

Noting the presence of the high degree of correlation among BE variables (*e.g.* areas of high residential density often have mixed land use and shorter street block lengths), Cervero and Radisch (1996) attempted to overcome the multi-collinearity problem by introducing a subjectively defined location indicator, as opposed to using multiple environment variables, in their mode choice models. The location indicator is used to identify the two selected study areas that have very different BE: Rockridge, which represents a prototypical transit oriented community, and Lafayette, which represents a primarily auto oriented neighborhood. Two binomial mode choice models − one for work trips and the other for non-work trips − were estimated to examine the choice between the automobile mode and the other modes (including transit, walk, and bicycle). The authors found that residents from Rockridge are more likely to make work trips using the non-automobile modes relative to the otherwise-similar residents from Lafayette. Since the two study areas produce similar number of non-work trips per day and Rockridge has higher rates of walking trips than Lafayette, the authors concluded that the Rockridge residents substitute internal walk trips for external automobile trips. In the case of work trips, the subjectively-defined location indicator was not statistically significant, suggesting that the BE does not impact the commute mode choice. Cervero and Duncan (2003) took an alternative approach to overcome the multi-collinearity issue. They used factor analysis to collapse the potentially correlated vector of environment variables into two environmental factors: one representing pedestrian/bike friendliness and the other representing the land-use diversity within 1-mile radius. Both factors were computed for the origins and destinations of the sampled non-work trips. Two binomial mode choice models were estimated: one for walking vs. auto and the other for bicycle vs. auto. Interestingly, the land-use diversity within 1 mile of the trip origin was the only environmental factor significant at the 5% level and only for the walk model, suggesting that increased land use diversity at the trip origin end (but not the destination end) increases the substitution between auto and walking (but not bicycling).

It is important to note that, by design, mode choice analyses (including the ones cited above) focus on the relative attractiveness of different modes while holding trip rates as constant. The premise is that changes in the BE may lead to substitution between modes for a given trip, but do not lead to more or fewer total number of trips made by an individual. Thus, the mode choice modeling framework precludes the possibility of any complementary or synergistic use of alternative modes, rendering the framework unsuitable for comprehensively evaluating the full impacts of strategies such as New Urbanism.

2.2. Trip Generation Studies

The possibility that BE factors may increase or decrease individuals' travel demand has been considered within the trip generation analysis framework. For example, Boarnet and Crane (2001) focused on the impact of the BE on the number of non-work auto trips. They used a 2-step procedure, whereby trip price variables (distance and speed) are first regressed against land use variables. The predicted values of the price variables are then used as exogenous variables in the trip frequency equations. Based on data from the San Diego area, they found that commercial land use concentration in the home tracts is associated with shorter non-work trip distances and slower trip speed, and that slow speeds lead to fewer non-work auto trips.

Handy and Clifton (2001) examined the frequency of walk trips for shopping. They circumvented the multi-collinearity issue by examining the differences in walk trip frequencies among residents of "traditional", "early-modern", and "late-modern" neighborhoods in Austin, Texas. Three shopping-related urban form measures that reflect the respondents' perception as customers and pedestrians were considered in their linear regression models: quality of stores, walking incentive (within walking distance, difficult to park), and walking comfort (safety and convenience). Other variables included distance to the nearest store, socio-demographics, frequency of strolling around the neighborhood (to reflect basic preference for walking), and location constants. The study found that the distance to a shopping location is a highly significant predictor of shopping trip frequency. Also, the more positively one rates the shopping-related urban form measures and the more often one strolls around the neighborhood, the more likely s/he is to walk, suggesting the importance of individuals' perception of their environment and their intrinsic preference in explaining the frequency of walking to stores.

Trip generation studies such as Boarnet and Crane (2001) and Handy and Clifton (2001) inform us about the impacts of the BE on a specific mode use, but not on the relationship between modes. Moreover, analyses of auto trip rates as in Boarnet and Crane leave the impact on public health unaddressed, while analyses of non-motorized trip rates as in Handy and Clifton do not address the impact of the proposed policies on motorized traffic-related congestion. These earlier studies, therefore, do not address our research questions regarding the substitutive, complementary, and synergistic use between motorized and non-motorized modes.

2.3. Joint Mode Choice and Trip Generation Analysis

A study that does shed light on our research questions was undertaken by Kitamura *et al.* (1997). In this study, separate regression models were developed for the numbers and the fractions of trips by auto, transit, and non-motorized modes. The exogenous variables considered included socio-demographic variables, neighborhood descriptors, and attitude factors. Using data on five neighborhoods in the San Francisco Bay Area, Kitamura *et al.* (1997) found that total trip generation at the person level is largely determined by socio-demographics and is not strongly associated with land use. However, modal split between auto, transit, and non-motorized modes is strongly associated with land use characteristics. For example, distance to the nearest bus stop and distance to the nearest park were negatively correlated with the fraction of non-motorized trips, but positively correlated with the fraction of auto trips. Overall, the findings from the study imply that changes in the BE will result in substitution between motorized and non-motorized modes, as opposed to complementary or synergistic relationships among the modes.

2.4. Summary and Current Research

In summary, significant efforts have been devoted to investigate the presence and strength of the connection between the BE and mode use. Yet, the empirical findings remain very mixed and inconclusive, and points to a need for further analyses of how BE influences both the number of trips generated *and* the relative attractiveness of different modes. Furthermore, the possibility of differential responsiveness to BE characteristics across the population needs to be considered, an issue that has been largely ignored in earlier studies. This is because failure to isolate the preferences and needs of different population segments may lead to over- or under-estimates of aggregate behavioral changes due to localized BE improvements.

