HOUSEHOLD TRAVEL APP

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note: coefficients expressed in this report are not up-to-date. a more current version of this research exists behind a pay wall at : http://journals.sagepub.com/doi/pdf/10.1177/0042098014560991

Contents

Executive Summary

The potential to moderate travel demand by changing the built environment is the most heavily researched subject in urban planning. Yet, the existing literature is short on external validity or generalizability. The models estimated for Portland, OR or Southern California cannot necessarily be applied to the rest of the United States. To fill this gap in the literature, we have estimated travel models based on pooled household travel data and built environment data from six diverse regions of the United States. This application, referred to as the Household Travel App, is perhaps the most critical of all within the scenario planning software package, Envision Tomorrow Plus (ET+). The reason is that the outputs of this app feed into many other apps.

The Household Travel App consists of five models, with household travel outcomes as the dependent variables, and so-called D variables as the independent variables. The predicted outcomes are vehicle trips, walk trips, bike trips, transit trips, and vehicle miles traveled (VMT). The D variables are the demographics of households and the density, diversity, design, destination accessibility, and distance to transit for buffers around their places of residence. The six D's affect the accessibility of trip productions to trip attractions, and hence the generalized cost of travel by different modes to and from different locations. This affects the utility of different travel choices.

Multilevel modeling (MLM) is used to account for dependence among observations, in this case the dependence of households within a given region. All households within a given region share the characteristic of that region. This dependence violates the independences assumption of ordinary least squares ("OLS") regression. Therefore, MLM produces a more accurate coefficient and standard error estimates.

VMT increases with the household size, number of employed household members, and real household income. The coefficient values suggest that household VMT does not rise as fast household size or income. Household VMT declines with four built environmental variables characterizing one-mile buffers around households: activity density, intersection density, percentage of 4-way intersections, and transit stop density. In addition, VMT declines as the percentage of regional employment accessible within a 10 minute drive time increases. Again, those who live in highly accessible places (characterized by these five D variables) generate less VMT than those in less accessible places.

The number of household walk trips increases with household size and declines with household income. High income households have greater access to private vehicles. Walk trips increase with land use entropy (mix) within a quarter mile of home and activity density within a mile of home. These measures of density and diversity place destinations within walking distance of home. Walk trips also increase with transit stop density within a mile of home. Transit service is complementary to walking, as households with good access to transit own fewer private vehicles and hence are more likely to use alternative modes.

The bike trip model is the simplest of the six models estimated. Bike trip frequency increases with household size, land use entropy within a quarter mile, activity density within a mile, and percentage of 4-way intersections within a mile. All three built environmental variables tend to reduce bicycling distances between home and trip attractions, thereby reducing the generalized cost of bicycling relative to automobile use.

The number of household transit trips increases with household size and employment, and declines with household income. The number increases with land use entropy, activity density, and percentage of 4-way intersections. Transit-oriented development is virtually defined by these three variables. Controlling for these variables, transit trips increase with two transit service variables, transit stop density within a quarter mile and percentage of regional employment reachable within 30 minutes by transit.

Introduction

Some of today's most vexing problems, including sprawl, congestion, oil dependence, and climate change, are prompting states and localities to turn to land planning and urban design to rein in automobile use. But how much effect can land planning and urban design have on automobile use, walking, biking, and transit use?

This chapter describes the 6D household travel app. This application within the Envision Tomorrow Plus (ET+) suite is perhaps the most critical of all. This is because the outputs of this app feed into many other apps. For example, the vehicle emission app depends on two outputs of this app, household vehicle miles traveled (VMT) and household vehicle trips (VT). The public health app depends on three outputs, walk bike, and transit trip frequency. All told, six apps are linked to this one app.

D Variables

The potential to moderate travel demand by changing the built environment is the most heavily researched subject in urban planning. In travel research, such influences have often been named with words beginning with D. The original "three Ds," coined by Cervero and Kockelman (1997), are density, diversity, and design, followed later by destination accessibility and distance to transit (Ewing & Cervero, 2001; Ewing and Cervero, 2010; Ewing, Greenwald, & Zhang, 2011). While not part of the environment, demographics are the sixth D, controlled as confounding influences in travel studies.

A number of studies, including Crane (1996), Cervero and Kockelman (1997), Kockelman (1997), Boarnet and Crane (2001), Cervero (2002a), Zhang (2004), and Cao, Mokhtarian, and Handy (2009b), provide economic and behavioral explanations of why built environments might be expected to influence travel choices. Basically, the first six Ds affect the accessibility of trip productions to trip attractions, and hence the generalized cost of travel by different modes to and from different locations. This, in turn, affects the utility of different travel choices. For example, destinations that are closer as a result of higher density or greater diversity are easier to walk to than distant destinations. As the Ds increase (and distance to transit decreases), the generalized cost of travel by alternative modes decreases, relative utility increases, and mode shifts occur.

Table 1 indicates how D variables are typically measured. Note that these are rough categories, divided by ambiguous and unsettled boundaries that may change in the future. Some dimensions overlap (e.g., diversity and destination accessibility). Still, it is a useful framework to organize the empirical literature and provide order-of-magnitude insights.

