

MODELS FOR ANTICIPATING NON-MOTORIZED TRAVEL CHOICES, AND THE ROLE OF THE BUILT ENVIRONMENT

Mobashwir Khan
Travel Demand Modeler
Cambridge Systematics
Oakland, California
mobashwir@gmail.com

Kara M. Kockelman
(Corresponding author)
Professor and William J. Murray Jr. Fellow
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu
Phone: 512-471-0210

Xiaoxia Xiong
The University of Texas at Austin
summerholiday623@gmail.com

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ABSTRACT

This paper uses detailed travel data from the Seattle metropolitan area to evaluate the effects of built-environment variables on the use of non-motorized (bike + walk) travel modes. Several model specifications are used to understand and explain non-motorized travel behavior in terms of household, person and built-environment (BE) variables. Marginal effects of covariates for models of vehicle ownership levels, intrazonal trip-making, destination and mode choices, non-motorized trip counts per household, and miles traveled (both motorized and non-motorized) are presented. Mode and destination choice models were estimated separately for interzonal and intrazonal trips and for each of three different trip purposes, to recognize the distinct behaviors at play when making shorter versus longer trips and serving different activities.

The results underscore the importance of street connectivity (quantified as the number of 3-way and 4-way intersections in a half-mile radius), higher bus stop density, and greater non-motorized access in promoting lower vehicle ownership levels (after controlling for household size, income, neighborhood density and so forth), higher rates of non-motorized trip generation (per day), and higher likelihoods of non-motorized mode choices. Intrazonal trip likelihoods rose with street connectivity, transit availability, and land use mixing.

Across all BE variables tested, street structure offered the greatest potential benefits, alongside accessibility indices (for both motorized and non-motorized access). For example, non-motorized trip counts are estimated to rise 26% following a one standard deviation increase

in this variable, and walk probabilities by 27% following a one standard deviation increase in this index at the destination zone. Regional and local accessibility and density (of population plus jobs) variables were also important, depending on response being modeled. Simulated model applications illuminate when and to what extent significant travel behavior changes may be witnessed, as land use settings and other variables are changed.

Key words: Pedestrians, Cyclists, Non-motorized Transport, Built Environment, Demand Modeling

INTRODUCTION

The 2009 National Household Travel Survey (NHTS 2009) data suggest that 9.7% of all person-trips made in the U.S. relied on non-motorized travel (NMT) modes, versus just 6.3% in 1995 (Kuzmyak et al. 2011). NMT offers many benefits to individuals and the wider community. For example, researchers have found that those traveling more often by non-motorized modes enjoy better physical and mental health (Frank and Engelke 2001 and Litman 2003). Shorter trips and non-motorized trips also reduce a variety of emissions and roadway congestion (see, e.g., Litman [2003] and Rietveld [2001]). Travel time savings from reduced congestion, along with cost-savings from a reliance on less expensive forms of transport, can provide significant economic benefits (Litman 1999).

In order to achieve higher NMT shares, engineers, planners, and policymakers must understand how various built environment (BE), household, personal and other factors affect NMT choices. Despite the abundance of literature on non-motorized modes, there is still a lack of consensus among studies and researchers in this area. This paper adds to the NMT literature by analyzing the effect of different land-use characteristics at very fine spatial resolutions. The analysis is based on a variety of behavioral models estimated (and then applied) using household travel survey data from the Seattle region in Washington State (PSRC 2006). These include models of vehicle ownership, household vehicle-miles and non-motorized-miles traveled, NMT trip generation, the choice of destination outside one's origin zone (which has important mode-choice implications), destination, and mode choice models. Taken together, the results highlight a variety of recurring, key factors for NMT travel choices. Before presenting data set details, model specifications and results, a review of the extensive NMT literature is provided.

LITERATURE REVIEW

Despite a number of NMT and BE investigations, this field of research is not yet conclusively understood (Kuzmyak et al. 2011, Pratt et al. 2012). One of the more detailed studies is by Cervero and Duncan (2003), using San Francisco Bay Area data to investigate the effect of BE factors on biking and walking. After controlling for various demographic, environmental, and design factors, their discrete-choice model results suggest that built-environment factors have relatively little effect. They conclude that demographic factors and trip conditions are far better predictors of NMT choice than BE characteristics.

A more recent study, by Cervero et al. (2009), takes a close look at Bogotá, Colombia, which boasts an extensive network of bike lanes and is known for its sustainable urban transport system. Their work suggests that cycling choices are affected more by the configuration, connectivity and density of streets rather than other BE factors (such as density, land-use mix and destination accessibility). Pratt et al.'s (2012) extensive review of the NMT travel effects of system changes concludes that the "if you build it, they will come" phenomenon mostly exists

with bike and walk facilities (and policies), particularly if system connectivity is thoughtfully provided. Dill and Gliebe's (2008) GPS-based data set from 164 adult cyclists in Portland, Oregon suggest that cyclists prefer roadways with bicycle infrastructure and low traffic volumes, and try to reduce travel times by minimizing waits at traffic signals and signs (consistent with results by Stinson and Bhat [2004]).

Ewing and Cervero's (2010) meta-analysis of the travel-BE relationship suggests that the extent of walking (measured as either trip frequency, trip length, mode share or vehicle-miles traveled [VMT]) is mostly affected by intersection density, jobs-housing balance, distances to stores, and transit stop proximity – after controlling for demographic attributes. Moudon et al. (2005) also found that a household's distances to neighborhood destinations (such as grocery stores, retail shops, and restaurants) had a significant effect on walk time per week. And Kitamura et al. (1997) noted how sidewalk presence, higher population densities, and distance to one's nearest bus stop, among other attributes, are positively correlated with the number of NMT trips made by a person per day. Of course, bicycling and walking are also affected by climate, topography, darkness, and safety concerns (Kuzmyak et al. 2011), though these are less commonly controlled for in models (in part because they vary by time of day, day of year, and route).