3. RESEARCH DESIGN

In light of our objective of comprehensively assessing the modal substitutive, complementary, and synergistic effects due to the BE, the current study examines the impact of BE on an individual's auto and non-motorized trip frequencies in a bivariate ordered probit analysis framework. The analysis is based on data from the San Francisco Bay area. Below, we describe the data sources used in the analysis (Section 3.1) and the sample formation process (Section 3.2). The considerations and efforts in formatting our measures of BE characteristics are discussed in Section 3.3. Relevant characteristics of the final sample data are presented in Section 3.4, followed by a description of the bivariate ordered probit modeling framework in Section 3.5.

3.1. Data Sources

The primary data source used for the current analysis is the San Francisco Bay Area Transportation Survey (BATS) conducted in 2000 for the Metropolitan Transportation Commission (MTC), California, by MORPACE International Inc. The survey collected information on all activity and travel episodes undertaken by individuals from over 15,000 households in the nine counties in the Bay Area for a two-day period (see MORPACE International Inc., 2002, for details on survey, sampling, and administration procedures). It also gathered information about individual and household socio-demographics, household auto ownership, household location, housing type, individual employment-related characteristics, and internet access and usage. Unlike many conventional travel surveys that release location information only at the zonal level, the BATS data provides the latitude and longitude coordinates of the household and trip locations, allowing the spatial factors be analyzed at a high spatial resolution. Furthermore, the BATS data collection period spanned all the months of the year 2000. This enables our analysis to identify seasonal fluctuations in the travel patterns and the effect of weather conditions on mode preference.

In addition to the 2000 BATS data, a number of other data sources are used to derive measures characterizing the urban environment in which the survey respondents pursue their activities and travel. The MTC provided land use data for the Traffic Analysis Zones (TAZ) in the Bay Area region as well as a GIS line layer describing existing bicycle facilities, including class 1 facilities (separate paths for cyclists and pedestrians), class 2 facilities (painted lanes solely for cyclists), and class 3 facilities (signed routes on shared roads). The Census 2000 TIGER files are the source of two GIS line layers representing the highway network (including interstate, toll, national, state and county highways) and the local roadways network (including local, neighborhood, and rural roads). The spatial distribution of businesses by type was extracted from the InfoUSA business directory. The hourly precipitation data and surface temperature data are also obtained from the National Climatic Data Center (NCDC).

3.2. Sample Formation

Several data processing steps were undertaken to obtain the sample for analysis. First, individuals who were under 18 years of age or who were not licensed to drive were removed from the data to avoid confounding effects of mobility dependency on the analysis. Second, only trips originating from home and that were pursued for either maintenance or discretionary activities at the destination ends were retained. Maintenance activities include maintenance shopping (gas stations, grocery store), personal business (including household chores, personal services, volunteer, religious, drop-off/pick-up passenger), and medical visits. Discretionary activities include recreation, social, meals, non-maintenance shopping, and pure recreation. Third, the travel mode used for each trip was identified as either auto (including car/van/truck/motorcycle, carpool vehicle, taxi), non-motorized (including bicycle and walk), or transit (including bus, ferry, rail, air and any other modes). Subsequently, the trips that were made by the transit mode were removed because of the small number of transit trip records and also because of lack of information about transit LOS in the area. Fourth, the number of person trips by purpose and by mode was aggregated for each individual. Fifth, the trip counts, together with data on individual level socio-demographic, household level socio-demographic, day of survey (season of survey day and whether the survey day was a weekend day or a weekday), weather (total precipitation and average temperature on travel day), and BE characteristics (described in the next section), were appropriately compiled into a person-level file. Finally, several screening and consistency checks were performed and records with missing or inconsistent data were eliminated. The final sample for analysis included data for 19,437 individuals.

3.3. Built Environment Characteristics

Several BE measures were used in the analysis to capture and isolate the effects of different aspects of the BE on trip making behavior. We prefer this approach to Cervero and Radisch's (1996) approach of using location indicators, Cervero and Duncan's (2003) factor analysis approach, and Handy and Clifton's (2001) neighborhood comparison approach because these alternative approaches are not able to isolate the effect of individual BE characteristics on travel behavior (Crane and Crepeau, 1998). Also, the earlier approaches do not allow the examination of interaction between demographic characteristics and specific BE characteristics (see Bhat and Guo, 2006, for a detailed discussion of this point).

As listed in Table 1, three groups of BE measures are considered in our analysis: (a) neighborhood measures, (b) regional accessibility measures, and (c) county measures.

The neighborhood measures were computed using the buffer approach, in which various geo-referenced data were overlaid onto circular buffers centered around the residential locations of individuals using a geographic information system. Two buffer sizes were used for this analysis: ¼ mile (to account for the immediate neighborhood) and 1 mile (to account for the more extended surrounding)[1]. Table 2 shows that most values of neighborhood measures used in the paper were only modestly correlated, suggesting that our subsequent analysis results are not likely to be confounded by multi-collinearity effects.

The inclusion of regional accessibility measures (see Table 1) is motivated by our belief that an individual's trip-making propensity and mode preference depend not only on the environment surrounding his/her residence, but also how the residence relates spatially to the rest of the urban area. The county indicators are used to control for any unobserved locational variations in trip making propensities across counties.

[1] New Urbanism is a neighborhood-level strategy implemented over scales of a few blocks. Yet many non-work trips cover areas larger than what are typically consider as the immediate neighborhood. The issue of geographical scale of analysis is therefore important in the analysis of built environment impacts (Kitamura et al, 1997; Boarnet and Samiento, 1998; Guo and Bhat, 2004).

