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How Affordable is HUD Affordable Housing?

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HOW AFFORDABLE IS HUD AFFORDABLE HOUSING?

Final Report

NITC-RR-705

by

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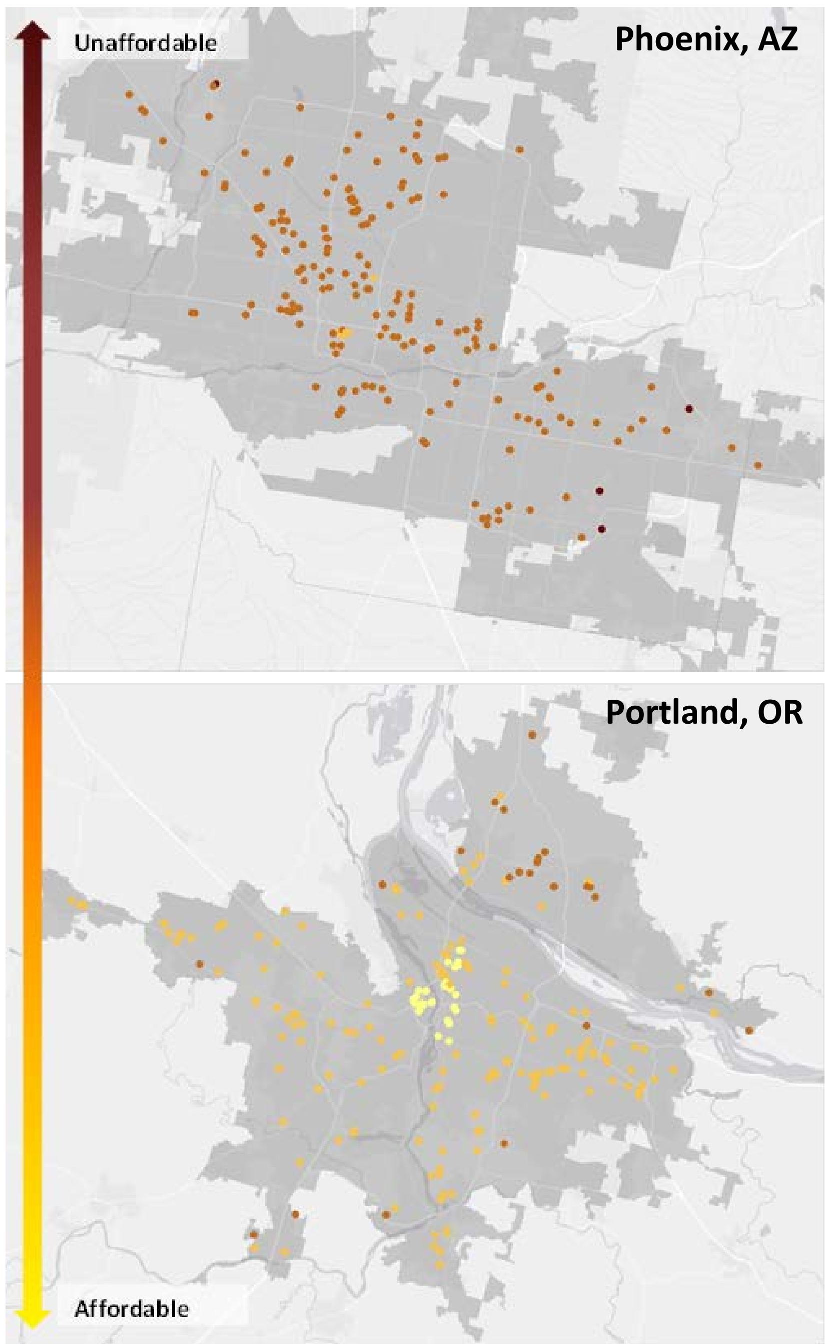

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16. Abstract

This paper assesses the affordability of HUD rental assistance properties from the standpoint of transportation costs. HUD housing is, by definition, affordable from the standpoint of housing costs due to limits on the amounts renters are required to pay. However, there are no such limitations on transportation costs, and common sense suggests that renters in remote locations may be forced to pay more than 15 percent of income, a nominal affordability standard, for transportation costs. Using household travel models estimated with data from 15 diverse regions around the U.S., we estimated and summed automobile capital costs, automobile operating costs, and transit fare costs for households at more than 18,000 HUD rental assistance properties. The mean percentage of income expended on transportation is 15 percent for households at the high end of the eligible income scale. However, in highly sprawling metropolitan areas, and in suburban areas of more compact metropolitan areas, much higher percentages of households exceed the 15 percent threshold. This suggests that locational characteristics of properties should be considered by HUD when establishing eligibility for rental assistance subsidies.

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Introduction

The U.S. Department of Housing and Urban Development (HUD)'s measure of housing affordability is the most widely used and the most conventional measure of housing affordability. According to the HUD measure, total housing costs at or below 30 percent of gross annual income are affordable (Belsky, Goodman & Drew, 2005). This is often considered as the definition of housing affordability (Linneman & Megbolugbe, 1992) and has shaped views of who has affordability problems, the severity of problems, and the extent of the problems (Belsky, Goodman & Drew, 2005). It is simple to compute and the raw data is easily available from a few recognized sources (Bogdon & Can, 1997), such as the U.S. Census Bureau and the American Housing Survey.

The HUD measure is also the legislative standard used to qualify applicants for housing assistance. It is used in the administration of rental housing subsidies, such as the Section 8 housing vouchers (Bogdon & Can, 1997). Under these programs, participants can pay no less than 30 percent, and no more than 40 percent, of their adjusted income toward housing rent. We can assume, therefore, that housing costs alone are affordable for households participating in HUD rental assistance programs. But is the housing under HUD rental assistance programs still affordable when taking into account the transportation costs?

HUD has no way of knowing since transportation costs fall outside its purview and regulations. But transportation costs, after housing, is the second biggest expenses in the budgets of most American households, particularly for those settled along the urban fringe. Less costly alternatives to automobile travel, particularly public transit, are typically much less accessible and thus largely impractical in suburban and exurban locations relative to central cities. Since 2006, fuel costs have risen nationally, consuming progressively larger shares of income.

Previous studies show that there is a clear tradeoff between the housing and transportation expenses of working families. Families that spend more than half of their total household expenditures on housing put 7.5 percent of their budget towards transportation. By contrast, families that spend 30 percent or less of their total budget on housing spend nearly one-quarter of their budget on transportation - three times as much as those in less affordable housing (Dietz, 1993; Lipman, 2006).