Table 1. The D Variables

D Variable	Measurement
Density	Density is always measured as the variable of interest per unit of area. The area can be gross or net, and the variable of interest can be population, dwelling units, employment, or building floor area. Population and employment are sometimes summed to compute an overall activity density per areal unit.
Diversity	Diversity measures pertain to the number of different land uses in a given area and the degree to which they are represented in land area, floor area, or employment. Entropy measures of diversity, wherein low values indicate single-use environments and higher values more varied land uses, are widely used in travel studies. Jobs-to-housing or jobs-to-population ratios are less frequently used.

Design	Design measures include average block size, proportion of four-way intersections, and number of intersections per square mile. Design is also occasionally measured as sidewalk coverage (share of block faces with sidewalks); average building setbacks; average street widths; or numbers of pedestrian crossings, street trees, or other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones.
Destination accessibility	Destination accessibility measures ease of access to trip attractions. It may be regional or local (Handy 1993). In some studies, regional accessibility is simply distance to the central business district. In others, it is the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral ones. The gravity model of trip attraction measures destination accessibility. Local accessibility is a different animal. Handy (1993) defines local accessibility as distance from home to the closest store.
Distance to transit	Distance to transit is usually measured as an average of the shortest street routes from the residences or workplaces in an area to the nearest rail station or bus stop. Alternatively, it may be measured as transit route density, distance between transit stops, or the number of stations per unit area. In this literature, frequency and quality of transit service are overlooked.

Literature

Qualitative Reviews

There are at least 14 surveys of the literature on the built environment and travel (Badoe and Miller, 2000; Brownstone 2008; Cao, Mokhtarian, and Handy, 2009a; Cervero, 2003; Crane, 2000; Ewing and Cervero, 2001; Handy, 2005; Heath, Brownson, Kruger, Miles, Powell, and Ramsey, 2006; McMillan, 2005; McMillan, 2007; Pont, Ziviani, Wadley, Bennet, and Bennet, 2009; Saelens, Sallis, and Frank, 2003; Salon, Boarnet, Handy, Spears, and Tala, 2012; Stead and Marshall, 2001). There are another 15 surveys of the literature on the built environment and physical activity, including walking and biking (Badland and Schofield, 2005; Cunningham and Michael, 2004; Ferdinand, Sen, Rahurkar, Engler, and Menachemi, 2012; Frank, 2000; Frank and Engelke, 2001; Humpel et al., 2002; Kahn et al., 2002; Krahnstoever-Davison et al., 2006; Lee and Moudon, 2004; McCormack et al., 2004; National Research Council, 2005; Owen et al., 2004; Saelens and Handy, 2008; Trost, Owen, Bauman, Sallis, and Brown, 2002; Wendel-Vos, Schuit, de Niet, Boshuizen, Saris, and Kromhout, 2004). There is considerable overlap among these reviews, particularly where they share authorship. The literature is now so vast it has produced three reviews of the many reviews (Bauman and Bull, 2007; Gebel, Bauman, and Petticrew, 2007; Ding and Gebel, 2012).

From the original review by Ewing and Cervero (2001), the most common travel outcomes modeled are trip frequency, trip length, mode choice, VT (vehicle trips), and VMT (vehicle miles traveled) as a composite measure of travel demand. That review concluded that trip frequency is primarily a function of socioeconomic characteristics of travelers and secondarily a function of the built environment; trip length is primarily a function of the built environment and secondarily of socioeconomic characteristics; and mode choice depends on both, though probably more on socioeconomics. VMT and vehicle hours of travel (VHT) also depend on both. Trip lengths are generally shorter at locations that are more accessible, have higher densities, or feature mixed uses. This holds true both when comparing home-based trips from different residential neighborhoods and trips to non-home destinations in different activity centers. Destination accessibility is the dominant environmental influence on trip length. Transit use varies primarily with local densities and secondarily with the degree of land-use mixing. Some of the density effect is, no doubt, due to better walking conditions, shorter distances to transit service, and less free parking. Walking varies as much with the degree of land use mixing as with local densities.

The third D, design, has a more ambiguous relationship to travel behavior than do the first two. Any effect is likely to be a collective one involving multiple design features. It also may be an interactive effect with other D variables. This is the idea behind composite measures such as Portland, Oregon's urban design factor, which is a function of intersection density, residential density, and employment density.

Quantitative Syntheses

In a meta-analysis, Ewing and Cervero (2010) computed weighted averages of results from more than 60 studies. The resulting elasticities are shown in Tables 2 through 4. These results tell us the following. For all variable pairs, the relationships between travel variables and built environmental variables are inelastic, that is, they have absolute values less than one. The weighted average elasticity with the greatest absolute magnitude is 0.39, and most elasticities are much smaller. Still, the combined effect of several built environmental variables on travel could be quite large.