3.4. Sample Characteristics of Trip Making

The distribution of the mode use patterns among the 19,437 sampled individuals is summarized in Table 3. A higher fraction of individuals are found to make at least one non-motorized trip for discretionary travel compared to maintenance travel (see the last row). Moreover, the total number of non-motorized trips made for discretionary purposes is higher than the total number of non-motorized trips made for maintenance purposes, even though the combined total number of trips is higher for the maintenance purpose.

3.5. Modeling Framework

To answer the research questions of the present study, we use a bivariate ordered probit model structure to jointly analyze motorized and non-motorized mode use frequencies. Separate bivariate models are developed for travel for maintenance activities and for discretionary activities to examine if BE factors differentially affect travel for different purposes. The model structure is formally defined as follows. For each individual q (q = 1, 2,…, Q), let m represents the number of auto trips (m = 1, 2,…, M) and let n represent the number of non-motorized trips (n = 1, 2,…, N). The equation system that captures the latent trip-making propensities takes the following form:

$$f_q^* = \alpha' x_q + u_q,\ \ f_q = m \quad \text{if} \ \ \delta_{m-1} < f_q^* < \delta_m$$
$$g_q^* = \beta' y_q + v_q,\ \ g_q = n \ \ \text{if} \ \ \theta_{n-1} < g_q^* < \theta_n$$

where f_q^*, and g_q^* are the latent trip-making propensities associated with auto and non-motorized modes, respectively; x_q and y_q are exogenous variables, including socio-demographic factors and the multitude of built and natural environment factors described in Section 3.3; α and β are corresponding coefficient vectors to be estimated; u_q and v_q are jointly normal distributed with a mean vector of zeros and a correlation coefficient ρ. f_q and g_q are, respectively, the observed number of auto and non-motorized trips pursued by individual q. The latent propensities are related to the observed number of trips through threshold bounds δ and θ that need to be estimated.

The model structure stated above is suitable for identifying the alternative effects of the BE on mode use frequency for a number of reasons. First, the ordinal nature of the ordered-response structure – originally proposed by McKelvey and Zavonia (1975) – has been recognized in the transportation literature as suitable for analyzing the frequency of trip-making and stop-making (see, for example, Agyemang-Duah and Hall, 1997, and Bhat and Zhao, 2002). Second, the effects of observable BE factors – with or without interacting with socio-demographic variables – on mode preference can be identified through the coefficient vectors α and β. Finally, any predisposition for total travel, and/or for one mode over the other, due to unobserved factors is absorbed in the correlation coefficient ρ, thereby ensuring that the estimates of α and β are unbiased.

The unknown parameters, α, β, δ, θ, and ρ are estimated by maximizing the following log-likelihood function:

$$LL = \sum_{q=1}^{Q} \sum_{m=1}^{M} \sum_{n=1}^{N} I_q(m,n) \cdot P_q(m,n),$$

where

$$I_q(m,n) = \begin{cases} 1, \text{if individual } q \text{ made } m \text{ auto trips and } n \text{ non - motorized trips,} \\ 0, \text{otherwise.} \end{cases}$$

and $P_q(m,n)$, the probability of a individual q making m auto trips and n non-motorized trips, is given by:

$$\begin{aligned} P_q(m,n) &= \text{Prob}\left(\delta_{m-1} < f_q^* < \delta_m \text{ and } \theta_{n-1} < g_q^* < \theta_n\right) \\ &= \text{Prob}\left(\delta_{m-1} - \alpha' x_q < u_q < \delta_m - \alpha' x_q \text{ and } \theta_{n-1} - \beta' y_q < v_q < \theta_n - \beta' y_q\right) \\ &= \Phi_2\left(\delta_m - \alpha' x_q, \theta_n - \beta' y_q; \rho\right) - \Phi_2\left(\delta_{m-1} - \alpha' x_q, \theta_n - \beta' y_q; \rho\right) \\ &\quad - \Phi_2\left(\delta_m - \alpha' x_q, \theta_{n-1} - \beta' y_q; \rho\right) + \Phi_2\left(\delta_{m-1} - \alpha' x_q, \theta_{n-1} - \beta' y_q; \rho\right), \end{aligned}$$

where Φ_2 is the bivariate cumulative normal distribution function.

4. EMPIRICAL RESULTS

We estimated two sets of bivariate ordered probit models using the Bay area data. In both sets of models, we estimated separate models for maintenance activity and discretionary activity. The difference between the two sets lies in the variables considered in the specifications. While socio-demographic variables, temporal indicators, weather factors, and BE variables are considered in both sets of models, the interactions between socio-demographic and BE variables are considered only for Model Set 2. These interaction terms were systematically added to the utility functions to accommodate heterogeneous responses to BE characteristics across different population groups. Comparisons of the model fits among the two sets indicated that accommodating heterogeneity responses to BE variables provides statistically superior models compared to the case of not accommodating heterogeneity responses. This is an important result that is ignored in most earlier studies examining the impact of the BE. Due to space constraints, we present only the results of the statistically superior Model Set 2 results in the current paper.

Table 4 provides the final estimation results. While the primary interest of the current study lies in the impact of the BE on person trip frequencies by mode, the estimation results associated with other variables are important indicators of the validity of our study. Thus, the results with respect to variables other than the BE variables are presented in Section 4.1, followed by a discussion of the results associated with the BE factors and the interaction terms in Section 4.2. The estimates obtained for the correlation coefficient ρ are discussed in Section 4.3.