This study seeks to determine whether HUD rental assistance programs provide "affordable housing" when transportation costs are factored in. This study is built on the work of the Center for Neighborhood Technology (CNT) with their Housing + Transportation (H+T) Affordability Index and the more recent Location Affordability Index (LAI). Under CNT's guideline, housing is affordable if the sum of H+T is no more than 45 percent of household income, and that transportation costs alone is no more than 15 percent of income. This study uses the same guideline, but we model household transportation costs very differently than does CNT, and estimate models that have greater validity and reliability than CNT's because they are based on more robust data and an improvement in the methodology. Also the models in this study are specific to low-income households, a group that has received little attention in the travel literature.

Using a large national sample (up to 34,000 properties) listed in HUD's Multifamily Portfolio Dataset enables us to draw effective conclusions about HUD rental assistance programs. We will also draw effectiveness conclusions about DOT transit assistance programs, particularly New Starts, since they may prove responsible for keeping housing "affordable" in a holistic sense in areas of relatively high-priced housing.

Literature Review

Housing Affordability

The majority of studies of housing affordability focus on housing cost and its relationship to household income as the sole indicator of affordability (Belsky et al., 2005; Bogdon & Can, 1997; Combs et al., 1994; Linneman & Megbolugbe, 1992; O'Dell et al., 2004; Robinson et al., 2006; U.S. HUD, 2006; Yip & Lau, 2002). The main providers of affordability indexes in the U.S. are real estate institutes and government agencies. The National Association of Realtors (NAR), for example, publishes a Housing Affordability Index for existing single-family homes by metropolitan area. The NAR affordability index measures whether or not a typical family could qualify for a mortgage loan on a typical home. An index above 100 signifies that a family earning the median income has more than enough income to qualify for a mortgage loan on a median-priced home, assuming a 20-percent down payment, while an index value less than 100 means that such a family cannot afford a median-priced home.

These indices and standards are structurally flawed in that they only consider costs directly related to housing, ignoring those related to utilities and transportation. We know from the Consumer Expenditure Survey that the typical American household spends about 26.3 percent of income on housing, excluding utilities and public services costs. For the typical household, therefore, housing is affordable. But the typical household also spends 16.7 percent for transportation. Housing plus transportation costs consumed 43 percent of household income in 2011. If a household's transportation costs were zero but its housing costs were 35 percent of income, we would say that its housing was unaffordable, when in fact the household would be no worse off than the typical American household. Likewise, if a household's transportation costs were 20 percent of income and is housing costs were 30 percent of income, we would say that housing was affordable when it, in fact, might not be.

Addressing this issue, the Center for Neighborhood Technology (CNT) and the Center for Transit Oriented Development (CTOD) in 2006 developed an innovative tool called the “Housing + Transportation Affordability Index” that measured true housing affordability. The H+T Affordability Index took into account not only the cost of housing, but also the intrinsic value of location, as quantified through transportation costs (CTOD & CNT, 2006).

The H+T affordability index built on the analysis and theory of the location efficient mortgage (LEM), a lending product that was developed by a group of researchers for Fannie Mae in 2000. The LEM was rolled out in three regions. The LEM was very similar to the H+T affordability index in that it combined the costs of housing and transportation, and presumed that homebuyers could afford a bigger mortgage if they choose a neighborhood near public transit where they could realize significant savings on transportation (Holtzclaw et al., 2001). However, the LEM (and related Smart Commute Mortgage) program was abandoned in 2008 due to a lack of uptake. Chatman and Voorhoeve (2010) attribute the failure of these programs to a lack of advertising amongst lenders, logistical difficulties and concerns about risk. Moreover, they noted that buyers did not benefit much in comparison to other loan products available at the time. Finally, transit agencies did not push strongly for such mortgage programs.

In 2010-13, the departments of transportation and housing and development funded the development of a refined H+T-like index called the Location Affordability Index (LAI). The LAI is based on an updated methodology and uses the most recent and better quality data with more coverage. [i]

Shortcomings of CNT's and LAI's Transportation Cost Models

The H+T Index has received praise for its assistance to planners and transit-oriented development advocates. However, it has also received criticism (Abt Associates, 2010; Econsult Corporation & Penn Institute for Urban Research, 2012; Tegeler, 2011).

The first problem with these models is the limited characterization of the built environment. The model of auto use (vehicle miles traveled, or VMT) only accounts for variations in two built-environment variables—gross density and average block size—plus demographic and socioeconomic variables. Go back to the earliest travel behavior studies and the built environment was operationally defined strictly in terms of density. However, for the past 15 years, the built environment has been defined more broadly in terms of five types of D variables. The original three Ds, coined by Cervero and Kockleman (1997), were density, diversity and design. The Ds were later expanded to include destination accessibility and distance to transit (Ewing and Cervero, 2001). Excluding key built-environment variables—those related to diversity, destination accessibility, and distance to transit—limits the explanatory power of CNT's auto use model and may introduce bias due to omitted variables. Destination accessibility has a particularly strong effect on household VMT (Ewing & Cervero, 2010).

The second problem with the CNT models is the reliance on VMT data from only one state. The VMT model was calibrated with odometer readings from Massachusetts alone. Massachusetts' households are not typical of U.S. households generally. They drive about 15 percent fewer miles per year (CNT, 2010). Drivers in Massachusetts also likely have better access to public transportation than those in many other places, which could affect the predicted relationships between auto use and the independent variables used in the model. By relying on data for a single state, the CNT auto use model lacks an important quality researchers refer to as external validity, which translates roughly as generalizability.

The third problem with the CNT models is that auto ownership is modeled with aggregate data from the 2009 ACS. CNT documentation states that average vehicles per occupied housing unit were calculated at the census-block group scale. Models based on aggregate (block group) data rather than disaggregate (household) data may suffer from aggregate bias. The data fail to account for variations in vehicle ownership and sociodemographic variables from household to household in the same block group. They also fail to account for variations in the built environment within the same census geography.

The fourth problem with the CNT models is the treatment of transit costs. CNT documentation states: "Because no direct measure of transit use was available at the block group level, a proxy was utilized for the measured data representing the dependent variable of transit use. From the ACS, Means of Transportation to Work was used to calculate a percent of commuters utilizing public transit." Beyond the problem of aggregation bias (whether for census-block groups or much larger census tracts), the obvious limitation of this approach is that non-commuting trips by transit are ignored.

The fifth problem with the CNT models is the use of national-level unit cost data. Auto operating costs are calculated using national-level fleet data and national average fuel costs, which may not be representative of individual metropolitan regions. There are substantial and persistent variations in fuel costs from region to region. In 2010, fuel cost ranged from $2.51 per gallon in Springfield, MO, to $ 3.37 per gallon in Honolulu, HI. A review of statewide average fuel costs in the Texas Transportation Institute's Urban Mobility Database suggests that variations from place to place have been persistent and relatively stable.