One common problem that researchers face when evaluating the relationship between BE characteristics and travel is self-selection. Self-selection essentially is an individual's decision to live in a particular residential location based on his/her travel preferences (Frank et al. 2008), which is counter to the causal direction normally assumed by researchers (from BE to behavior). Cao et al. (2006a) concluded that self-selection has more influence on non-motorized trip making than automobile and transit trips. Kitamura et al. (1997) found that attitudinal effects (or self-selection) have greater impact than the BE on the extent of NMT trip-making, while Schwanen and Mokhtarian (2004), Khattak and Rodriguez (2005), and Zhou and Kockelman (2008) all concluded that BE effects exceed those of self-selection (for overall travel decisions, proxied by VMT). Despite some specific differences in magnitude and sometimes order of effect, there is a general consensus among leading researchers that BE characteristics do affect travel choices. For example, Cao et al. (2006b) reviewed 28 empirical studies on this very topic and showed how BE characteristics have statistically significant effects on travel, even after self-selection is controlled for. The question that remains is how great are such BE effects, and will design decisions and public policy make a cost-effective difference on travel choices? This paper analyzes a spatially detailed data set for a closer look at this important question.

DATA DESCRIPTION

The data used in this paper come from the Puget Sound Regional Council (PSRC) 2006 household travel survey, which obtained data from 10,510 individuals across 4,741 households residing in the King, Kitsap, Pierce and Snohomish counties of Washington State. The data are summarized in Table 1, and contain a substantial proportion of non-motorized trips (8.77%). Each respondent was asked to keep a travel diary for two consecutive days, all of which were weekdays (with all two-weekday combinations being distributed equally). The sample appears reasonably representative of the Seattle population across household sizes and auto-ownership levels (Cambridge Systematics 2007).

In addition to the travel survey, very fine parcel-level information from the region was inventoried by PSRC. The entire region consists of 1,177,140 parcels, and each trip in the trip file is connected to an origin and destination parcel identification number or "id". Each

household is connected to a household parcel id. In contrast to other regions’ traffic-analysis-zone- (TAZ-) based data sets, land-use information is reported *for each parcel*, and each trip in the Seattle data is associated with an origin-parcel and a destination-parcel, along with parking, transit and land use attributes within quarter-mile and half-mile buffers/radii around each of these parcels (as summarized in Table 2). Buffer-based variables include number of housing units, numbers of jobs (by sector), average parking costs (both hourly and daily), number of free *off-street* parking spaces, number of intersections (by type: four-way, three-way, and “point”/dead-end nodes), number of local and express bus stops, (network) distance to nearest bus stop, and other variables. The wealth of information provided makes this data set unique and well suited for the analyses performed in this paper.

Table 1: Summary Statistics of Person- and Household-level Attributes

	Mean	St Dev.	Min	Max
<i>Person Records (N=10,510)</i>				
Age (years)	41.9	21.8	0	99
Male Indicator	0.47	0.50	0	1
Driver’s License Indicator	0.78	0.42	0	1
Student Indicator	0.21	0.4	0	1
<i>Household Records (N=4,741)</i>				
Household Size	2.22	1.21	1	8
Household Number of Workers	1.13	0.85	0	5
Household Number of Vehicles	1.89	1.07	0	10
Number of Licensed Drivers	1.69	0.73	0	5
Household Income (\$/year)	71,400	42,300	5,000	175,000
Employment – Jobs within 1/4 mile	513	2090	0	32,314
# of Daily Paid Parking Spaces - 1/4 mile	70	587	0	9,414
# of Hourly Paid Parking Spaces - 1/4 mile	67	581	0	9,318
# of Free Off-street Parking Spaces - 1/4 mile	30	219	0	6,716
Avg. Price Daily Parking - 1/4 mile (\$)	0.31	1.96	0	22.2
Avg. Price Hourly Parking - 1/4 mile (\$)	0.13	0.86	0	11.01
# of Dead Ends - 1/2 mile	24.9	16.0	0	96
# of 3-way Intersections - 1/2 mile	44.3	25.1	0	142
# of 4-way (or more) Intersections - 1/2 mile	23.7	31.0	0	254
Distance to Nearest Express Bus Stop (miles)	1.39	2.01	0.01	29.48
Distance to Nearest Local Bus Stop (miles)	0.52	1.22	0.01	27.71
# of Express Bus Stops - 1/4 mile radius	1.72	3.94	0	51
# of Local Bus Stops - 1/4 mile radius	5.29	6.28	0	67
Urban Home-location Indicator	0.43	0.50	0	1
Suburban Home-location Indicator	0.41	0.49	0	1
Rural Home-location Indicator	0.16	0.37	0	1

Table 2: Land-use Variables at Trip Origins and Destinations

	Land-use Variables	$N_{trips} = 42,651$	Mean	St Dev.	Min	Max
Destination	# of Daily Paid Parking Spaces – within 1/4 mile		538	2,020	0	14,058
	# of Hourly Paid Parking Spaces - 1/4 mile		520	2,020	0	14,422
	# of Free Off-street Parking Spaces - 1/4 mile		145	637	0	9,956
	Avg. Price Hourly Parking - 1/4 mile (\$)		0.692	2.15	0	11.7
	# of Dead Ends - 1/2 mile		21.6	12.8	0	82
	# of 3-way Intersections - 1/2 mile		48.9	21.9	0	132
	# of 4-way (or more) Intersections - 1/2 mile		45.9	53.1	0	254
	Distance to Nearest Express Bus Stop (miles)		0.885	1.49	0.01	29.3
	Distance to Nearest Local Bus Stop (miles)		0.215	0.668	0	27.5
	# of Express Bus Stops - 1/4 mile		4.06	9.14	0	58
	# of Local Bus Stops - 1/4 mile		9.56	11.40	0	73
Origin	# of Daily Paid Parking Spaces - 1/4 mile		292	1,500	0	14,058
	# of Hourly Paid Parking Spaces- 1/4 mile		283	1,500	0	14,422
	# of Free Off-street Parking Spaces - 1/4 mile		82	477	0	9,956
	Avg. Price Hourly Parking - 1/4 mile (\$)		0.386	1.64	0	11.72
	# of Dead Ends - 1/2 mile		23.5	14.6	0	82
	# of 3-way Intersections - 1/2 mile		49.5	22.7	0	133
	# of 4-way (or more) Intersections - 1/2 mile		40.3	46.7	0	254
	Distance to Nearest Express Bus Stop (miles)		1.12	1.68	0.01	2,948
	Distance to Nearest Local Bus Stop (miles)		0.353	0.859	0	2,771
	# of Express Bus Stops - 1/4 mile		2.85	7.14	0	58
	# of Local Bus Stops - 1/4 mile		7.25	9.41	0	73

Zone-level Characteristics for Destination Choice (DC) Models

Accessibility Indices

The logsum of a multinomial logit- (MNL-) based destination choice (DC) model's systematic utilities is the expected maximum utility for such a choice set shifted by a constant, and so can be used as a measure of accessibility (Ben-Akiva and Lerman 1985, Niemeier 1997). Two such accessibility indices (for each TAZ) were constructed: one for the drive-alone mode (SOV AI) and the other for the non-motorized modes (NMT AI).