First we consider the D variables that influence VMT (see Table 2). As in an earlier meta-study (Ewing and Cervero, 2001), the D variable that is most strongly associated with VMT is destination accessibility. The elasticity of VMT with respect to "job accessibility by auto" in this meta-analysis, -0.20. In fact, the -0.20 VMT elasticity is nearly as large as the elasticities of the first three D variables (density, diversity, and design) combined. This too is consistent with our earlier meta-study.

Next most strongly associated with VMT are the design metrics intersection density and street connectivity. This is surprising, given the emphasis in the qualitative literature on density and diversity, and the relatively limited attention paid to design. The weighted average elasticities of these two street network variables are identical. Both short blocks and many interconnections apparently shorten travel distances to about the same extent.

Also surprising are the small elasticities of VMT with respect to population and job densities. Conventional wisdom holds that population density is a primary determinant of vehicular travel, and that density at the work end of trips is as important as density at the home end in moderating VMT. This does not appear to be the case once other variables are controlled.

Next we consider the D variables that influence walking. The meta-analysis shows that mode share and likelihood of walk trips are most strongly associated with the design and diversity dimensions of built environments. Intersection density, jobs-housing balance, and distance to stores have the greatest elasticities. Interestingly, intersection density is a more significant variable than street connectivity. Intuitively this seems right, as walkability may be limited even if connectivity is excellent when blocks are long. Also of interest is the fact that jobs-housing balance has a stronger relationship to walking than the more commonly used land use mix (entropy) variable. Several variables that often go hand-in-hand with population density have elasticities that are well above that of population density. Also, as with VMT, job density is less strongly related to walking than is population density. Table 2 suggests that having transit stops nearby may stimulate walking.

Finally, we consider the D variables that influence transit use (see Table 3). The mode share and likelihood of transit trips are strongly associated with transit access. Living near a bus stop appears to be an inducement to ride transit, supporting the transit industry's standard of running buses within a quarter mile of most residents. Next in importance are road network variables and, then, measures of land use mix. High intersection density and great street connectivity shorten access distances, and provide more routing options for transit users and transit service providers. Land use mix makes it possible to efficiently link transit trips with errands on the way to and from transit stops. It is sometimes said that “mass transit needs ‘mass’”, however this is not supported by the low elasticities of transit use with respect to population and job densities in Table 3.

No clear pattern emerges from scanning across Tables 2 through 4. Perhaps what can be said with the highest degree of confidence is that destination accessibility is most strongly related to both motorized (i.e., VMT) and non-motorized (i.e., walking) travel and that among the remaining Ds, density has the weakest association with travel choices. The primacy of destination accessibility may be due to lower levels of auto ownership and auto dependence at central locations. Almost any development in a central location is likely to generate less automobile travel than the best-designed, compact, mixed-use development in a remote location.

The relatively weak relationships between density and travel likely indicate that density is an intermediate variable that is often expressed by the other Ds (i.e., dense settings commonly have mixed uses, short blocks, and central locations, all of which shorten trips and encourage walking). Among design variables, intersection density more strongly sways the decision to walk than does street connectivity. And among diversity variables, jobs-housing balance is a stronger predictor of walk mode choice than land-use mix measures. Linking where people live and work allows more to commute by foot, and this appears to shape mode choice more than sprinkling multiple land uses around a neighborhood.

Table 2. Weighted Average Elasticities of VMT with Respect to D Variables (Ewing and Cervero 2010)

		Total number of studies	Number of studies with controls for self-selection	Weighted average elasticity of VMT (e)
Density	Household/population density	9	1	-0.04
	Job density	5	1	0.00
Diversity	Land use mix (entropy index)	10	0	-0.09
	Jobs-housing balance	4	0	-0.02
Design	Intersection/street density	6	0	-0.12
	% 4-way intersections	3	1	-0.12
Destination accessibility	Job accessibility by auto	5	0	-0.20
	Job accessibility by transit	3	0	-0.05
	Distance to downtown	3	1	-0.22
Distance to transit	Distance to nearest transit stop	6	1	-0.05

Table 3. Weighted Average Elasticities of Walking with Respect to D Variables (Ewing and Cervero 2010)

		Total number of studies	Number of studies with controls for self-selection	Weighted average elasticity of walking (e)
Density	Household/population density	10	0	0.07
	Job density	6	0	0.04
	Commercial floor area ratio	3	0	0.07
Diversity	Land use mix (entropy index)	8	1	0.15
	Jobs-housing balance	4	0	0.19
	Distance to a store	5	3	0.25
Design	Intersection/street density	7	2	0.39
	% 4-way intersections	5	1	-0.06
Destination accessibility	Jobs within one mile	3	0	0.15
Distance to transit	Distance to nearest transit stop	3	2	0.14

Table 4. Weighted Average Elasticities of Transit Use with Respect to D Variables (Ewing and Cervero 2010)

		Total number of studies	Number of studies with controls for self-selection	Weighted average elasticity of transit use (e)
Density	Household/population density	10	0	0.07
	Job density	6	0	0.01
Diversity	Land use mix (entropy index)	6	0	0.12
Design	Intersection/street density	4	0	0.23
	% 4-way intersections	5	2	0.29
Distance to transit	Distance to nearest transit stop	3	1	0.29