While LAI represents a vast improvement over the old H+T methodology of CNT, it still has important limitations in two of its three component models. The VMT model is now based on Illinois odometer readings for Chicago and St. Louis rather than odometer readings for Massachusetts. Massachusetts had lower VMT per capita than the U.S. as a whole, which may not be the case for Chicago and St. Louis. However, the two metropolitan areas are hardly representative of the entire U.S. As important, auto ownership is modeled with aggregate data from the ACS. Models based on aggregate (block group or census tract) data rather than disaggregate (household) data may suffer from aggregation bias. For the past 20 years, vehicle ownership has been modeled in the peer-reviewed literature with disaggregate data. Using aggregate data to model vehicle ownership represents a giant methodological step backwards.

This study is built on the work of the CNT and the more recent LAI indices. But, addressing their shortcomings, we estimate models that have greater validity and reliability because they are based on more robust data and a more accurate methodology. Our models account for all the so-called D variables found to affect travel and vehicle ownership in the peer-reviewed literature. The Ds are development density, land use diversity, street design, destination accessibility, and distance to transit. They have been shown to affect household travel decisions in more than 200 peer-reviewed studies (see the meta-analysis by Ewing & Cervero, 2010; also see literature reviews by Badoe & Miller, 2000; Brownstone, 2008; Cao, Mokhtarian & Handy, 2009a; Cervero, 2003; Crane, 2000; Ewing & Cervero, 2001; Handy, 2005; Heath, Brownson, Kruger, Miles, Powell & Ramsey, 2006; McMillan, 2005, 2007; Pont, Ziviani, Wadley, Bennet & Bennet, 2009; Saelens, Sallis & Frank, 2003; Salon, Boarnet, Handy, Spears & Tala, 2012; Stead & Marshall, 2001).

Methods

In this study, we use the same methodology as CNT and estimate household transportation costs as the sum of three terms:

Household T Costs = $[C_{AO} * F_{AO}(X)] + [C_{AU} * F_{AU}(X)] + [C_{TU} * F_{TU}(X)]$

where

C = cost factor (i.e., dollars per mile)

F = function of the independent variables (F_{AO} is auto ownership, F_{AU} is auto use, and F_{TU} is transit use)

However, our Cs and the Fs will be different from CNT's. The availability of disaggregate data at the household level leads to better estimates of transportation costs for low-income households at any location.

With the new models in hand, we then geolocate more than 34,000 rental housing assistance properties in HUD's Multifamily Portfolio Dataset and apply the new transportation cost models to *typical low-income* households living *at these locations* to determine whether their transportation costs are more or less than 15 percent of household income.

Sample

This analysis is specific to low-income households who qualify for HUD rental assistance; that is, those with extremely low, very low, and low incomes (less than 30 percent, 50 percent and 80 percent of area median household income). The travel and vehicle ownership patterns of low-income households are likely to be qualitatively different from those of higher-income households.

For the purpose of modeling, we use household travel survey databases for diverse regions in which have collected in the last few years. At present, we have consistent datasets for 13 regions. The resulting dataset consists of 51,497 households in the 13 regions (see Table 2). The regions are diverse as Boston and Portland at one end of the urban form continuum and Houston and Kansas City at the other. In our database, we have thousands of low-income households. Based on changes in the consumer price index, we have inflated reported household incomes for earlier survey years to 2012 dollars. We have then applied the HUD low-income standard for each region and household size to our surveyed households, and found that 17,916 households would qualify for HUD rental assistance, a number which will expand as we add regions to our household travel database.

To our knowledge, this is the largest sample of household travel records ever assembled for such a study outside the National Household Travel Survey (NHTS). And relative to NHTS, our database provides much larger samples for individual regions, and permits the calculation of a wide array of built-environment variables based on the precise location of households. NHTS provides geocodes (identifies households) only at the census-tract level.

Table 1. Fifteen-Region Integrated Travel Database

	Survey Date	All Households	Low-Income Households
Atlanta	2011	9,575	2,486
Austin	2005	1,450	301
Boston	2011	7,826	1,281
Denver	2010	5,551	450
Detroit	2005	939	416
Eugene	2011	1,679	1,010
Houston	2008	5,276	2,069
Kansas City	2004	3,022	2,356
Minneapolis-St. Paul	2010	8,234	1,198
Portland	2011	4,513	517
Provo-Orem	2012	1,464	1,126
Sacramento	2000	3,520	923
Salt Lake City	2012	3,491	615
San Antonio	2007	1,563	1,022
Seattle	2006	3,908	2,146
Total		62,011	17,916

Data and Variables

Our analysis is based on disaggregate (household) travel and vehicle ownership data for tens of thousands of households in many diverse metropolitan regions of the U.S. Our current household travel database consists of 13 metropolitan regions.

All surveys provide XY coordinates for households and their trips. This allows travel to be modeled in terms of the precise built environment in which households reside and travel occurs. For individual trips, trip purpose, travel mode, travel time, and other variables are available from the survey dataset. Distance traveled on each trip was either supplied or computed with GIS from the XY coordinates. For travelers, individual age, employment status, driver's licensure, and other variables are available from the survey data set. For households, household size, household income, vehicle ownership, and other variables are available from the survey dataset. This allows us to control for sociodemographic influences on travel at the household level.

Other datasets have been collected for the same years as the travel surveys in order to estimate values of many D variables for quarter-mile, half-mile and one-mile radius buffers around each household. These include a geocoded parcel land use layer; geocoded street and transit layers; and travel time skims, population, and employment by traffic analysis zone as supplied by the regions' metropolitan planning organizations.

Variables extracted from these datasets and used in subsequent modeling are shown in Table 2. The table only makes reference to half-mile buffers, but data for quarter-mile and one-mile buffers are also available. The variables in this study cover all of the Ds, from density to demographics. All variables are consistently defined from region to region.