All logsum values were scaled to lie between 0 and 1 by assigning the maximum logsum a value of 1 and the rest pro-rated accordingly; their spatial patterns are shown in Figure 1. The distributions of these scaled logsum parameters exhibit long left tails and skew, with most drive-alone (SOV) and bike/walk (NMT) AI values clustered near the 0.88 mean values. While the bike/walk or NMT AIs tend to be more mixed/dispersed than the CBD-focused drive-alone (or SOV AI) values, their correlation is fairly high, with $\rho = +0.830$.

Land Use Entropy

A normalized-entropy measure of land use balance (and mixing, essentially, since the zones are small) was calculated using five land use categories, as follows:

$$LU\ Balance = - \sum_{k=1}^5 p_k \ln(p_k) / \ln 5$$

where p_k is the proportion of activities (jobs or dwelling units) in land-use category k (with categories of retail jobs, office jobs, industry jobs, other jobs, and residences). These five categories were chosen based on Cervero's (2002) entropy term, which had office jobs, retail jobs, "other" jobs, and dwelling units as shares of their total count). This measure of land-use balance was calculated for each TAZ.

Population + Jobs Density

Both population and jobs densities are routinely used as statistically and practically significant covariates in a wide range of travel behavior models. Cervero (2002) suggested simply an unweighted jobs plus population *Density* variable, as used here. This measure of density was computed for each TAZ, by summing the (estimated) population and employment values of all parcels within that TAZ. Figure 1 maps these densities across the region.

MODELING RESULTS

In order to appreciate the effects of this region's built environment (BE), demographic, and other attributes on the non-motorized travel patterns, a wide variety of behavioral models (and specifications) were used:

- Household Vehicle Ownership Model (Poisson)
- Non-motorized Trip Generation Model (Zero-Inflated Negative Binomial)
- Intrazonal vs Interzonal Trip Type Model (Binary Logit)
- (Interzonal) Destination Choice Models, by Trip Purpose (Multinomial Logit)
- Intrazonal and Interzonal Mode Choice Models, by Trip Purpose (Multinomial Logit)
- Vehicle and Non-Motorized Miles Traveled Models (Tobit)

This section describes these models and their results, with emphasis on elasticity parameters (which characterize the practical significance of covariates), rather than coefficients and their t -statistics. In all cases, covariates were removed (via a process of stepwise deletion) if they did not achieve a cut-off p -value of 0.2. In addition to this strategy for developing the final model specifications, variables with coefficient signs that did not make intuitive sense were also dropped.

Household Vehicle Ownership

As a count variable, household vehicle ownership levels can be modeled using a negative binomial (NB) specification, with a kernel Poisson and a random parameter (to reflect unobserved heterogeneity across households). The results of the NB regression produced an overdispersion parameter estimate statistically equivalent to zero, so the specification collapsed to a Poisson regression. Due to space constraints, the results of this Poisson model (and most of the 14+ models developed for this research) are not shown here, but are provided in Khan (2012).

Interpreting Practical Significance via Marginal Effects Estimates

To appreciate and compare the practical significance of model covariates, one can compute elasticities, which quantify the percentage change in the response variable (e.g., number of vehicles owned by a household) for a 1 percent change in the associated covariate (e.g., household size). Such estimates are common in the literature, but a 1 percent change in one covariate (such as income) may be easier to achieve than a one percent change in another attribute, (like SOV AI, which has a mean of 0.884 and a standard deviation of just 0.092). One way around this inconsistency is to estimate the percentage change in response following a one standard-deviation (SD) change in each covariate, which has been done here for all models. There are some potential drawbacks of using a SD change since some variables such as age, when increased by one SD can be very unrealistic. However, for the majority of the built-environment variables tested in this paper, an SD change is realistic. Another problem arises when evaluating elasticities of dummy variables such as gender or drivers license status, since one cannot necessarily assign fractions to such variables. Despite this imperfection, treating discrete variables as continuous variables and calculating their elasticities can give a general idea of the response, hence some such results are presented in this paper.

A related question is what set of covariate values to use when evaluating the marginal effects: one can perform such calculations at mean or median values for all explanatory variables, but such an “average” individual, household, or trip generally does not exist. Furthermore, for nonlinear functions, the function computed at the average does not equal the average of the functions and therefore it is not appropriate to use the former instead of the latter. Here, marginal effects were computed across the entire data sample, and then averaged, to provide a sense of the overall change one may expect from shifting all data record’s covariate values up by 1 SD (i.e., applying the policy to all persons in the Seattle data set).

In the case of Vehicle Ownership, Table 3’s marginal effects estimates suggest that household size, number of licensed drivers, and NMT accessibility have the greatest impact on vehicle ownership. Other BE variables, such as the density and nearby bus-stop intensity of one’s home neighborhood, also have some impact on household vehicle ownership but their impact is relatively slight (-4.9% and -6.3% changes in average vehicle ownership following a 1 SD increase in density and bus stop frequency, for example). In the end, the presence of licensed drivers and household size have the greatest impact (with effects of 43% and 24%, respectively), as one would expect, since vehicle purchases are designed to serve household members.

Non-motorized Trip-making per Household

The number of non-motorized trips per household was determined by simply summing the number of non-motorized person-trips (those made purely by walk or bike modes) in each household over the two-day survey period. Interestingly, most households (70%) did not report any NMT over the two-day survey period. Due to the excessive number of zero NMT households, a zero-inflated negative binomial (ZINB) count specification was used to model non-motorized trip counts, as a function of household and land-use variables. A zero-inflated model essentially consists of two successive models: a binary logit (BL) model that differentiates zero and non-zero NMT trip-making and a NB model that predicts NMT trip counts for the non-zero NMT trip-making households.