4.1. Parameter Estimates for the Socio-demographic, Day of Travel, and Weather Variables

4.1.1 Maintenance trip making

The positive parameter estimates obtained for the household size and structure variables in Table 4 for the number of auto trips for the maintenance purpose imply that a person from a larger household (a nuclear or single parent household) has a higher propensity to undertake maintenance trips using auto compared to an otherwise similar individual from a smaller household (other household structure). These same household size and structure variables, however, do not have a significant bearing on an individual's use of non-motorized modes for maintenance travel. Rather, it is the household's income level and mode availability that are associated with the household member's use of non-motorized modes. In particular, low household income, high number of bicycles, and low number of vehicles per household member are associated with higher propensity of non-motorized mode usage for maintenance trips.

Several individual level attributes are also found to influence the propensity to use motorized or non-motorized modes for maintenance activities. Individuals between 18 and 30 years of age make fewer maintenance trips than people of other age groups, regardless of their mode preference. This is presumably a result of the busier life style of young adults in general. Senior adults, on the other hand, are likely to travel more often for maintenance activities and use motorized modes to do so. Females are found to have a higher likelihood of making motorized trips for maintenance purposes than males, perhaps because female individuals tend to bear a higher share of household maintenance responsibilities than their male counterparts (Turner and Niemeier, 1997). Compared to other ethnicity groups living in the Bay area, the African-American population is associated with lower levels of non-motorized travel for maintenance purposes. The parameters associated with the "physically challenged" variable suggest that, in the context of maintenance travel, physical challenges reduce a person's propensity for walking or bicycling, but does not reduce the propensity for making motorized trips. Employed individuals, people who use internet during the survey day, and people who go to school or work during the survey day are less likely to make maintenance trips. This may be attributed to the limited amount of time at these people's disposal for pursuing maintenance activities.

Finally, the negative signs associated with the weekday and summer variables may be partially explained by time constraints (for the weekday effect) and time use preferences for discretionary activities (for the summer variable effect). However, no variation is found for non-motorized trip frequencies due to the day of travel indicators. Rain and temperature also show no statistically significant association with maintenance trip rates by motorized and non-motorized modes.

4.1.2 Discretionary trip making

The parameters associated with household size have a negative sign and are statistically significant, for both the number of auto trips and non-motorized trips. This indicates that individuals from larger households have a lower propensity than smaller households to make discretionary trips. Compared to individuals from other types of household structure, individuals from nuclear families make more auto trips, and individuals from single parent families make fewer non-motorized trips for discretionary purposes. Households with higher income are inclined to make more motorized discretionary trips, possibly because these individuals can afford to pursue discretionary activities at locations that would be difficult to access by non-motorized modes. The positive signs associated with the number of bicycles per person are intuitive because high bicycle ownership often indicates a preference for an active life style, which can lead to higher numbers of both motorized and non-motorized discretionary trips. On the other hand, high auto ownership can be considered as an indication of an individual's preference for a physically inactive life style, and thus is associated with fewer non-motorized trips. Finally, among the household sociodemographics, individuals residing in single detached houses have a high propensity to make motorized discretionary trips than otherwise similar individuals. This correlation between housing type and trip making propensity is possibly due to individuals' predisposed life style preferences.

Among the individual-level socio-demographic factors, African Americans, Asians, individuals who are physically challenged and employed, individuals who use the internet during the survey day, and individuals going to work or school during the survey day are statistically significantly associated with lower propensity for making discretionary trips. Meanwhile, senior adults and Hispanic individuals have a lower propensity to pursue non-motorized trips for discretionary purposes.

The significant and negative parameter estimates associated with the "weekday" variable suggests that people in general make more discretionary trips on the weekends compared to weekdays. Variation in trip frequency is also found between seasons. Summer is associated with more non-motorized mode use for discretionary activities, while the Fall season is associated with less auto use for discretionary activities. Notable is that, similar to the results found for maintenance travel, no weather-related factors are associated with the number of discretionary trips by either mode. This may be because of the reasonably temperate weather conditions all through the year in the San Francisco Bay area.

4.2. Parameter Estimates for the Built Environment Variables

It is evident from Table 4 that BE factors have an impact on trip rates by different modes and for different purposes. The degree of the impacts also varies across population groups. In view of the objectives of the present study, it is important to interpret the parameter estimates in the context of the substitutive, complementary, and synergistic effects on relative mode use. Specifically, given a BE factor and a trip purpose, if the parameter estimates associated with motorized and non-motorized modes are both statistically significant and have opposite signs, it implies that the BE factor leads to substitutive use between the modes. If the parameter estimates associated with a given BE factor are both statistically significant but have the same signs, then the BE factor has a synergistic effect on motorized and non-motorized mode use. If only one of the two mode-specific parameter estimates is statistically significant, then the effect on mode use is a complementary one.

We now discuss the impact of each of the BE factors in the context of maintenance travel (Section 4.2.1) and discretionary travel (Section 4.2.2).

4.2.1 Maintenance trip making

The estimates associated with the regional accessibility measures indicate that regional accessibility has no bearing on the number of trips generated for maintenance purposes. The neighborhood level measures, on the other hand, do influence individuals' propensities to pursue motorized and non-motorized trips. These effects are as follows.

<u>Land use</u>

The land use mix measured within 1 mile of the individual's residence has a significant and positive effect on single parents' number of auto trips, but not on their number of non-motorized trips. This implies that, as a result of the increased land use mix in their immediate neighborhood, single parents are likely to complement their existing non-motorized trips with more motorized trips for maintenance purposes. The increased land use mix is also likely to result in reduced non-motorized travel among individuals from households with high vehicle availability. These findings regarding the effect of land use mix is contrary to the claims of New Urbanist concepts and warrant careful further investigation.

The fraction of residential land use within 1 mile of an individual's residence also has complementary effects on mode use for maintenance purposes. Increased residential land use coverage increases the propensity for auto travel among individuals from nuclear families, from single-person households, from households with low vehicle availability, and Caucasian individuals. Notably, fraction of commercial land use has not effects on maintenance travel.