Table 2. Category, Definition and Scale of Variables Proposed for Use in the Household Transportation Cost Model

Category	Symbol	Definition	Level
Outcome variables	vmt	Household VMT	Household
	transit	Household number of transit trips	Household
	veh	Number of household vehicles	Household
Household sociodemographic variables	hsize	Number of household members	Household
	emp	Number of household workers	Household
	inc	Household income (in 1982 dollars)	Household
Transit variables	rail	Rail station within a half mile (dummy variable; yes=1, no=0)	Household
	tfreq	Aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period	Block group
Built-environmental variables	actden	Activity density within a half mile (sum of population and employment divided by gross land area in square miles)	Household
	jobpop	Job-population balance within a half mile of a household (index ranging from 0, where only jobs or residents are present within a quarter mile, to 1, where there is one job per five residents)	Household
	entropy	Land use mix within a half mile of a household (entropy index based on net acreage in different land use categories that ranges from 0, where all developed land is in one use, to 1, where developed land is evenly divided among uses)	Household
	intden	Intersection density within a half mile (number of intersections divided by gross land area in square miles)	Household
	int4way	Proportion of 4-way intersections with a half mile (4 or more way intersections divided by total intersections)	Household
	emp10	Proportion of regional employment accessible within a 10 minute travel time via automobile	Household
	emp20	Proportion of regional employment accessible within a 10 minute travel time via automobile	Household
	emp30	Proportion of regional employment accessible within a 10 minute travel time via automobile	Household
	sf	Single family housing unit (dummy variable; yes=1, no=0)	
Regional variables	rpop	Total regional population	Regional
	remp	Total regional employment	Regional
	ract	Total regional activity (sum of population and employment)	Regional
	index	Regional compactness index (index measuring compactness vs. sprawl based on a combination of four factors that measure density, land use mix, degree of centering, and street accessibility); higher values	Regional

		signify great compactness*ii* (Ewing and Hamidi, 2014)	

Statistical Methods

As shown in Table 2, our data structure is multilevel with households "nested" within regions. This creates a dependence among households in the same region, which violates the independence assumption of ordinary least squares regression and leads to inefficient and biased regression coefficients and standard error estimates (Raudenbush & Bryk, 2002). That is to say, households in Boston are likely to have very different travel and vehicle ownership patterns than households in Houston, irrespective of their socioeconomic and neighborhood characteristics. Such a nested data structure requires multilevel modeling (MLM) to account for the shared characteristics of households in the same region. MLM partitions variance between the household/neighborhood level (Level 1) and the regional level (Level 2), and then seeks to explain the variance at each level in terms of D variables.

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

The proper solution to the problem of excess zero values (what is referred to in the econometric literature as "zero inflation") is to estimate two-stage "hurdle" models (Greene, 2012, pp. 443, 824-826). The stage 1 model categorizes households as either generating VMT or not.

The stage 2 model estimates the amount of VMT generated for households with any (positive) VMT. The predicted VMT is just the product of the probability of households having VMT times and the amount of VMT generated by households with any VMT. We are aware of no previous application of hurdle models to the planning field.

The other two variables that we wish to model are transit trip counts and household vehicle ownership. 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. The two models – Poisson and negative binomial – differ in their assumptions about the distribution of the dependent variable. Poisson regression is appropriate if the dependent variable is equi-dispersed, meaning the variance of counts is equal to the mean. Negative binomial regression is appropriate if the dependent variable is overdispersed, meaning that the variance of counts is greater than the mean. 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.

The other statistical complication is the excess number of zero values for the transit trip variable. About 87 percent of households have no transit trips. Again, the solution to the problem of zero inflation is to estimate two-stage hurdle models. The first stage is the estimation of logistic regression models to distinguish between households with and without walk, bike or transit trips. The second stage is the estimation of negative binomial regression models for the number of trips by these modes for households that have such trips.

Models were estimated with HLM 7, Hierarchical Linear and Nonlinear Modeling software (Raudenbush, Bryk, Cheong & Congdon, 2010). HLM 7 allows the estimation of multilevel models for continuous, dichotomous and count variables and, for the last of these, can account for overdispersion.

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 or more. 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 greatest log-likelihood.

Transportation Models

The best-fit model for the dichotomous variable, any VMT (1=yes, 0=no), is presented in Table 3. The likelihood of a household generating any VMT increases with household size, number of employed members, real household income and living in single-family housing. The likelihood of any VMT declines with percentage of regional employment accessible within 10 minutes by automobile; with land use entropy within a quarter mile of a household; with intersection density within a half mile; with percentage of four-way intersections within a half mile; and with average transit frequency within a quarter mile of the block group. Basically, those who live in highly accessible places (characterized by these five D variables) are better able to make do without automobile trips. However, the probability of any VMT remains high for all cohorts.

Table 3. Logistic Regression Model of Log Odds of Any Household VMT

	coefficient	standard error	t-ratio	p-value

constant	1.72	0.172	9.96	<0.001
hhsize	0.226	0.052	4.36	<0.001
hhworkers	0.315	0.103	3.054	0.003
hhincome	0.0331	0.0030	11.00	<0.001
sf	0.850	0.102	8.33	<0.001
emp10a	-0.0224	0.0061	-3.67	0.001
entropyqmi	-0.709	0.115	-6.14	<0.001
intdenhmi	-0.0025	0.0006	-4.039	<0.001
int4whmi	-0.0129	0.0015	-8.51	<0.001
tfreq	-0.00092	0.0002	-5.33	<0.001
-2 log-likelihood ratio 44,084 pseudo-R2 0.62				

The best-fit model for the continuous variable natural logarithm of VMT (for households that generate VMT) is presented in Table 4. Results parallel those for the dichotomous variable of any VMT, though the exact specification of the model is different. Household VMT increases with household size, number of employed household members, and real household income. Household VMT declines with percentage of regional employment accessible within 10 minutes by automobile, and with average transit frequency. Household VMT also declines with two land use variables characterizing quarter-mile buffers around households: activity density and land use entropy. Finally, household VMT declines with intersection density and percentage of four-way intersections within a half mile. Again, those who live in highly accessible places (characterized by these D variables) generate less VMT than those in less accessible places.

Table 4. Linear Regression Model of Log of Household VMT (for households with any VMT)

	coefficient	standard error	t-ratio	p-value
constant	2.55	0.081	31.69	<0.001
hhsize	0.164	0.024	6.97	<0.001
hhworkers	0.185	0.0076	24.28	<0.001
hhincome	0.0072	0.0008	9.06	<0.001
emp10a	-0.0076	0.0018	-4.13	<0.001
actdenhmi	-0.0046	0.0014	-3.03	0.001

entropyhmi	-0.297	0.037	-8.02	<0.001
intdenhmi	-0.0015	0.00018	-8.37	<0.001
int4whmi	-0.0026	0.0005	-5.49	<0.001
tfreq	-0.000089	0.00003	-3.39	0.001
--2 log-likelihood ratio 40,294 pseudo-R2 0.19				

The number of household vehicles increases with household size, number of employed members, real income and living in a single-family housing unit (see Table 5). Household vehicle ownership declines with percentage of regional employment accessible within 10 minutes by automobile; activity density within a quarter mile; land use entropy within a quarter mile; percentage of four-way intersections within a half mile; intersection density within a half mile; and with transit frequency.