The ZINB results suggest that, as household size increases, the probability of the household having zero NMT trips falls (as expected). The NB component of the trip generation model shows that for non-zero NMT households, household size and number of workers are

associated with higher levels of NMT trip-making, while number of vehicles (a somewhat endogenous variable) plays a negative role. Somewhat surprisingly, household income is associated with more NMT trip-making, perhaps due to an opportunity for exercise, ability to afford to live within walking or biking distance to work, safer neighborhoods, and other features of higher-income living. Elasticity estimates are shown in Table 3.

Table 3 values suggest very strong, but opposing, effects of the two AIs, on non-motorized trip generation. One standard deviation change in the average NMT AI is apparently associated with an over 26% increase in non-motorized trip generation. In contrast, a one standard deviation change in the SOV AI is associated more than 15 percent drop in the mean-valued household's NMT trip count.

A Model for Interzonal versus Intrazonal Trips

Mode choices are likely to differ for interzonal and intrazonal trips, since intrazonal trips tend to be quite local, much shorter (with an average distance of 1.36 miles in this data set), and often for personal business and/or shopping purposes (38% of all intrazonal trips in the Seattle 2006 data set). Interzonal trips are longer (averaging 6.57 miles) and primarily serve business and personal purposes (24% and 16% of all interzonal trips, respectively). For this reason, a binary logit model was run to first segregate intra from- inter-zonal trips, on the basis of trip-maker and origin-zone attributes.

The results suggest that households that own more vehicles are more likely to make interzonal trips, while larger households and those having higher incomes are more likely to make intrazonal trips. In terms of individual attributes, licensed males are the least likely to make trips within their origin zone. Coefficients and t-statistics can be found in Khan (2012).

The averaged marginal effects estimates highlight the importance of balanced land use (and mixed land use, given PSRC's relatively small zone sizes) on intrazonal trip making. For example, a 1 SD increase in land-use entropy (across all trips) corresponds to a 75% increase in the probability of choosing to stay within the zone (versus making an interzonal trip). Higher AI values (SOV and NMT AIs), however, are estimated to reduce the probability of intrazonal trip-making. This implies that zones with higher land-use entropy but less accessibility will generate the maximum shares of intrazonal trips. While SOV AI values may believably result in more interzonal trip-making, the NMT AI result is not so believable. The reason for this apparently spurious result most likely is the fact that zone sizes fall with higher densities, common in central locations. Thus, trips are more likely to leave such zones because intrazonal distances become very short (with the smallest TAZs in the data set having an effective radius of just hundreds of feet, rendering them very easy to leave).

In retrospect, a model of "nearby vs. not-nearby" trip-making (e.g., trips under and over 1-mile in network distance, since 1 mile is a common limit of most walk trips) would be more consistent across trips, for analysis of BE effects. However, planning agencies often do not have such information on actual trip distances (with trips lacking parcel coordinates and distances relying on centroid connectors in networks that are only partially coded). As data becomes more spatially detailed and privacy concerns less of an issue, such distance-based local versus non-local models may become common.

Table 3: Marginal Effects of Covariates in Vehicle Ownership, Non-motorized Trip Generation, and Intrazonal Trip Choice Models (Average % Change in Predicted Response Level Associated with 1 Standard Deviation Change in Covariate, across Sample Records)

Variables	E[#Vehicles] (Poisson)	E[#NMT Trips] (NB)	Pr(Intrazonal Trip) (BL)
Household Size	24.2%	21.6%	-
Household Number of Workers	3.30%	12.2%	-
Household Number of Vehicles	-	-11.0%	-8.28%
Household Number of Licensed Drivers	43.3%	-9.42%	-
Household Income	8.32%	7.77%	3.60%
Licensed Indicator	-	-	-13.8%
Male Indicator	-	-	-8.17%
Rural Home Indicator	2.98%	-	-
Home/Origin TAZ SOV AI	-	-15.9%	-23.1%
Home/Origin TAZ NMT AI	-2.51%	25.9%	-18.6%
Home/Origin TAZ Entropy	-	-	74.9%
Home/Origin TAZ Density	-4.92%	1.88%	-
Distance to Closest Bus Stop	1.80%	-	9.53%
Number of Dead-ends (half mile radius)	-	-	9.95%
Number of 3-way Nodes (half mile radius)	-	0.49%	15.6%
Number of 4-way Nodes (half mile radius)	-2.20%	9.28%	-
Hourly Parking Price (quarter mile radius)	-	3.32%	-3.93%
Free Parking Spaces (quarter mile radius)	-	-3.78%	-
Number of Bus Stops (quarter mile radius)	-6.29%	0.95%	5.48%
Commute trip Indicator	-	-	-53.7%
Mid-day trip Indicator	-	-	5.42%
PM Peak trip Indicator	-	-	-3.07%
Nighttime trip Indicator	-	-	-10.2%
<i>Base Case</i>	2.70 vehs.	6.06 trips	3.88%

Note: The bold values correspond to the most practically significant variables (i.e., those that have the greatest magnitudes of effect) in estimating different response variable Y's. "-" indicates the explanatory variables that are practically insignificant. Base case values come from prediction at mean covariate values. Home TAZ land use values were used for the first two models; the intrazonal choice model's results rely on trip origin zone attributes.

Mode Choice

MNL specifications were used to model mode choices for both intrazonal and interzonal trips, after segregating by trip purposes (consistent with standard modeling practice, to reflect different needs and behaviors across trip types). Due to very low bike (BK) and transit (TR) shares, only three modes – drive-alone (DA), shared-ride (SR), and walking (WK) – serve as alternatives in the intrazonal mode choice models, with various demographic, land-use and mode-specific variables serving as covariates. The interzonal mode choice models are similar but have all five modes in the choice set, thanks to much larger sample sizes.

Travel times for motorized modes were present in the skim data, but travel times for bike and walk modes were estimated based on respondent-reported NMT travel times using network distances, resulting in average speeds of 0.124 miles per minute (7.4 miles per hour) for biking and 0.0479 miles per minute (2.9 mi/hr) for walking. The three trip purposes for both intrazonal and interzonal trip types are home-based work (HBW), home-based other (HBO), and non-home-based (NHB) trips. Intrazonal HBW trips are so rare (n=49 in the PSRC data) that this model (with only DA and WK modes evident in the data) is not discussed here. ***Mode Choice for Intrazonal HBO Trips***

There are many intrazonal HBO trips (n=1,013) in the PSRC data set, with healthy shares of drive-alone, shared-ride, and walk modes present. Surprisingly, there were very few intrazonal bike choices in the data, evidently since the zones are so small to begin with (in most locations), so these data points were dropped for the mode choice analysis.