Density

In Table 4, the parameter estimates associated with population density (without any interaction) are both negative, implying a synergistic reduction in motorized and non-motorized travel due to increase population density. However, the parameters associated with the interactions of population density with socio-demographic factors suggest a more confounded effect of population density. Thus, the overall effect of population density depends on the socio-demographic composition of the population that resides in the area where the population density change takes place.

The intensity of maintenance businesses (as measured by the natural log of the total number of maintenance businesses within ¼ mile of individuals' residence) also has differing effects for different population groups. In response to the increased number of maintenance businesses in the neighborhood, individuals who reside in single detached houses are likely to increase their frequency of auto travel than those who reside in other types of housing. On the contrary, young adults and Caucasian individuals are likely to reduce their number of auto trips while maintaining their non-motorized trip frequencies. Asian individuals, people without email access at home, and people from large households are associated with reduced non-motorized travel for maintenance purposes.

The intensity of discretionary businesses is found to be associated with a higher propensity of maintenance trips by non-motorized modes. This is not surprising because of the complementary effect of different types of businesses in promoting economic vitality, and the high correlation found in our empirical data between the intensities of maintenance businesses and of discretionary businesses.

Local transportation network

The highway density within 1 mile radius of a household appears to be a deterrent for auto travel for Caucasian and Asian individuals, and a deterrent for non-motorized travel for Hispanic individuals. This negative impact of highway density is probably related to residents' concerns regarding safety and local access.

Bikeway density and network connectivity both have a statistically significant and positive effect on non-motorized trip frequency for maintenance purposes. This is in accordance with the expected outcomes of New Urbanist designs. That is, bikeway facilities and better street connectivity promote more walking and bicycling. However, it should be noted that our empirical evidence suggests no reduction in motorized travel due to these design features.

4.2.2 Discretionary trip making

As may be observed in Table 4, trip purpose clearly plays a significant role in the relationship between the BE and person trip rates by mode for discretionary trips. Firstly, the regional recreation accessibility parameter is significant and positive, suggesting that improved recreation accessibility is likely to raise the frequency of non-motorized travel. However, this may also be a consequence of residential sorting effects where physically active and auto disinclined individuals self-select themselves into neighborhoods that are non-motorized travel friendly.

Land use

In the context of discretionary travel, land use mix measured within 1/4 mile of one's residence has the potential of reducing motorized travel, as indicated by its negative parameter estimate. However, for single parents and people with access to cars (*i.e.* number of vehicles per person is greater than 0), land use mix is positively correlated with the number of motorized trips. The fraction of residential land use and fraction of commercial land use both have complementary effects on mode use frequency. While the former is associated with higher number of motorized trips, the latter is associated with higher number of non-motorized trips. Interestingly, after the interaction between land use mix and socio-demographic characteristics are accounted for, the impacts of the fractions of residential and commercial land use do not differ across population groups.

Density

The parameter estimates associated with population density are negative for both motorized and non-motorized trip frequencies, implying a synergistic reduction in discretionary travel due to increased population density. This is perhaps attributed to the discomfort and safety concerns related to traveling in an overly congested area.

Business intensities, on the other hand, are positively correlated with non-motorized travel. The intensity of discretionary businesses has more profound impact on people who attend schools than on the general public.

Local transportation network

The highway density within 1 mile of an individual's residence is negatively correlated with the number of auto trips made for discretionary purposes, with the magnitude of the correlation being higher for senior individuals. Although the auto-deterring effect of highway density is intuitive, it is surprising that highway density does have any effect on non-motorized trip frequency.

The impacts of bikeway density and network connectivity on discretionary travel are more complex than their respective impacts on maintenance travel. The parameter estimates associated with bikeway density and the interaction term with income together suggest that increased bikeway density results in more non-motorized trips among lower income individuals (with annual household income below $17,000), but fewer non-motorized trips among higher income individuals.

Interestingly, network connectivity has a synergistic effect on young adults' use of motorized and non-motorized modes, as reflected by the positive parameter estimates associated with the interaction term for both modes. As the two parameter values cannot be compared directly, identification of the relative magnitude of the increase in motorized and non-motorized travel at the aggregate level can only be done by applying the model. Network connectivity is also positively correlated with non-motorized trip frequency for all individuals, although the impact is milder on people who attend schools (presumably because school-goers have limited time available to pursue discretionary travel outside of school).

The association between transit availability and non-motorized trip frequency is not surprising, as transit and non-motorized modes are often considered as complementary (Greenwald, 2003). A well defined transit system coupled with transit oriented development may encourage more walking and bicycling to complement any existing auto-travel that an individual makes.

4.3. Parameter Estimates for the Correlation Coefficient

As discussed in Section 3.5, the advantage of estimating a bivariate model over estimating two independent models is that any pre-dispositioned propensity for travel or modal preference due to unobserved factors can be appropriately absorbed by the correlation coefficient ρ. Our estimation results reveal that, in both models of maintenance travel and discretionary travel, the parameter estimates of ρ are statistically insignificant. This implies that, in this particular empirical context, no statistically significant correlation is present due to unobserved factors, and therefore the bivariate ordered probit model can be reduced to two independent ordered probit models.

5. SUMMARY AND CONCLUSIONS

The relationship between BE and non-motorized travel is coming to the forefront of transportation planning and public health research because of the increasing traffic congestion level, worsening pollution, and health concerns. Despite a voluminous empirical literature, most past studies have painted, at best, a partial picture about the impact of the BE on motorized versus non-motorized travel demands. As Crane (2000) and others have indicated, providing solid and verifiable evidence for the purpose of designing and implementing policy has proven challenging.