Table 5. Negative Binomial Model of Household Vehicle Ownership

	coefficient	standard error	t-ratio	p-value
constant	-0.108	0.042	-2.56	0.027
hhsize	0.060	0.008	7.86	<0.001
hhworkers	0.142	0.011	13.21	<0.001
hhincome	0.0086	0.0006	14.71	<0.001
sf	0.301	0.021	14.11	<0.001
emp10a	-0.0019	0.0009	2.094	0.036
actdenqmi	-0.0057	0.0010	-5.90	<0.001
entropyqmi	-0.142	0.021	-6.81	<0.001
intdenhmi	-0.00089	0.0001	-7.86	<0.001
int4whmi	-0.0013	0.0003	-4.90	<0.001
tfreq	-0.00029	0.00008	-3.83	<0.001
-2 log-likelihood ratio 32,769 pseudo-R2 0.30				

The likelihood of a household having any transit trips increases with household size and number of employed members, and declines with income and single-family housing (see Table 6). It also depends on land use diversity; entropy within a quarter mile of a household; design of the environment around a household; intersection density; and percentage of four-way intersections within a half mile of a household's location. Transit-oriented development is virtually defined by these variables. Also one transit service variable affects the likelihood of transit trips: transit frequency.

Table 6. Logistic Regression Model of Log Odds of Any Transit Trips

	coefficient	standard error	t-ratio	p-value
constant	-2.82	0.24	-12.10	<0.001
hhsize	0.157	0.025	6.27	<0.001
hhworkers	0.266	0.051	5.26	<0.001
hhincome	-0.021	0.0032	-6.43	<0.001
sf	-0.791	0.083	-9.47	<0.001
entropyqmi	0.480	0.098	4.89	<0.001
intdenhmi	0.0029	0.0003	9.34	<0.001
int4whmi	0.013	0.0027	4.77	<0.001
tfreq	0.00093	0.0002	5.93	<0.001
-2 log-likelihood ratio 43,942 pseudo-R2 0.51				

The number of household transit trips for the subset of households that use transit increases with household size and declines with household income (see Table 7). The number increases with land use entropy within a quarter mile of a home. It has long been speculated that mixed-use areas would generate more transit trips because of the feasibility of trip chaining on the access trip to transit; that is, stopping along the way to conduct other personal business. Interestingly, controlling for these variables, transit trips do not appear to depend on the transit service variable of transit frequency. It is as if once households make a decision to use transit, their frequency of use is determined only by sociodemographics and the built environment.

Table 7. Negative Binomial Regression Model of Household Transit Trips

	coefficient	standard error	t-ratio	p-value
constant	0.853	0.107	7.96	<0.001

hhsize	0.135	0.015	8.96	<0.001
hhincome	-0.0057	0.0015	-3.79	<0.001
entropyqmi	0.173	0.084	2.05	0.040
-2 log-likelihood ratio 3,215 pseudo-R2 0.15				

In the preceding tables, -2 times log-likelihood ratios are shown as measures of model fit. The fitted model is being compared to the null model with only constant terms. Multiplying by -2 causes the resulting statistic to follow a chi-square distribution. By this statistic, our models fit the data well. Also shown are pseudo-R2s, largely because urban planners are used to dealing with R2s and may want this information. Pseudo-R2s in multilevel 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 R2 does in conventional regression analysis.

Travel Outcome Computations

The models developed in this study give us natural logarithms, log odds, and expected values of variables. Model outputs must be transformed to compute effects. The transformations involve several steps.

For example, the logistic equation in Table 6 allows us to compute the odds of any transit trip by exponentiating the log odds, and then to compute the probability of any transit trip with the formula for the probability in terms of the odds.

Odds of any transit trips = exp (log odds any transit trips)

probability of any transit trips = odds of any transit trips/(1 + odds of any transit trips)

From the negative binomial equation in Table 7, we next compute the expected number of any transit trips for households, again by exponentiating:

number of transit trips (for households with transit trips) = exp (log of expected number of transit trips)

The expected number of transit trips for all households is just the product of the two.

Number of transit trips (for all households) = probability of any transit trips x number of transit trips (for households with transit trips)

We followed the same procedure to predict VMT per household.

Cost Calculations

Transportation costs consist of vehicle costs (household's expenses to own and use private vehicles) and public transit costs (transit fares). Vehicle costs are divided into fixed and variable costs. Fixed or ownership costs are not generally affected by the amount a vehicle is driven. Depreciation, insurance, and registration fees are considered fixed. Variable costs are the incremental costs which increase with vehicle mileage. Fuel is a variable vehicle cost; it is proportional to mileage (Litman, 2009).

We computed vehicle fixed costs based on our household vehicle ownership model and the average cost of car ownership specific to the most popular cars for low-income households and also specific to the states which HUD rental assistance properties are located. Our average car ownership costs are based on a car ownership costs calculator called True Cost to Own®*iii* pricing (TCO®) system developed by Edmunds Inc. The components of TCO® are depreciation, interest on financing, taxes and fees, insurance premiums, fuel, maintenance, repairs and any federal tax credit that may be available. In this paper we used all categories but fuel because we treat fuel as a variable vehicle cost. Since some costs are often categorized as fixed, such as depreciation and insurance, but are not totally fixed and actually increase with vehicle mileage, TCO® assumes that vehicles will be driven 15,000 miles per year. TCO® calculated the costs of driving for cars made after 2009.

TCO® values are specific to states and also to the vehicle's make, model and year. We were interested in costs for the most popular vehicles' model and make for low-income households. Therefore, we created a sample of low-income households from the National Household Travel Database (NHTS) based on the HUD low-income standard and identified the 15 most popular vehicles owned by households in this sample. These vehicles account for more than 34 percent of vehicles owned by low-income households in the NHTS database. The most popular vehicle is the Ford F-series pickup, followed by the Chevrolet Silverado, Toyota Camry and Honda Accord (see Table. 8). We acquired, for each state, the five-year average costs of car ownership for these 15 vehicles for the earliest year (2009) reported by the TCO® since, according to the NHTS database, low-income households tend to buy and own older cars. We then weighted the five-year average costs by the popularity of each make and model for low-income households in the NHTS database to obtain the average vehicle ownership costs for each state. We multiplied this by the predicted number of cars owned by a household to obtain the household's ownership or fixed vehicle costs.