As shown in Table 4's marginal effects estimates, at least two BE variables practically quite significant in terms of walk mode choice. As expected, the zone's NMT accessibility index has a positive impact, and network connectivity (measured as 4-way intersections within 0.5 miles) plays a major role: a single SD change in this variable (averaged across all records) is estimated to increase walking's probability by 34%. Parking prices and free-parking availability variables were not found to have much of an effect, but do interact with the shared-ride indicator in a statistically significant way.

Table 4: Intrazonal Trips - Percentage Changes in Pr(Mode) Associated with One SD Change in Individual Specific Variables

Variable	Home-Based Other Trips			Non-Home-Based Trips		
	Pr(DA)	Pr(SR)	Pr(WK)	Pr(DA)	Pr(SR)	Pr(WK)
Age	35.19%	-13.72%	-25.93%	26.75%	-23.23%	-16.05%
Male Indicator	13.15%	-10.77%	-4.30%	-10.19%	2.18%	14.57%
Student Indicator	6.08%	6.08%	-12.52%	8.82%	-18.80%	8.82%
Employed Indicator	15.90%	-0.46%	-17.18%	13.39%	-28.53%	13.39%
Vehicle per Licensed Driver	6.79%	6.79%	-14.00%	5.81%	5.81%	-17.24%
Income per Member	14.48%	-12.33%	-4.30%	6.26%	-13.34%	6.26%
NMT AI	-7.17%	-7.17%	14.78%	-	-	-
Land Use Entropy	2.95%	2.95%	-6.08%	-	-	-
Jobs + Pop Density	3.89%	3.89%	-8.02%	-	-	-
# of Dead-ends -1/2 mile	6.10%	6.10%	-12.57%	-	-	-
# of 3-way Intersections	-7.39%	-7.39%	15.22%	-	-	-
# of 4-way Intersections	-16.44%	-16.44%	33.86%	-20.70%	-10.01%	47.87%

Hourly Parking Price	0.22%	-0.48%	0.22%	0.07%	-0.16%	0.07%
Free Parking Spaces	-7.08%	15.67%	-7.08%	-2.73%	5.82%	-2.73%
Base Shares	36.20%	31.12%	32.68%	42.85%	31.94%	25.20%

Note: All land use variables apply to both the trip's origin and destination, since these are intrazonal trips' mode choices. *Base share* refers to the estimated probability of choosing a certain mode holding all attributes at their sample mean values. Bolded values correspond to the most practically significant variables for the interzonal HBO and NHB mode choice decision. "-" indicates explanatory variables that are not practically significant. Marginal effects estimates for HBW trips are not shown, due to their very limited sample size (n=49).

Mode Choice for Intrazonal NHB Trips

Several of the land-use variables (entropy, density, accessibility) appear as statistically insignificant in the NHB intrazonal, mode-choice context. Nevertheless, as with HBO intrazonal trips, roadway connectivity (characterized as the number of 4-way intersections within a half-mile radius of one's origin parcel) dramatically increases the walk mode's likelihood. A 49% increase in walking's likelihood for a one-SD increase in this variable surpasses all others in Table 4, including tripmaker age (a very important attribute for intrazonal mode choice, with older persons less likely to walk), gender, student and worker status, among others. As expected, vehicle ownership levels (a somewhat endogenous variable here) are negatively associated with walking choice.

Mode Choice for Interzonal HBW Trips

There are 6,358 trips in the HBW interzonal trip category, with all five modes adequately represented. All land-use measures were tested at both trip origin and destination ends of each trip, with a variety of demographic, network, and land use attributes having strong mode-specific effects. Table 5 shows marginal effects estimates for all variables, mode by mode. For example, the number of dead ends, 3-way, and 4-way intersections within ½-mile of one's origin parcel have marginal effects on the walk and bike mode probabilities that range from +26 to +57 percent (following a 1 SD increase in the associated covariate). While not as pronounced, the destination parcel's network connectivity effects are also solid (e.g., +32 percent in walk mode choice following a 1 SD increase in 3-way density). However, these percentages are relative, and the "base shares" of walk and bike modes for interzonal trips are computed as mean covariate values and so are near zero. Thus, increases of even 112 percent (for walk probability's response to a 1 SD increase in destination's NMT AI) may not mean a noticeable shift in other modes' shares. In other words, doubling a 1 percent base share does not have a large effect on other modes, which will see almost no change in their choice shares. In fact, the most sizable impacts come with the (rather endogenous) variable of vehicle ownership (vehicles per driver in the household), whose 1 SD increase is associated with 24%, 52%, and 57% drops in SR, TR, and WK mode probability predictions, respectively. Gender, dead-ends (at origin), and free parking space availability (at origin) also have sizable effects on the SR mode share for interzonal HBW trips, as shown in Table 5.

Mode Choice for Interzonal HBO Trips

HBO are all home-based non-work trips, and constitute the largest share of all PSRC trips (33.6 percent, or 15,549 trips in total). The results highlight the importance of several land-use variables. Higher land use mixing at the trip's origin is estimated to increase biking's utility (relative to other modes' utility levels); the numbers of 4-way intersections at both trip ends increase the utility of both bike and walk modes; NMT accessibility at one's destination zone improves walking's likelihood. The density at one's destination reduces the chance of walking, perhaps due to congestion issues and perceptions of traveler safety, but probably more likely due to competing variables (like network density, as discussed earlier).

Transit trips are estimated to be positively affected by NMT access and bus-stop access at the destination. Parking prices and availability does not appear to directly impact one's choice of walking, biking or transit trips, but do impact the utility of shared-rides (with higher prices and fewer spaces increasing the likelihood of shared-ride mores, relative to the alternative modes). An origin's land use entropy also appears to increase the likelihood of ride sharing.