In view of the uncertainty surrounding the New Urbanism planning strategies as a tool for relieving congestion and promoting active, healthy, life styles, the present study is directed toward analyzing the effects of the various BE factors on the substitutive, complementary, or synergistic use of motorized versus non-motorized modes. Focus is also placed on the heterogeneous sensitivity to BE factors across different population groups. Our analysis is based on data describing sampled residents and their environment in the San Francisco Bay area. Contrary to the multinomial logit models typically used in prevailing studies of relative mode use and BE, the bivariate ordered probit model structure is used in the present study to account for any complementary and synergistic relationships between motorized and non-motorized mode use. We examine the impacts of BE factors on person trip frequencies by mode and by trip purpose, while controlling for an array of other explanatory factors, including socio-demographic attributes, temporal indicators, and weather factors.

The most salient findings of this study are as follows. First, the models that consider the heterogeneous sensitivity to BE factors across different population groups are found to be statistically superior to their counterparts that do not consider such heterogeneity. As the models that recognize such heterogeneity provide more behavioral insights regarding people's response to BE changes, the models are more spatially transferable and are likely to provide more accurate forecasts of spatial policy intervention outcomes. Although such models do not readily offer explanations about behavioral causality, they help us formulate hypotheses for further research.

Second, in the context of trip making for maintenance purposes, discretionary business intensity, bikeway density, and street network connectivity are positively correlated with the number of non-motorized trips for all individuals. This suggests that these three BE design dimensions lead to the complementary and increased use of non-motorized modes, thereby resulting in improved public health, but no change in auto use.

Third, the direction and the strength of the correlations between the number of motorized trips for maintenance purposes and BE factors such as land use mix, population density, and maintenance business intensity vary for different socio-demographic groups. Policy makers should therefore be cautious about changing these design elements with the hope of achieving transportation or public health improvement. Prior to policy implementation, one should evaluate the possible impacts of changing these BE elements at the individual's level and/or at the aggregate level. This can be achieved by applying the predictive models and using the Monte Carlo method to simulate the behavioral outcomes. Since our models are sensitive to the differential responsiveness across individuals, they are especially suitable for evaluating localized implementation of BE changes.

Fourth, in the context of discretionary travel, several BE factors are associated with complementary mode use. The fraction of residential land use is positively correlated with auto use, while the fraction of commercial land use, maintenance business intensity, and discretionary business intensity are positively correlated with increased walking and bicycling. As the impacts of these BE elements are uniform across population groups, they are good candidates for across-the-board implementation to boost general public health.

Fifth, while bikeway density and street network connectivity both have the potential to increase the non-motorized trip frequency for discretionary purposes, their impact may be limited to individuals with relatively low household income and individuals above 30 years of age, respectively. Policy making related to these BE elements therefore requires careful planning.

The explicit inclusion of interactions terms and the consideration of all possible relationships between relative mode uses in our analysis have yielded new insights about the impacts of the BE on travel behavior. It should be noted, however, that the above interpretation of our empirical results has been made by assuming away the possible effects of residential sorting, i.e. the possibility that individuals choose their residential location based in part on how they wish to travel. As the issue of residential sorting may not be trivial, an extension of this research is to integrate the models presented in this paper with models of residential location choice in a framework similar to that proposed by Bhat and Guo (2006). The integrated modeling system will be capable of accounting for any residential relocation due to BE changes, thereby producing more accurate forecasts of policy effects.

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LIST OF TABLES

Table 1 Built environment measures used in the study

Measure	Definition	Note
Neighborhood Measures		
Fraction of Residential Land Use	$FR_i = R_i / T_i$	where T_i is the total area of buffer i; and R_i, C_i, and O_i are the acreage of residential, commercial, and other land use type.
Fraction of Commercial Land Use	$FC_i = C_i / T_i$	
Fraction of Other Land Use	$FO_i = O_i / T_i$	
Land Use Mix	$LUMIX_i = 1 - \left(\left\lvert FR_i - \frac{1}{3}\right\rvert + \left\lvert FC_i - \frac{1}{3}\right\rvert + \left\lvert FO_i - \frac{1}{3}\right\rvert\right) \cdot \frac{3}{2}$	A larger value indicates more mixed land use.
Population Density	Number of residents per square mile	
Maintenance Activity Intensity	Number of maintenance business establishments per square mile. The natural log transformed versions of these measures were also considered.	Maintenance businesses include grocery stores, gas stations, laundry mats, banks, post offices, medical facilities, repair shops, beauty salons, car washes, day care centers, and religious organizations.
Discretionary Activity Intensity	Number of discretionary business establishments per square mile. The natural log transformed versions of these measures were also considered.	Discretionary businesses include retail stores, restaurants, coffee and snack shops, art and dance studios, sports and entertainment centers, libraries, museums, theaters, and zoos.
Highway Density	Miles of highway per square mile	
Bikeway Density	Miles of bikeway facility per square mile	
Street Network Grain Size	Number of street blocks per square mile	This measure serves as a proxy of the street connectivity.
Transit Availability Indicator	A dummy variable taking a value of 1 if transit is available in the TAZ and 0 otherwise.	This measure serves as a proxy of other unobserved network design factors.