Table 8. Top 15 Popular Automobiles for Low-income Households According to NHTS

Rank	make name	model name	Number of cases
1	FORD	F-Series pickup	3,934
2	CHEVROLET	C, K, R, V-Series pickup/Silverado	2,842
3	TOYOTA	Camry	2,691
4	HONDA	Accord	2,023
5	FORD	Taurus/Taurus X	2,018
6	TOYOTA	Corolla	1,781

7	DODGE	Caravan/Grand Caravan	1,644
8	FORD	Ranger	1,642
9	HONDA	Insight	1,534
10	FORD	Bronco II/Explorer/Explorer Sport	1,272
11	CHEVROLET	Impala/Caprice	1,238
12	DODGE	Ram Pickup	1,194
13	CHEVROLET	Full-size Blazer/Tahoe	1,136
14	JEEP	Cherokee	1,088
15	MERCURY	Marquis/Monterey	990

Second, we computed auto operating costs based on our household VMT model calibrated with data for low-income households from 15 metropolitan regions and gasoline price data specific to the regions in which HUD rental assistance properties are located. As illustrated in Table 9, average gasoline prices vary greatly from region to region. We acquired metropolitan-level average gasoline prices for 2010 from the Oil Price Information Service, inflated them to 2014 dollars and then multiplied the fuel costs per gallon by the predicated VMT to obtain the household's operating or variable vehicle costs.

Table 9. Five Most and Least Expensive Regions for Average Gasoline Price per Gallon (2010)

Most expensive regions ($ per gallon)	
Honolulu, HI	$3.37
Anchorage, AK	$3.35
San Francisco, CA	$3.19
Bakersfield, CA	$3.16
Santa Barbara-Santa Maria, CA	$3.15
Least expensive regions ($ per gallon)	
Springfield, MO	$2.55
Joplin, MO	$2.56
Augusta-Aiken, GA-SC	$2.56
Greenville-Spartanburg, SC	$2.57
Cheyenne, WY	$2.57

Third, we computed transit costs based on our household transit trip model calibrated with data for low-income households from 15 metropolitan regions and average transit fares specific to the regions in which HUD rental assistance properties are located. Transit fare data comes from the National Transit Database. We computed average transit fare for each region by dividing the total transit revenue by total number of unlinked passenger trips for the region. We multiplied the amount of fare per transit trip by the predicted number of transit trips to obtain the household's public transit costs.

To estimate the overall household transportation costs for each property in our sample, we added up the three transportation cost components. Finally, we calculated the percentage of a household's income spent on transportation for households who qualify for HUD rental assistance. That is, those with extremely low, very low, and low incomes (less than 30 percent, 50 percent, and 80 percent of county median household income). As for the household income, we used the income limit for low-income households (80 percent of county median household income). Since the average household size in our 15-region travel survey database for eligible households is 2.39, we used the income limit for a typical household size of three in our transportation affordability calculation.

Results and Discussion

We found that, on average, a typical low-income household that qualified for HUD assistance spends 15 percent of its budget on transportation, which agrees with LAI's recommended 15-percent threshold for transportation affordability. Figure 1 shows the frequency distribution of transportation affordability (percentage of income spent for transportation costs) for 18,030 properties in our sample. Interestingly, properties with the lowest and highest transportation costs both are located in the same state, California. A typical low-income household that qualified for HUD assistance in downtown Los Angeles spends only $1,988 per year on transportation, which is less than 3.5 percent of its budget. The same household in a distant and inaccessible location in Portland, ME, spends $13,950 (28 percent of its budget) on transportation.

Figure 1. Frequency Distribution of Predicted Transportation Affordability (percentage of income spent for transportation costs)

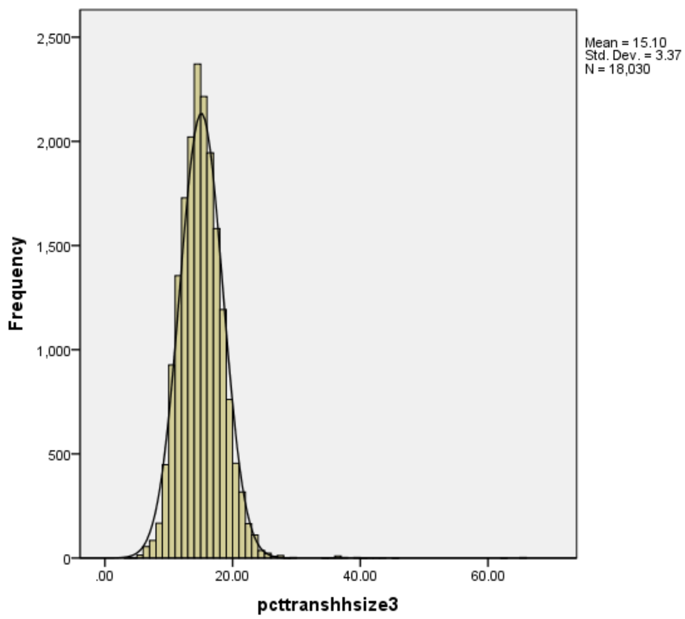
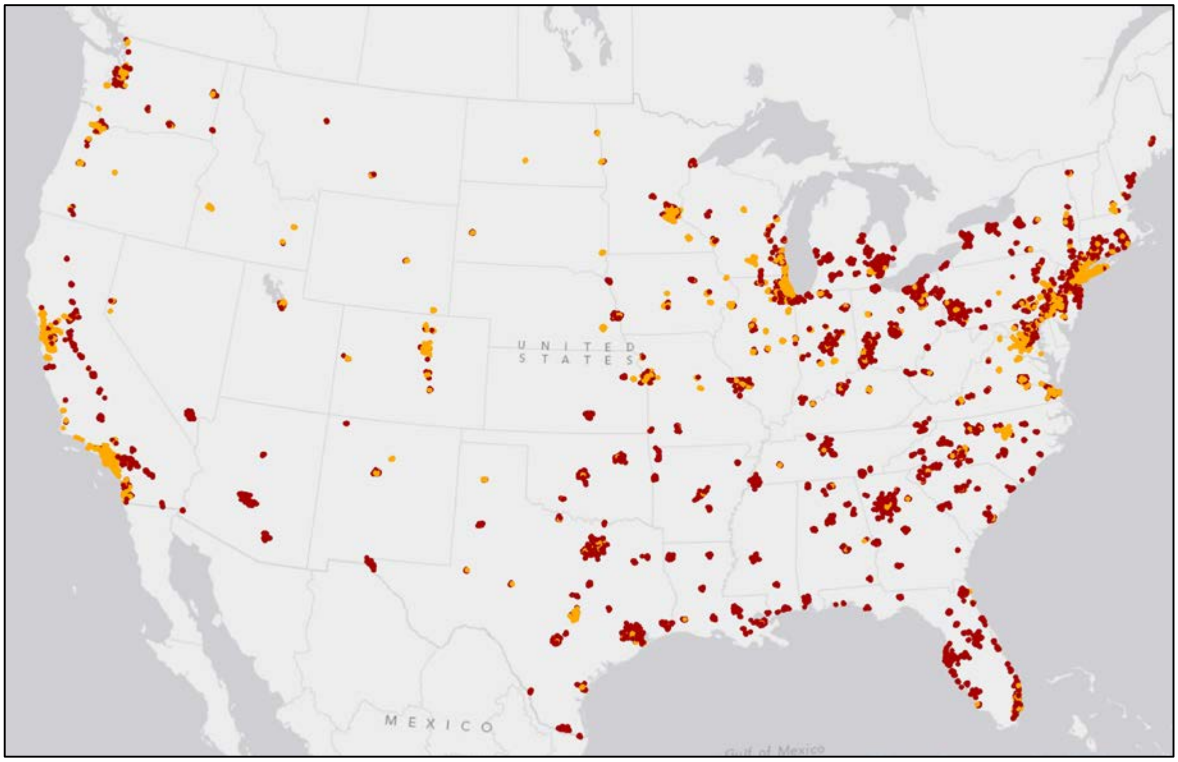