Mode Choice for Interzonal NHB Trips

Non-home-based interzonal trips are the last of the six mode choices modeled here, and these consist of 17,244 trips, with all five modes present in the MNL specification. The results highlight some interesting land-use influences on mode choice. Consistent with the other mode choice models, street connectivity quantified as the number of 4-way intersections within a half-mile radius appears to positively influence the utility of walking. On the other hand, the number of dead-ends within a half-mile radius of either of the trip ends, appears to negatively impact the utility of biking. This underscores the importance of having more open and connected streets to promote non-motorized activity. The NMT accessibility index at the origin, not surprisingly, positively impacts the utility of walking, underscoring the importance of making zones more accessible to non-motorized modes to promote biking and walking.

The only land-use measure that appears to significantly impact the utility of choosing transit is the number of bus stops present within a quarter-mile radius. The utility of choosing shared-ride trips is affected by parking characteristics at both trip ends as well as density and SOV accessibility index at both trip ends.

Mode Choice Models' Marginal Effects

The relative impact of the explanatory variables on mode choice was investigated by calculating the marginal effects on response variables from a one-standard-deviation change in each explanatory variable. Here, indicator variables were treated like continuous variables: i.e., the marginal effect was calculated by increasing the average value of the indicator variable by one standard deviation. As an example of this, Table 4 shows the marginal effects associated with individual, household and land-use specific variables for all five interzonal HBW modes.

Table 5. Change in Mode Choice Probability Associated with One SD Change in Variables (Interzonal Trips)

Variable	Home-Based Work (HBW) Trips					Home-Based Other (HBO) Trips					Non-Home-Based (NHB) Trips				
	Pr(DA)	Pr(SR)	Pr(TR)	Pr(WK)	Pr(BK)	Pr(DA)	Pr(SR)	Pr(TR)	Pr(WK)	Pr(BK)	Pr(DA)	Pr(SR)	Pr(TR)	Pr(WK)	Pr(BK)
Age	1.26%	1.26%	-19.11%	1.26%	-27.0%	23.3%	-23.7%	6.96%	-1.30%	23.3%	13.7%	-20.6%	-8.93%	-16.9%	-8.93%
Male Indicator	1.44%	-18.4%	1.44%	19.3%	63.4%	3.70%	-3.65%	-17.28%	3.70%	69.7%	1.13%	-1.72%	1.13%	22.2%	39.5%
Student Indicator	-	-	-	-	-	9.61%	-9.83%	9.61%	-1.49%	68.8%	3.22%	-4.91%	3.22%	3.22%	3.22%
Employed Indicator	-	-	-	-	-	3.70%	-3.68%	-13.67%	3.70%	38.2%	18.2%	-28.0%	33.27%	18.20%	54.1%
Vehs/Driver	5.76%	-24.2%	-52.4%	-56.7%	5.76%	8.16%	-7.79%	-83.3%	-29.01%	8.16%	6.70%	-9.26%	-56.3%	-43.7%	-20.2%
NMT AI (Origin.)	-	-	-	-	-	-0.37%	-0.37%	123.2%	-0.37%	-0.37%	0.00%	0.00%	0.00%	46.0%	0.00%
SOV AI (Origin.)	-1.29%	16.48%	-1.29%	-1.29%	-1.29%	-	-	-	-	-	-2.77%	4.23%	-2.77%	-2.77%	-2.77%
Entropy (Origin.)	-	-	-	-	-	-1.72%	1.76%	-1.72%	-1.72%	17.7%	-	-	-	-	-
Density (Origin.)	1.09%	1.09%	-16.52%	1.09%	1.09%	-	-	-	-	-	0.00%	0.00%	0.00%	-14.50%	0.00%
# Dead-ends (O)	1.23%	-15.65%	1.23%	26.2%	-29.9%	0.07%	0.07%	-22.5%	-10.93%	0.07%	0.00%	0.00%	0.00%	0.00%	-42.1%
# 3-way Ints. (O)	0.00%	0.00%	0.00%	40.3%	35.5%	2.61%	-2.66%	2.61%	2.61%	-15.8%	0.00%	0.00%	0.00%	11.34%	0.00%
# 4-way Ints. (O)	0.83%	0.83%	-12.55%	56.6%	30.0%	0.05%	0.05%	-17.37%	30.01%	16.9%	0.00%	0.00%	0.00%	25.7%	0.00%
Free Park Spa (O)	1.37%	-17.49%	1.37%	1.37%	1.37%	7.02%	-7.18%	7.02%	7.02%	7.02%	0.56%	-0.86%	0.56%	0.56%	0.56%
# Bus-stops (O)	-1.20%	-1.20%	18.18%	-1.20%	-1.20%	-	-	-	-	-	-0.10%	-0.10%	16.73%	-0.10%	-0.10%
NMT AI (Destin.)	0.00%	0.00%	0.00%	111.6%	0.00%	0.00%	0.00%	0.00%	26.89%	0.00%	-	-	-	-	-
SOV AI (Destin.)	1.50%	-19.1%	1.50%	1.50%	1.50%	0.11%	0.11%	-36.5%	0.11%	0.11%	-3.90%	5.95%	-3.90%	-3.90%	-3.90%
LU Entropy (D)	-0.70%	-0.70%	10.67%	-17.5%	-0.70%	0.00%	0.00%	0.00%	0.00%	-12.16%	-	-	-	-	-
Density (D)	-0.32%	4.05%	-0.32%	-0.32%	-26.5%	0.00%	0.00%	0.00%	-13.75%	0.00%	0.96%	-1.47%	0.96%	0.96%	0.96%
# Dead-ends (D)	-	-	-	-	-	0.00%	0.00%	0.00%	13.02%	-30.46%	0.00%	0.00%	0.00%	11.82%	-57.2%
# 3-way Ints. (D)	0.74%	-9.47%	0.74%	31.8%	0.74%	-	-	-	-	-	0.00%	0.00%	0.00%	0.00%	42.8%
# 4-way Ints. (D)	-0.53%	6.69%	-0.53%	11.77%	9.64%	0.00%	0.00%	0.00%	9.17%	0.00%	0.00%	0.00%	0.00%	34.2%	0.00%
Hour Park Price (D)	-0.70%	8.78%	-0.70%	-0.70%	-0.70%	-1.89%	1.92%	-1.89%	-1.89%	-1.89%	-	-	-	-	-
Free Park Spac (D)	-	-	-	-	-	0.66%	-0.68%	0.66%	0.66%	0.66%	0.68%	-1.04%	0.68%	0.68%	0.68%
# Bus-stops (D)	-1.81%	-1.81%	27.49%	-1.81%	-1.81%	-0.08%	-0.08%	26.5%	-0.08%	-0.08%	-0.07%	-0.07%	11.76%	-0.07%	-0.07%

Note: Bold values denote the most *practically* significant variables in estimating interzonal mode choices (identifying those variables that have the greatest magnitude of effect of outcome probabilities).