Self-Selection

More than anything else, the possibility of self-selection bias has engendered doubt about the magnitude of travel benefits associated with compact urban development patterns. Residential self-selection refers to the tendency of people to select neighborhoods that support their travel preferences, for example, those want to walk and would walk anyway, may choose to living in walkable neighborhoods. According to a National Research Council report (2005), "If researchers do not properly account for the choice of neighborhood, their empirical results will be biased in the sense that features of the built environment may appear to influence activity more than they in fact do. (Indeed, this single potential source of statistical bias casts doubt on the majority of studies on the topic to date.)" (p. 5-7)

At least 38 studies using nine different research approaches have attempted to control for residential self-selection (Mokhtarian & Cao, 2008; Cao, Mokhtarian, & Handy, 2009a). Nearly all of them found "resounding" evidence of statistically significant associations between the built environment and travel behavior, independent of self-selection influences (Cao, Mokhtarian, et al. 2009a, p. 389). However, nearly all of them also found that residential self-selection attenuates the effects of the built environment on travel.

We have no ability to control for residential self-selection in the multi-region study that follows, as most of the underlying household surveys do not ask relevant attitudinal questions. But this may not be a major limitation. In Ewing and Cervero (2010), controls for residential self-selection appear to increase the absolute magnitude of elasticities if they have any effect at all. There may be good explanations for this unexpected result. In a region with few pedestrian- and transit-friendly neighborhoods, residential self-selection likely matches individual preferences with place characteristics, increasing the effect of the D variables, a possibility posited by Lund et al. (2006, p. 256).

". . . if people are simply moving from one transit-accessible location to another (and they use transit regularly at both locations), then there is theoretically no overall increase in ridership levels. If, however, the resident was unable to take advantage of transit service at their prior residence, then moves to a TOD (transit-oriented development) and begins to use the transit service, the TOD is fulfilling a latent demand for transit accessibility and the net effect on ridership is positive."

Similarly, Chatman (2009, p. 1087) hypothesizes that "Residential self-selection may actually cause underestimates of built environment influences, because households prioritizing travel access—particularly, transit accessibility—may be more set in their ways, and because households may not find accessible neighborhoods even if they prioritize accessibility." He carries out regressions that explicitly test for this, and finds that self-selection is more likely to enhance than diminish built environmental influences.

Still, we are left with a question. Most of the literature reviewed by Cao, Mokhtarian, et al. (2009a) shows that the effect of the built environment on travel is attenuated by controlling for self-selection, whereas Ewing and Cervero (2010) find no effect (or enhanced effects) after controlling for self-selection. The difference may lie in the different samples included in the two studies or in the crude way Ewing and Cervero (2010) operationalized self-selection (lumping all studies that control for self-selection together regardless of methodology).

Methods

This is a multivariate cross sectional study pooling household travel data and built environmental data from six diverse regions of the United States. What distinguishes this study from the hundreds of earlier studies is the external validity (generalizability) that comes with such a large and diverse database. A study using data from, say, Portland OR or Houston TX could be challenged for relevance to other regions of the country, particularly when different dependent and independent variables are used in each study. A study that pools data from six diverse regions, and uses consistently defined built environmental variables to predict several consistently defined travel outcome variables, should be ready for use in large metropolitan areas across the U.S.

Data

A main criterion for inclusion of regions in this study was data availability. Regions had to offer:

- regional household travel surveys with XY coordinates for trip ends, so we could geocode the precise locations of residences and measure the precise lengths of trips; and
- land use databases at the parcel level with detailed land use classifications, so we could study land-use intensity and mix down to the parcel level.

Most U.S. regions fall short on one or both counts. While nearly all metropolitan planning organizations (MPOs) have conducted regional household travel surveys as the basis for the calibration of regional travel demand models, most have geo-coded trip ends only at the relatively coarse geography of traffic analysis zones. Likewise, while most MPOs have historical land use databases that are used in model calibration, these too provide data only for the relatively coarse geography of traffic analysis zones. Traffic analysis zones vary in size from region to region, but as a general rule, are equivalent to census block groups. They will ordinarily not coincide with relevant built environments for individual households.

The regions included in our sample met both criteria, and in addition, were able to supply GIS data layers for streets, transit stops, and population and employment at the traffic analysis zone level. Buffers were established around household geocodes locations with three different buffer widths, ¼ mile, ½ mile, and 1 mile. Built environmental variables were computed for each household and all three buffer widths. The rationale for using different buffers is that different travel outcomes may depend on the built environment at different widths around home locations. For example, the number of walk trips may depend on conditions within a short distance of the home location, while the number or length of vehicle trips may depend on conditions over a larger area.

Regions, survey dates, and sample sizes are shown in Table 5. Not all variables were calculable for all cases, so effective sample sizes are somewhat smaller. Still, to our knowledge, this is largest sample of household travel records ever collected for such a study outside of the National Household Travel Survey. And relative to NHTS, our database provides much larger samples for individual regions and permits that calculation of wider array of built environmental variables for use in modeling travel outcomes.