Figure 2 shows the variation of transportation costs for HUD multifamily properties in U.S. metropolitan areas. The red color shows unaffordable properties where a typical low-income household spends more than 15 percent of its budget on transportation. The orange color represents affordable properties where transportation costs are less than 15 percent for typical low-income households. As shown in the figure, cities with good public transit service such as Portland, OR, have, in general, lower transportation costs, particularly in the downtown area. Properties in auto-oriented cities such as Las Vegas, NV, and Orlando, FL, have high transportation costs, even housing units in downtown areas.

Figure 2. Transportation Affordability for HUD Multifamily Properties in U.S. Metropolitan Areas (The red color shows unaffordable properties and the orange color represents affordable properties where transportation costs are less than 15 percent for typical low-income households.)



Figures 3 and 4 show two compact (New York and San Francisco) and two sprawling metropolitan areas (Phoenix and Detroit-Warren). As shown in the figures, transportation costs increase with distance from downtown. As one would expect, suburban areas have much higher transportation costs than properties in central cities. These results are in line with the LAI transportation costs calculator, which shows that a typical household in an accessible central location spends significantly less on transportation than the same household in a distant area (Jain & Brecher, 2014).

We found that, out of 18,300 properties, households in 8,857 properties (48 percent of all properties in the sample) spend, on average, more than 15 percent of their income on transportation costs. In other words, transportation is unaffordable by the CNT definition for low-income households at these properties. Pittsburgh, PA, has the highest number of unaffordable properties in terms of transportation, followed by Houston, TX; Cleveland, OH; Phoenix, AZ; and Atlanta, GA (see Table 10). Not surprisingly, these and other metropolitan areas in Table 10 are found to be among the most sprawling MSAs in the country by previous studies (Ewing & Hamidi, 2014). Accordingly, the more compact metropolitan areas are found to have the highest number of affordable housing supplied by HUD (See Table 11). This is not to suggest, of course, that rental assistance be limited to compact metropolitan areas, but rather to suggest that channeling subsidies into accessible neighborhoods is even more important in sprawling metropolitan areas than compact ones.

Figure 3. Transportation Affordability for HUD Multifamily Properties in New York (left) and Chicago (right)

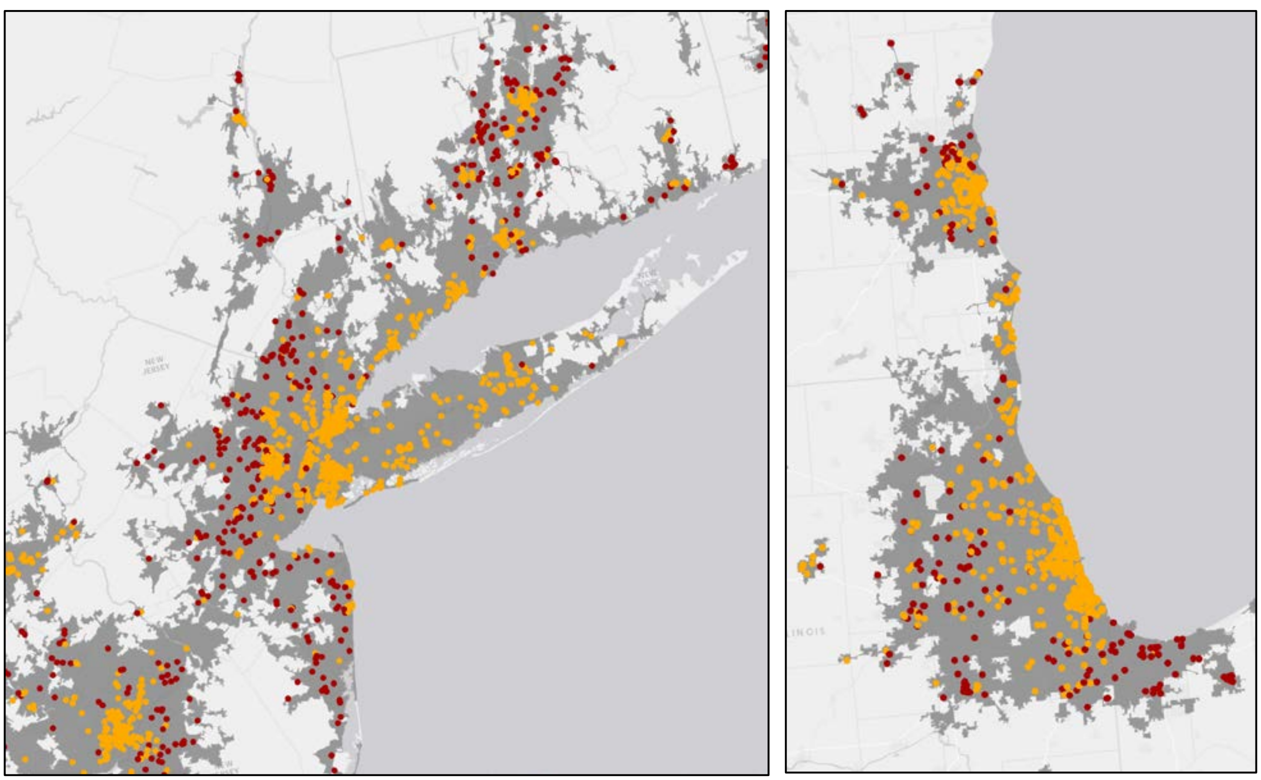


Figure 4. Transportation Affordability for HUD Multifamily Properties in Atlanta (left) and Detroit-Warren (right)