Interzonal Destination Choice

As noted earlier, destination choice models nest above the MNL mode choices models, for each purpose, for the case of interzonal trips. Logsums across all 5 modes' systematic utilities (from the mode choice models) serve as an important covariate. Consistent with mode choice, models were estimated for HBW, HBO, and NHB purposes; and destination-zone attributes were interacted with demographic covariates, like gender, age, and licensed status, to allow these non-generic variables to play a role in destination choice. Travel distances, costs, and times were controlled for, along with a wide set of destination-zone BE attributes, as seen in earlier models. Most land use variables emerged as very statistically significant ($p\text{-value} < 0.2$) in one form or another: for example, land use entropy emerges with a negative coefficient by itself in the HBW model of destination choice, but has positive coefficients when interacted with male gender, senior citizen, and licensed status variables, and these can, in combination, offset its initially negative effect. Travelers from higher-income households, however, appear less attracted to zones of greater land use balance, for HBW interzonal trip-making. Since region-wide destination choice models have thousands of alternatives, all viable at relatively low probabilities individually, elasticities and other measures of marginal effects of zone-specific attribute changes on choice probabilities tend to be negligible. To address this limitation, this work examined the *average-trip-distance* impacts of modifying each variable by 1 SD, one variable at a time. Thus, all alternatives' systematic utilities were affected simultaneously. Interestingly, average distances for all three models (all three trip purposes) hardly changed, when all destination alternatives' attributes changed simultaneously – presumably because every alternative became more or less attractive simultaneously. The variables with the greatest impacts in such settings were demographics ones, with licensed status resulting in 14 to 21 percent longer average (model-predicted) travel distances across the three models, and male gender resulting in 2.3 to 9.8 percent longer distances. Among BE variables, destination zones' density and 4-way intersection intensity were estimated to have the biggest impacts on average distances, when increased uniformly (1 SD across all destination zones), but these were negligible (less than 1 percent change in response to a 1 SD BE value change). Changing BE attributes may be most meaningful when impacting the share of trips that are intrazonal, rather than changing destinations of trips that leave a zone.

A less complicated way to look at distance effects of covariates is to look at household VMT and non-motorized miles traveled (NMMT), as described below. In this setting, BE variables at the home zone are controlled for (rather than those at destination zones).

Models of Miles Travelled: Motorized and Non-Motorized

Miles travelled over short durations gives rise to many zeros in the data set, especially in the case of NMT, where 70% of households reported zero such travel over the two-weekday window. Thus, a Tobit (left-censored) model specification was used to predict household miles travelled here, both by drive-alone and shared-ride (personal vehicle) modes, with marginal effects estimates shown in Table 6 (and parameter estimates shown in Khan [2012]).

As apparent in Table 6, density (population plus jobs), parking attributes, and accessibility indices were not found to be statistically significant predictors, in either of these models, after distance to the CBD, 4-way intersection density and entropy were controlled for. Of course, intersection density is not just a proxy for network continuity, but for density and perhaps other of these BE variables, with tight grids more typical of older, more central locations, with smaller parcel sizes and generally higher density. Distance to the region's

downtown and land use balance in Seattle’s relatively small zones are also correlated with density, parking cost and availability, and accessibility. It is interesting to see which BE variables “win out” in terms of sensitivity measures across the series of travel-behavior models.

Marginal effects (following a 1 SD change in each covariate) are high in these two MT models, with household size, vehicle ownership, worker count, and licensed drivers playing key roles, as one might expect. The BE variables and distance to the CBD also play key roles. NMMT may more than double with a 1 SD increase in household size, thanks to the presence of younger persons in such households (often children who do not possess drivers licenses). The NMMT effects are consistently higher than those for VMT because it is much easier to change a small base distance value (just 0.205 miles of NMMT for the average Seattle household over 2 weekdays, versus 53.3 VMT).

Beyond model-specific parameter estimates for the average household or averaged across sample households (before and after a variable value is change), some simulated applications were examined here, where all sample households are moved around the region en masse, and behavioral predictions summarized, as described below.

Table 6: Marginal Effects of Covariates on Household VMT and NMMT
(Average Change in Predicted Response Level Associated with 1 Standard Deviation Change in Covariate, across Sample Records)

	E[VMT]	E[NMMT]
Household Size	25.1%	119%
Household # Workers	7.47%	17.0%
Household # Vehicles	8.79%	-25.8%
Household Income	6.21%	-
Number of Licensed Drivers	6.93%	-7.86%
Number of 3-way Nodes	-5.02%	-
Number of 4-way Nodes	-4.00%	42.8%
Home TAZ Entropy	-2.39%	7.34%
Distance to CBD	13.2%	-36.1%
<i>Base Miles Traveled</i>	53.3	0.205

Note: *Base Miles Traveled* refers to expected household two-weekday miles traveled, holding all attributes at their sample-mean values. Bold values denote the most *practically* significant variables in estimating destination choice decision (identifying those variables that have the greatest magnitude of effect). “-” indicates the explanatory variables that are not included in the final model specification.

SIMULATION RESULTS

The above models can be used to understand the impact of different built environment characteristics on various NMT-related choices. For example, if all sampled households are moved into Seattle’s downtown area (with its high parking costs, high NMT and SOV accessibilities, high densities and network intensities, and so forth), average household vehicle ownership is forecast to fall to 0.57 vehicles per household (from 1.89) -- an almost 70% reduction across the sample. And average NMT trips per household (per two-weekday period)

are forecasted to jump more than 6-fold, from 0.83 to 5.93 trips. These are without changing incomes, household sizes, numbers of workers, and so forth. Although such policy examples neglect issues of self-selection (where car-loving households and walk-disliking households may balk at shedding vehicles or walking more in a downtown setting), they illuminate some maximum changes one might expect thanks to BE variables on key travel behaviors.