Table 5. Regional Household and Trip Samples

	Survey Year	Surveyed Households	Surveyed Trips
Austin	2005	1,450	14,377
Boston	1991	2,599	20,756
Houston	1995	1,960	20,039
Portland	1994	3,832	50,574
Sacramento	2001	3,520	33,519
Seattle	2006	4,126	40,522
Total		17,487	179,787

Variables

The dependent and independent variables used in this study are defined in Table 6. Sample sizes and descriptive statistics are also provided. Only the unlogged independent variables are shown in Table 6. For each of them, there is a natural logged variable with the same variable name but for an "ln" at the beginning (for example, hhsize and lnhhsize). The logged variables have the potential to account for nonlinearity in the data set and to reduce the effect of outliers.

The variables in this app cover all of the Ds, from density to demographics. With different measures, different buffer widths, and both absolute and logged variables, a total of 50 independent variables were available to explain household travel outcomes. The variables were consistently defined across regions. That is one of the main strengths of this study.

Table 6. Dependent and Independent Variables

variable	description	N	Mean	S.D.
dependent variables				
posvmt	positive household VMT (1=yes, 0=no)	17,487	0.91	0.29
vmt	household VMT (for households with positive VMT)	17,423	51.90	54.90
auto	household private vehicle trips	17,424	8.33	7.38
walk	household walk trips	17,424	0.90	2.13
bike	household bike trips	17,424	0.13	0.78
transit	household transit trips	17,424	0.26	0.93
independent variables – household				
hhsize	household size	17,484	2.15	1.21
hhworkers	number employed	17,487	1.17	0.86
hhincome	real household income (1973 dollars)	15,432	30,486.85	18,146.16
independent variables – buffers				
actden1/4mi	activity density quarter mile (pop + emp per square mile)	16,854	16,217.05	30,531.49
jobpop1/4mi	job-population balance quarter mile	16,853	0.54	0.28
entropy1/4mi	land use entropy quarter mile	16,667	0.32	0.28
intden1/4mi	intersection density quarter mile	17,252	202.63	133.71

int4w1/4mi	percentage 4-way intersections quarter mile	17,022	31.33	25.39
stopden1/4mi	transit stop density quarter mile	17,252	38.00	57.00
actden1/2mi	activity density half mile (pop + emp per square mile)	17,087	13,630.93	22,142.57
jobpop1/2mi	job-population balance half mile	17,078	0.55	0.28
entropy1/2mi	land use entropy half mile	16,852	0.44	0.27
intden1/2mi	intersection density half mile	17,270	178.80	115.09
int4w1/2mi	percentage 4-way intersections half mile	17,193	29.94	20.81
stopden1/2mi	transit stop density half mile	17,270	31.67	38.43
actden1mi	activity density one mile (pop + emp per square mile)	17,157	12,506.68	18,487.08
jobpop1mi	job-population balance one mile	17,156	0.60	0.26
entropy1mi	land use entropy one mile	16,902	0.52	0.25
intden1mi	intersection density one mile	17,290	162.83	102.44
int4w1mi	percentage 4-way intersections one mile	17,229	29.29	18.03
stopden1mi	transit stop density one mile	17,290	26.86	30.56
rail1/2mi	rail station within one half mile (1=yes, 0=no)	17,450	0.25	2.21
emp10mina	percentage of regional employment within 10 minutes by auto	17,156	7.70	9.08
emp20mina	percentage of regional employment within 20 minutes by auto	17,159	30.56	23.64
emp30mina	percentage of regional employment within 30 minutes by auto	17,159	54.15	29.54
emp30mint	percentage of regional employment within 30 minutes by auto	17,286	12.58	18.08

Statistical Analysis

To increase statistical power and external validity, we are pooling household travel data from six diverse regions. Our data and model structure are hierarchical, with households nested within regions.

The solution to the problem of nested data is multilevel modeling (MLM), also called hierarchical modeling (HLM). MLM modeling is just beginning to be used in the planning field (Ewing et al. 2011). MLM accounts for dependence among observations, in this case the dependence of households within a given region. All households within a given region share the characteristics of that region. This dependence violates the independence assumption of ordinary least squares ("OLS") regression. Standard errors of regression coefficients based on OLS will consequently be underestimated. Moreover, OLS coefficient estimates will be inefficient. MLM overcomes these limitations, accounting for the dependence among observations and producing more accurate coefficient and standard error estimates (Raudenbush and Bryk 2002).

Regions such as Boston and Houston are likely to generate very different travel patterns irrespective of household characteristics. The essence of MLM is to isolate the variance associated with each data level. Despite the small number of Level 2 units (six regions) in this study, we can partition variance between the household level (Level 1) and the region level (Level 2). However, we cannot reliably explain Level 2 variance with Level 2 variables when the sample is this small. Variables such as regional population and density are unlikely to prove statistically significant predictors of household travel due to limited degrees of freedom. As the number of regions increases, we would expect Level 2 variables to gain statistical significance. It is our intent to eventually pool data from at least 10 different regions.