Table 1 (continued) Built environment measures used in the study

Measure	Definition		Note
Regional Accessibility Measures			
Shopping accessibility	$A_i^{Shop} = \sum_{j=1}^{N} \frac{1}{N} \frac{R_j}{d_{ij}}$	where R_j, E_j, and V_i are the number of retail employment, number of basic employment and vacant land acreage in TAZ *j*, respectively; d_{ij} is the distance between zones *i* and *j*.	Due to data constraints, these zonal accessibility measures are used in our analysis as proxies for point-to-region accessibility measures for each observed residence. Large values of the accessibility measures indicate more opportunities for activities in close proximity of that residence, while small values indicate residences that are spatially isolated from such opportunities.
Recreational accessibility	$A_i^{Rec} = \sum_{j=1}^{N} \frac{1}{N} \frac{V_j}{d_{ij}}$		
Employment accessibility	$A_i^{Emp} = \sum_{j=1}^{N} \frac{1}{N} \frac{E_j}{d_{ij}}$		
County Measures			
County indicators	A dummy variable is defined for each county, except the San Francisco county (which is selected as the base case), in the Bay Area. The variables take the value of 1 if the individual resided in the associated county and 0 otherwise.		

Table 2 Correlation between selected neighborhood measures based on 1/4mile-radius buffers

	Correlation between Built Environment Variables								
	Fraction of Residential Land Use	*Fraction of Commercial Land Use*	*Land Use Mix*	*Population Density*	*Natural Log of Maintenance Activity Intensity*	*Natural Log of Discretionary Activity Intensity*	*Highway Density*	*Bikeway Density*	*Street Network Grain Size*
Fraction of Residential Land Use	1	0.136**	0.010	0.356**	0.317**	0.264**	0.030**	0.084**	0.469**
Fraction of Commercial Land Use		1	0.462**	0.317**	0.343**	0.366**	0.145**	0.131**	0.321**
Land Use Mix			1	0.087**	0.133**	0.149**	0.096**	0.171**	0.045**
Population Density				1	0.546**	0.553**	0.022**	0.336**	0.675**
Natural Log of Maintenance Activity Intensity					1	0.854**	0.161**	0.319**	0.569**
Natural Log of Discretionary Activity Intensity						1	0.187**	0.324**	0.561**
Highway Density							1	0.004	-0.021**
Bikeway Density								1	0.324**
Street Network Grain Size									1

** Correlation is significant at 0.01 level

Table 3 Distribution of sampled person trips by purpose and by mode

	Maintenance Travel										Discretionary Travel									
	Number of non-motorized trips										*Number of non-motorized trips*									
Number of auto trips	**0**	**(%)**	**1**	**(%)**	**2**	**(%)**	**≥ 3**	**(%)**	**Total**	**(%)**	**0**	**(%)**	**1**	**(%)**	**2**	**(%)**	**≥ 3**	**(%)**	**Total**	**(%)**
0	10502	(54.03)	289	(1.49)	38	(0.20)	13	(0.07)	10842	(55.78)	10185	(52.40)	389	(2.00)	95	(0.49)	23	(0.12)	10692	(55.01)
1	4715	(24.26)	141	(0.73)	20	(0.10)	9	(0.05)	4885	(25.13)	5085	(26.16)	210	(1.08)	34	(0.17)	9	(0.05)	5338	(27.46)
2	2327	(11.97)	46	(0.24)	16	(0.08)	2	(0.01)	2391	(12.30)	2389	(12.29)	102	(0.52)	18	(0.09)	-	-	2509	(12.91)
3	756	(3.89)	21	(0.11)	4	(0.02)	1	(0.01)	782	(4.02)	663	(3.41)	31	(0.16)	1	(0.01)	2	(0.01)	697	(3.59)
4	327	(1.68)	9	(0.05)	-	-	-	-	336	(1.73)	153	(0.79)	6	(0.03)	-	-	-	-	159	(0.82)
5	121	(0.62)	3	(0.02)	-	-	1	(0.01)	125	(0.64)	33	(0.17)	2	(0.01)	-	-	-	-	42	(0.22)
6	45	(0.23)	2	(0.01)	-	-	-	-	47	(0.24)	7	(0.04)	-	-	-	-	-	-	-	-
≥ 7	29	(0.15)	-	-	-	-	-	-	29	(0.15)	-	-	-	-	-	-	-	-	-	-
Total	18822	(96.84)	511	(2.63)	78	(0.40)	26	(0.13)	19437	(100.00)	18515	(95.26)	740	(3.81)	148	(0.76)	34	(0.17)	19437	(100.00)

Table 4 Bi-variate ordered probit models of person trips by purpose

Explanatory Variables	Maintenance Trips				Discretionary Trips			
	Number of Auto Trips		Number of Non-motorized Trips		Number of Auto Trips		Number of Non-motorized Trips	
	parameter	t-stat	parameter	t-stat	parameter	t-stat	parameter	t-stat
Socio-Demographic Characteristics								
Household size	0.122	13.05	-	-	-0.019	-2.10	-0.092	-5.34
Household structure(other types as base)								
Nuclear Family	0.292	6.93	-	-	0.086	3.44	-	-
Single Parent Family	0.434	2.46	-	-	-	-	-2.88	-2.88
Household income ($10,000)	-	-	-0.016	-3.70	0.009	4.63	-	-
Number of bicycles per person	-	-	0.358	9.01	0.048	3.45	0.222	9.22
Number of cars per person	-	-	-0.303	-4.04	-	-	-0.328	-7.10
Single detached house	-	-	-	-	0.075	3.43	-	-
Individual Characteristics								
Age (between 30 and 65 as the base group)								
Between 18 and 30 (young adult)	-0.148	-3.68	-0.127	-2.00	-	-	-	-
Over 65 (senior adult)	0.154	5.01	-	-	-	-	-0.240	-4.02
Female	0.257	14.89	-	-	-	-	-	-
Ethnicity (other as the base group)								
African-American	-	-	-0.398	-2.28	-0.298	-5.32	-0.635	-4.05
Hispanic	-	-	-	-	-	-	-0.355	-3.45
Asian	-	-	-	-	-0.145	-4.76	-0.213	-3.35
Physically challenged	-	-	-0.721	-3.45	-0.331	-5.18	-0.487	-3.17
Employed	-0.248	-9.89	-0.226	-4.36	- 0.171	-6.90	-0.186	-3.96
Use internet during surveyed days	-0.036	-11.52	-0.030	-3.58	-0.011	-2.15	-0.020	-3.07
Went to work/school during surveyed days	-0.397	-17.16	-0.346	-7.07	-0.473	-20.86	-0.357	-0.98
Day of Travel Indicators								
Weekday	-0.045	-2.28	-	-	-0.410	-21.80	-0.242	-6.65
Season								
Summer	-0.059	-3.26	-	-	-	-	0.127	3.55
Fall	-	-	-	-	-0.076	-4.14	-	-