Besides sending all households to the CBD, one can imagine sending all households to areas hosting quartiles of the density (jobs plus population) variable. Various zones' attributes, with the 25%, 50%, 75%, 100% percentiles of density (taken across the sample's 4,741 households), were sought, and all sample households were assigned these neighborhoods' attributes. In addition to changing location attributes, household sizes, numbers of household workers, and numbers of licensed drivers were all increased by 1.0 and household incomes were raised by 20 percent, to get a sense of the relative impacts of such demographic effects on travel behaviors, vis-à-vis the changing neighborhood effects.

As expected, moving households into higher density areas is expected to reduce vehicle ownership and VMT, while increasing NMMT and non-motorized trip generation. However, only the act of moving households into the densest parts of the region (the 100% percentile) is estimated to have a sizeable effect on vehicle ownership. Interestingly, NMT trip generation is estimated to double (from about 0.5 to 1.0 non-motorized trips per day per household) when moving from a 25th percentile to 50th percentile location (with net densities of 4.2 and 10.2 persons + jobs per acre, among other land use changes), stay steady from the 50th to 75th percentile-density locations, and then more than double (from about 1.5 to 3.5 trips per day) when moving from the 75th to 100th percentile locations (with net densities of 20 and over 3,000 persons plus jobs per acre). On the other hand, VMT and NMMT fall and rise, respectively, in fairly linear ways (when plotted versus total density). NMMT was particularly sensitive to location in the region, exhibiting more than a three-fold increase (1 mile to 4 miles per day per household) when moved from the 25th to the 100th percentile household location. All demographic shifts tested showed relatively minor impact, except for addition of a household member (which adds noticeably to VMT and NMMT, as expected) or when increasing NMT generation, which is low to begin with (so 0.1 more non-motorized trips per two-day period is a significant percentage increase).

More applications of this nature would be helpful, to discern where BE attributes may trigger a clear savings in motorized travel dependencies. For example, these simulated cases may be suggesting that only at densities above 20 persons + jobs per acre (with associated BE factors in play) do walking and biking become truly viable modes for Americans. That seems a high threshold which will be difficult for most communities to pursue, except in multi-family-housing-rich or job-rich settings, though it is nearly the average density (and the 75th percentile home-location density) experienced by Seattle's sampled households. Moreover, it is not too far from Newman and Kenworthy's (2006, p. 35) belief that 35 residents plus jobs per hectare (or 14.2 per acre) is a "fundamental threshold of urban intensity ... where automobile dependence is significantly reduced." Of course, more attributes are at play here, including network intensity and connectivity, regional and local accessibilities, parking availability and prices, transit provision, and traveler demographics.

CONCLUSIONS AND FUTURE WORK

The results of all these models provide interesting insights into NMT and the role of various BE and demographic characteristics. While it is difficult to know how much is actually

due to self-selection, versus the characteristics themselves, formal analyses (such as those by Zhou and Kockelman [2008], Schwanen and Mokhtarian [2005] and Khattak and Rodriguez [2005]) find much evidence in favor of BE effects, as long as one controls for a reasonable number of demographic attributes (such as income, education, age, and household size, which correlate highly with location choices).

A wide variety of new and old covariates were tested here, to anticipate a number of distinctive travel behaviors. The results imply the importance of street connectivity (quantified as the number of 3-way and 4-way intersections in a half-mile radius), higher bus stop density, and greater non-motorized access in promoting lower vehicle ownership levels (after controlling for household size, income, neighborhood density and so forth), higher rates of non-motorized trip generation (per day), and higher likelihoods of non-motorized mode choices. Destination choices are also important for mode choices, and local trips lend themselves to more non-motorized options than more distance trips. Intrazonal trip likelihoods rose with higher street connectivity, transit availability, and land use entropy.

As expected, destinations with greater population and job numbers, located closer (to a trip's origin), offering lower parking prices and greater transit availability, are predicted to be more popular/attractive to travelers. Interestingly, those with more dead ends (or cul de sacs) attracted fewer trips. Among all BE variables tested, intersection density offered the greatest predictive benefits, alongside jobs and population (densities and counts).

The regional non-motorized travel (NMT) accessibility index (derived from the logsum of a destination choice model) also appears important, with NMT counts rising by 7% following a 1% increase in this variable – if the SOV AI is held constant (along with all other variables, evaluated at their means). Similarly, household vehicle ownership is expected to fall by 0.36% with each percentage point increase in the NMT AI, and walk probabilities rise by 26.9% following a one standard deviation increase in this index at the destination zone.

A traveler's demographics also have important impacts on NMT choices, typically serving as much stronger predictors of NMT choices than the BE. For example, the elasticity of NMT trip generation with respect to a household's vehicle ownership count is estimated to be -0.52. Males and those with driver's licenses are estimated to have 17% and 39% lower probabilities, respectively, of staying within their origin zone, relative to women and unlicensed adults (*ceteris paribus*). Non-motorized model choices also exhibit strong sensitivity to age and gender settings.

The marginal effects estimated throughout this work and the set of simulations/model applications are helpful for planners, policymakers, and the public, in understanding to what extent behaviorally-based models predict shifts toward and away from non-motorized trip-making. Such shifts are valuable to have in mind, when communities seek to reduce reliance on motorized travel by defining new built-environment contexts and pursuing distinctive policies. For example, parking prices and parking-space densities/availability are more easily manipulated, in existing settings, than (population and jobs) densities and street connectivity.

While the land-use variables controlled for here are reasonably extensive, buffered to addresses, and meaningful, they are limited. Since biking and walking are physical activities, various path attributes -- such as average incline, adjacent traffic volumes, presence (and width) of bike lanes and sidewalks, and the elevation difference between each O-D pair -- would be helpful in reflecting some key factors influencing bike and walk mode choices. Such factors are expensive to come by, but more and more transportation agencies are recognizing the value of such variables and seeking to expand their emerging inventories, to produce a next-generation set

of models and results. It is hoped that such variables will result in more accurate (and precise) forecasts, and better decision making, including investments and policies that support more sustainable urban futures.

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Figure 1: Maps of Various Land Use Variables for the PSRC Region (SOV AI, Land Use Entropy, NMT AI, and Density)