The dependent variables are of two types: continuous (VMT per household) and counts (vehicle trips, walk trips, and transit trips). VMT per household has two characteristics that complicate the modeling of it. First, it is non-normally distributed (see Figure 1). The solution to this problem is to take the natural logarithm of VMT, which becomes our dependent variable (see Figure 2). Second, it has a large number of zero values for households that generate no VMT. These households only use alternative modes such as transit or walking. About one in 10 households in the sample fall into this category. When VMT is log transformed, these households have undefined values of the dependent variable.

The solution to this problem is to estimate a two-stage “hurdle” model of VMT per household (Greene 2012, pp. 443, 824-826). We are aware of no previous application of hurdle models to the planning field. The stage 1 model categorizes households as either generating positive VMT or not, and the stage 2 model estimates the amount of VMT generated for those categorized as generating VMT. “In some settings, the zero outcome of the data generating process is qualitatively different from the positive ones. The zero or nonzero values of the outcome is the result of a separate decision whether or not to ‘participate’ in the activity. On deciding to participate, the individual decides separately how much to, that is, how intensively [to participate]” (Greene, 2012, p. 824).

Figure 1. Histogram of VMT per Household vs. a Normal Distribution

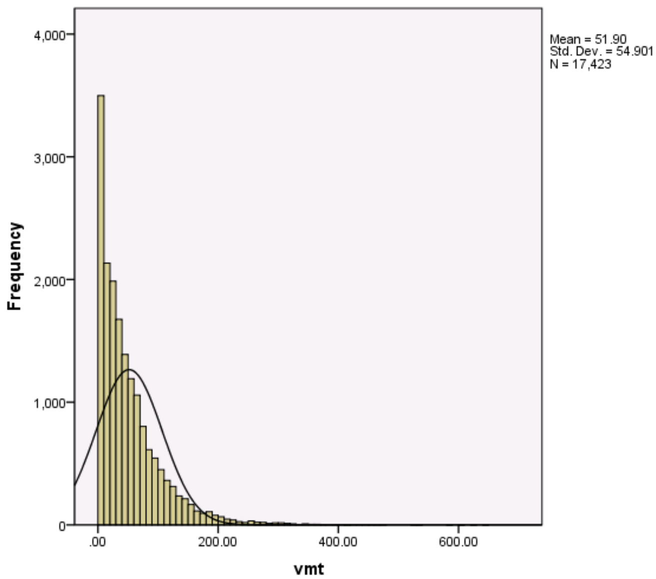
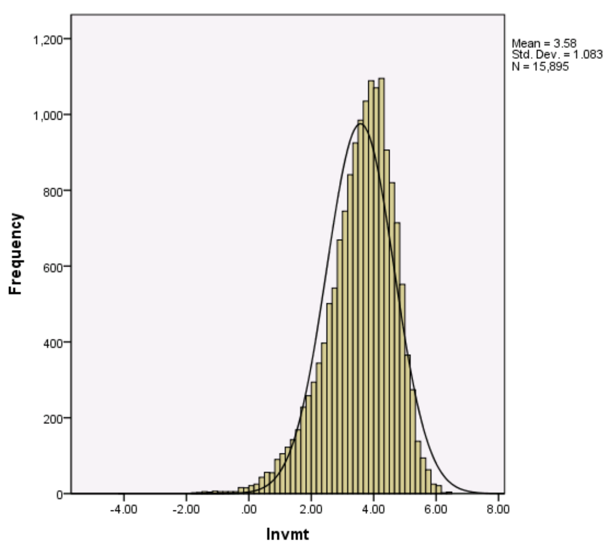


Figure 2. Histogram of the Natural Logarithim of VMT per Household vs. a Normal Distribution (excluding households with zero VMT)



The other type of variable that we need to model is trip counts. We have four trip counts among our dependent variables—household auto, walk, bike, and transit trip counts. Two basic methods of analysis are available when the dependent variable is a count, with nonnegative integer values, many small values and few large ones. The methods are Poisson regression and negative binomial regression, both fairly new to the planning field. They have mostly been used in crash studies because of the high skewed nature of crash counts (Dumbaugh & Rae 2008; Hadi et al., 1995; Marshall & Garrick, 2011; Schepers et al. 2011).

The two models, Poisson and negative binomial, differ in their assumptions about the distribution of the dependent variable. Poisson regression is the appropriate model form if the mean and the variance of the dependent variable are equal. Negative binomial regression is appropriate if the dependent variable is overdispersed, meaning that the variance of counts is greater than the mean. Because the negative binomial distribution contains an extra parameter, it is a robust alternative to the Poisson model.

"A central distributional assumption of the Poisson model is the equivalence of the Poisson mean and variance. This assumption is rarely met with real data. Usually the variance exceeds the mean, resulting in what is termed overdispersion… Overdispersion is, in fact, the norm and gives rise to a variety of other models that are extensions of the basic Poisson model. Negative binomial regression is nearly always thought of as the model to be used instead of Poisson when overdispersion is present in the data" (Hilbe, 2011, pg. 140).