Table 4 (continued) Bi-variate ordered probit models of person trips by purpose

Explanatory Variables	Maintenance Trips				Discretionary Trips			
	Number of Auto Trips		Number of Non-motorized Trips		Number of Auto Trips		Number of Non-motorized Trips	
	parameter	t-stat	parameter	t-stat	parameter	t-stat	parameter	t-stat
Regional Accessibility								
Recreation	-	-	-	-	-	-	0.238	2.57
Neighborhood Measures								
Land use								
Land use mix (0.25mi radius)	-	-	-	-	-0.188	-2.84	-	-
- Single parent	-	-	-	-	0.356	2.48	-	-
- Number of vehicles per person	-	-	-	-	0.317	5.86	-	-
Land use mix (1mi radius)								
- Single parent	0.848	2.63	-	-	-	-	-	-
- Number of vehicles per person	-	-	-0.343	-2.84	-	-	-	-
Fraction of residential land use (1mi radius)	-	-	-	-	0.318	5.56	-	-
- Nuclear family	0.199	2.63	-	-	-	-	-	-
- Single person household	0.169	2.74	-	-	-	-	-	-
- Number of vehicles per person	-0.189	-3.27	-	-	-	-	-	-
- Caucasian	0.338	6.67	-	-	-	-	-	-
Fraction of commercial land use (1mi radius)	-	-	-	-	-	-	0.427	2.59
Density								
Population density (1mi radius)	-2.664	-7.73	-1.211	-2.01	-1.531	-8.20	-1.068	-2.15
- Couple only household	1.018	3.77	-	-	-	-	-	-
- Number of bicycles per person	-	-	-1.250	-3.44	-	-	-	-
- Number of vehicles per person	1.953	4.71	-	-	-	-	-	-
LN(Maintenance businesses) (1/4mi radius)	-	-	-	-	-	-	0.073	3.24
- Household size	-	-	-0.46	-3.55	-	-	-	-
- Single detached house	0.033	3.73	-	-	-	-	-	-
- Young adult	-0.049	-2.84	-	-	-	-	-	-
- Caucasian	-0.044	-4.43	-	-	-	-	-	-
- Email access at home	-	-	0.051	2.79	-	-	-	-
- Asian	-	-	-0.081	-2.66	-	-	-	-
LN(Discretionary businesses) (1/4mi radius)	-	-	0.154	7.15	-	-	0.052	2.07
- School	-	-	-	-	-	-	0.162	3.81

Table 4 (continued) Bi-variate ordered probit models of person trips by purpose

Explanatory Variables	Maintenance Trips				Discretionary Trips			
	Number of Auto Trips		Number of Non-motorized Trips		Number of Auto Trips		Number of Non-motorized Trips	
	parameter	t-stat	parameter	t-stat	parameter	t-stat	parameter	t-stat
Local transportation network								
Highway density (1mi radius)	-	-	-	-	-0.046	-2.60	-	-
- Email access at home	0.074	3.15	-	-	-	-	-	-
- Caucasian	-0.102	-3.78	-	-	-	-	-	-
- Hispanic	-	-	-0.392	-2.44	-	-	-	-
- Asian	-0.097	-2.53	-	-	-	-	-	-
- Senior	-	-	-	-	-0.104	-2.79	-	-
Bikeway density (1mi radius)	-	-	0.026	3.02	-	-	0.039	4.67
- Income ($10,000)	-	-	-	-	-	-	-0.023	-2.79
Number of street blocks (1mi radius)	-	-	0.195	6.43	-	-	0.112	3.93
- Young adult	-	-	-	-	0.041	3.68	0.047	2.92
- School	-	-	-	-	-	-	-0.101	-2.44
Transit availability	-	-	-	-	-	-	0.035	2.77
County Indicators								
San Mateo	0.099	3.36	-	-	-	-	-0.199	-3.15
Santa Clara	0.060	2.62	0.257	4.23	-	-	-	-
Alameda	0.090	3.83	0.296	5.84	-	-	-	-
Napa	-	-	0.273	2.55	-	-	-	-
Marin	-	-	0.409	4.25	-	-	-	-
Thresholds								
1	0.124	2.90	1.864	22.93	-0.0245	-0.57	1.6068	16.09
2	0.930	21.53	2.666	32.39	0.8389	19.30	2.4175	23.20
3	1.623	36.43	3.179	33.29	1.6399	36.50	3.1037	25.92
4	2.108	45.12	-	-	2.3098	46.47	-	-
5	2.565	49.61	-	-	2.876	44.01	-	-
6	2.958	48.91	-	-	-	-	-	-
7	3.304	43.57	-	-	-	-	-	-
Correlation	-0.020 (-0.87)				-0.030 (-1.51)			
Number of Cases	19437				19437			
Log-Likelihood at Zero	-26131.30				-26023.03			
Log-Likelihood at Convergence	-24243.6				-24445.1			