Popular indicators of overdispersion are the Pearson and $\chi 2$ statistics divided by the degrees of freedom, so-called dispersion statistics. If these statistics are greater than 1.0, a model is said to be overdispersed (Hilbe, 2011, pp. 88, 142). By these measures, we have overdispersion of trip counts in our data set, and the negative binomial model is more appropriate than the Poisson model.

Results

There is no theoretically superior model involving different D variables and different buffer widths. Theoretically, buffers could be wide or narrow. Even a determinant as straightforward as walking distance could be anywhere from one quarter mile to one mile. Relationships may be linear (suggesting linear variables) or nonlinear (suggesting logarithmic variables). Different Ds may emerge as significant in different models. So trial and error was used to arrive at the best-fit models for the travel outcomes of interest. Variables were substituted into models to see if they were statistically significant and improved goodness-of-fit. For each dependent variable, we were looking for the model with the most significant t-statistics and the highest pseudo-R2.

The best-fit model for the dichotomous variable, positive VMT (1=yes, 0=no), is presented in Table 7. The likelihood of positive VMT increases with household size, number of employed household members, and real household income. These sociodemographics are associated with increased likelihood of vehicular travel. The likelihood of positive VMT declines with land use entropy within a quarter mile buffer around the household, with the percentage of 4-way intersections within a half mile, with transit stop density within a half mile, with activity density within a mile, and with intersection density within a mile. All variables are significant at the 0.001 level or beyond, except intersection density which is significant at the 0.002 level. Basically, those who live in highly accessible places (characterized by these five D variables) are better able to make do without vehicle trips. However, the probability of positive VMT remains high for all cohorts. The pseudo-R2 of this model only 0.15, suggesting that much of the variance in this dichotomous variable remains unexplained.

Table 7. Logistic Regression Model of Log Odds of Positive Household VMT

	coeff	std error	t-ratio	p-value
constant	-4.40	0.522	-8.44	<0.001
lnhhsize	0.755	0.082	9.26	<0.001
hhworkers	0.343	0.055	6.29	<0.001
lnhhincome	0.771	0.045	17.2	<0.001
lnentropy1/4mi	-0.744	0.128	-5.81	<0.001

stopden1/2mi	-0.0071	0.0009	-7.94	<0.001
actden1mi	-0.000019	0.000002	-10.4	<0.001
intden1mi	-0.00155	0.00049	-3.14	0.002
pseudo-R2 0.15				

The best-fit model for the continuous variable natural logarithm of VMT is presented in Table 8. Results parallel those for the dichotomous variable positive VMT, though the exact specification of the model differs. VMT increases with the household size, number of employed household members, and real household income. The coefficient values suggest that household VMT does not rise as fast as household size or income. Household VMT declines with four built environmental variables characterizing one-mile buffers around households: activity density, intersection density, percentage of 4-way intersections, and transit stop density. In addition, VMT declines as the percentage of regional employment accessible within a 10 minute drive time increases. Again, those who live in highly accessible places (characterized by these five D variables) generate less VMT than those in less accessible places.

Table 8. Linear Regression Model of Log Household VMT (for households with positive VMT)

	coeff	std error	t-ratio	p-value
constant	2.51	0.185	13.6	<0.001
lnhhsize	0.760	0.017	45.4	<0.001
hhworkers	0.158	0.011	14.9	<0.001
lnhhincome	0.172	0.012	14.2	<0.001
lnactden1mi	-0.102	0.014	-7.20	<0.001
intden1mi	-0.000767	0.000148	-5.17	<0.001
lnint4w1mi	-0.0951	0.0161	-5.91	<0.001
stopden1mi	-0.000942	0.000442	-2.13	0.033
lnemp10mina	-0.0525	0.0088	-5.95	<0.001
pseudo-R2 0.36				

The number of household private vehicle trips is roughly proportional to household size. Vehicle trip frequency levels off with rising income as household activity demand becomes saturated. Vehicle trip frequency declines with stop density and activity density, no doubt due to substitution of walk and transit trips for vehicle trips. Vehicle trip frequency increases with accessibility to employment (a proxy for trip attractions). This rise in trip making with enhanced accessibility is predicted by economic theory, since the generalized cost per trip is lower at accessible locations.

Table 9. Negative Binomial Model of Household Private Vehicle Trips

	coeff	std error	t-ratio	p-value
constant	-0.023	0.104	-0.633	0.84
lnhhsize	0.977	0.010	99.6	<0.001
lnhhincome	0.141	0.008	17.6	<0.001
stopden1/4mi	-0.00055	0.00011	-4.99	<0.001
actden1mi	-0.000010	0.000001	-18.3	<0.001
emp10mina	0.00619	0.00077	8.02	<0.001
pseudo-R2 0.53				

The number of household walk trips increases with household size and declines with household income. High income households have greater access to private vehicles. Walk trips increase with land use entropy (mix) within a quarter mile of home and activity density within a mile of home. These measures of density and diversity place destinations within walking distance of home. Walk trips also increase with transit stop density within a mile of home. Transit service is complementary to walking, as households with good access to transit own fewer private vehicles and hence are more likely to use alternative modes.

Table 10. Negative Binomial Model of Household Walk Trips

	coeff	std error	t-ratio	p-value
constant	-3.64	0.38	-9.55	<0.001
hhsize	0.424	0.012	36.2	<0.001
lnhhincome	-0.0892	0.0233	-3.83	<0.001
entropy1/4mi	0.379	0.067	5.69	<0.001
lnactden1mi	0.279	0.027	10.5	<0.001
int4w1mi	0.0114	0.0013	9.01	<0.001
stopden1mi	0.00507	0.00075	6.72	<0.001
pseudo-R2 0.26				

The bike trip model is the simplest of the six models estimated. Bike trip frequency increases with household size, land use entropy within a quarter mile, activity density within a mile, and percentage of 4-way intersections within a mile. All three built environmental variables tend to reduce bicycling distances between home and trip attractions, thereby reducing the generalized cost of bicycling relative to automobile use. The pseudo-R2 of this model is, predictably, also low.

Table 11. Negative Binomial Model of Household Bike Trips

	coeff	std error	t-ratio	p-value
constant	-5.91	0.37	-15.9	<0.001
hhsize	0.472	0.025	18.7	<0.001
entropy1/4mi	0.406	0.162	2.50	0.012
actden1mi	0.000006	0.000002	2.81	0.005
lnint4w1mi	0.726	0.084	8.64	<0.001
pseudo-R2 0.18				

The number of household transit trips increases with household size and employment, and declines with household income. The number increases with land use entropy, activity density, and percentage of 4-way intersections. Transit-oriented development is virtually defined by these three variables. Controlling for these variables, transit trips increase with two transit service variables, transit stop density within a quarter mile and percentage of regional employment reachable within 30 minutes by transit. The pseudo-R2 of this model is a negative number. A pseudo-R2 is not analogous to the R2 in linear regression, which can only assume positive values. One standard text on multilevel modeling notes that the variance can increase when variables are added to the null model. It goes on to say: "This is counter-intuitive, because we have learned to expect that adding a variable with decrease the error variance, or at least keep it at its current level… In general, we suggest not setting too much store by the calculation of [pseudo-R2s]" (Kreft and de Leeuw 1998, 119). For more discussion of negative pseudo-R2s, also see Snijders and Bosker (1999).

Table 12. Multilevel Model of Household Transit Trips

	coeff	std error	t-ratio	p-value
constant	-0.837	0.759	-1.10	0.32
lnhhsize	0.575	0.063	9.06	<0.001
hhworkers	0.255	0.039	6.60	<0.001

lnhhincome	-0.462	0.037	-12.3	<0.001
entropy1/4mi	0.321	0.115	2.80	0.005
stopden1/4mi	0.00229	0.00043	5.34	<0.001
lnactden1/2mi	0.161	0.045	3.59	<0.001
lnint4w1mi	0.299	0.071	4.21	<0.001
lnemp30mint	0.129	0.025	5.11	<0.001
pseudo-R2 NA				

Discussion

A number of caveats apply to these surprisingly robust results. First, the sample for this study, while large in terms of households, covers only six regions of the U.S. Thus we are unable to account for variations in household travel behavior across regions. As the sample of regions expands, so will the external validity of the study and our ability to explain variations.

Second, this app focuses exclusively on the home end of trips, when every trip has two ends. We set out to measure environmental conditions at all origins and destinations, but discovered that the analytical requirements exceeded the capacity of our software and hardware.

Third, the list of predictor variables, while longer than any previous study's, still omits certain variables that have presumptive effects on household travel. Among sociodemographic variables, life cycle and life style variables are missing. Among potential D variables, those related to demand management (particularly at the destination end of trips), are entirely absent from our data sets. Parking supplies and prices, particularly at the destination end of trips, may strongly affect mode choices of workers.

Fourth, the low pseudo-R2s of three models are a potential source of error. Still, model significance levels were high in this study. Pseudo-R2s in multi-level modeling are not equivalent to R2s in ordinary least squares regression, and should not be interpreted the same way. The pseudo R2 bears some resemblance to the statistic used to test the hypothesis that all coefficients in the model are zero, but there is no construction by which it is a measure of how well the model predicts the outcome variable in the way that R-squared does in conventional regression analysis.

Finally, we did not account for self-selection, where individuals who want to walk and use transit choose to live or work in MXDs. Nearly all studies of residential selection—the tendency of people to choose residential locations that match their travel preferences—have found that residential self-selection attenuates the effects of the built environment on travel. At the same time, nearly all of them have found "resounding" evidence of statistically significant associations between the built environment and travel behavior, independent of self-selection influences (Cao, Mokhtarian, et al. 2009, p. 389). Where the magnitude of the self-selection effect has been compared to the effect of the built environment on travel, the former has been found to be secondary (Ewing and Cervero, 2010). Thus, we shouldn't overstate the importance of this caveat.

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