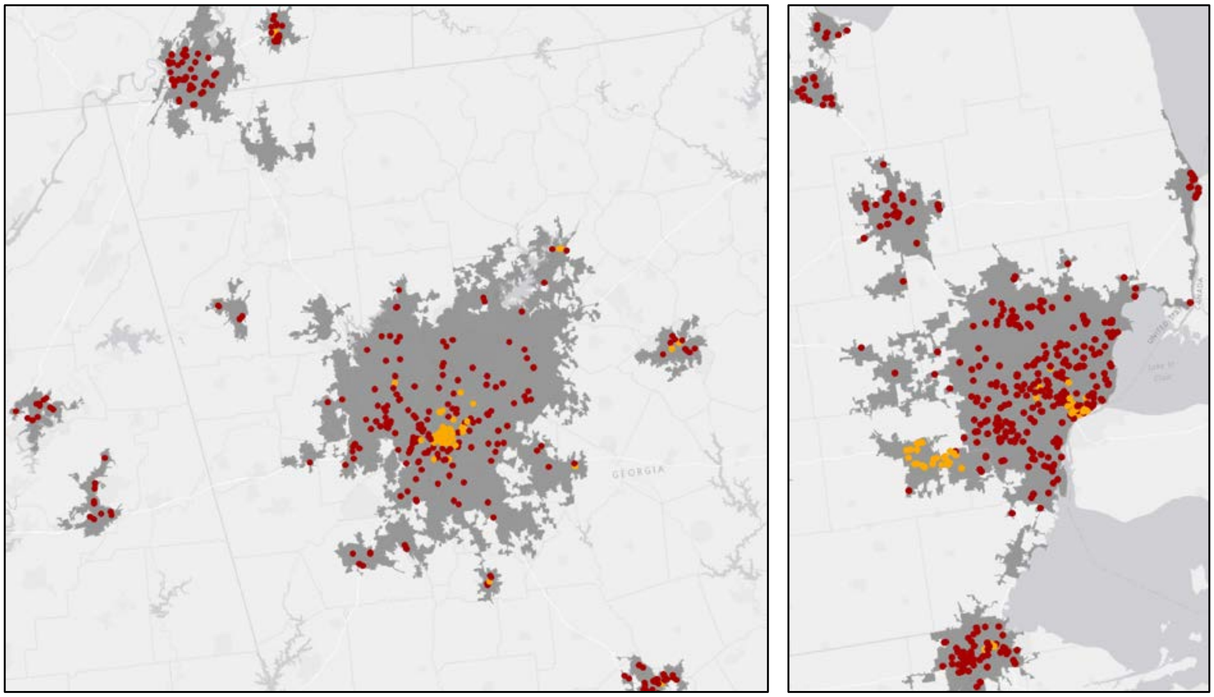


Table 10: Fifteen Metropolitan Areas with Highest Number of Unaffordable HUD Assistance Properties in Terms of Transportation Costs

MSA name	Number of affordable properties	Total number of properties	% of properties affordable
Columbus, OH	82	217	37.79
Cincinnati-Middletown, OH-KY-IN	90	260	34.62
Cleveland-Elyria-Mentor, OH	75	262	28.63
Dallas-Plano-Irving, TX	60	212	28.3
Atlanta-Sandy Springs-Marietta, GA	63	246	25.61
Detroit-Livonia-Dearborn, MI	48	208	23.08
Indianapolis-Carmel, IN	43	195	22.05
Houston-Sugar Land-Baytown, TX	46	240	19.17
Pittsburgh, PA	57	321	17.76
Buffalo-Niagara Falls, NY	24	145	16.55
San Antonio-New Braunfels, TX	18	133	13.53

Riverside-San Bernardino-Ontario, CA	11	129	8.53
Tampa-St. Petersburg-Clearwater, FL	5	182	2.75
Phoenix-Mesa-Glendale, AZ	5	191	2.62
Warren-Troy-Farmington Hills, MI	1	147	0.68

Table 11: Fifteen Metropolitan Areas with Highest Number of Affordable HUD Assistance Properties in Terms of Transportation Costs

MSA name	Number of affordable properties	Total number of properties	% of properties affordable
San Francisco-San Mateo-Redwood City, CA	156	156	100
Los Angeles-Long Beach-Glendale, CA	763	787	96.95
Denver-Aurora-Broomfield, CO	220	233	94.42
New York-White Plains-Wayne, NY-NJ	686	756	90.74
Portland-Vancouver-Hillsboro, OR-WA	197	220	89.55
Minneapolis-St. Paul-Bloomington, MN-WI	376	423	88.89
Oakland-Fremont-Hayward, CA	160	181	88.4
Washington-Arlington-Alexandria, DC-VA	311	353	88.1
Chicago-Joliet-Naperville, IL	596	693	86
Kansas City, MO-KS	164	208	78.85
Philadelphia, PA	205	261	78.54
Milwaukee-Waukesha-West Allis, WI	151	205	73.66
Baltimore-Towson, MD	188	281	66.9
Providence-New Bedford-Fall River, RI-MA	161	267	60.3
St. Louis, MO-IL	168	281	59.79

This study has limitations. Although we started with a national sample of 34,000 HUD rental assistance properties, due to lack of built environment and cost data availability, we were only able to estimate transportation costs for 18,300 properties. These properties are located in both metropolitan areas and urbanized areas. Also, we ultimately dropped properties in Massachusetts from our sample due to the lack of local employment dynamics data, a key data element for estimating transportation models.

Another limitation has to do with the transportation costs calculation. Our average fare variable is computed by dividing total fare revenue of transit agencies in urbanized areas by total unlinked passenger trips. We had no control over the mode of transit. Some modes such as commuter rail and ferryboats are more expensive, and perhaps less popular, than bus, light rail and heavy rail transit. This might be the reason for finding outliers in our sample is terms of average transit fare. Still, we believe that this is the best transit fare data available at the national scale and is more reliable than average base fare data from the American Public Transportation Association's Public Transportation Fare Database. The reason is simple: The Public Transportation Fare Database does not account for transit passes and other forms of transit fare subsidies that apply to many transit users.

Conclusions

This study is the first attempt to evaluate the affordability for HUD rental assistance program units. The high quality of this research results from its unprecedented assemblage of household travel and vehicle ownership data for 15 diverse metropolitan regions; its unprecedented linkage of these data to built environmental and transit data for buffers around individual households; its unprecedented use of multilevel modeling to estimate relationships between the built environment, travel outcomes and transportation costs; and its unprecedented application of resulting models to housing affordability assessments for low-income households living in HUD-subsidized rental units. Finally, our models are specific to low-income households, a group that has received little attention in the travel literature.

While the 15-region household travel dataset is proprietary, having been collected and processed over several years, the resulting models (Tables 3-7) are available to anyone who might wish to duplicate our results for a specific HUD property or study transportation affordability generally for low-income households. This evidence-based research suggests that HUD rental assistance programs, when they subsidize housing in sprawling auto-dependent areas, are not holistically affordable. It also suggests that HUD can provide more affordable units to low-income families by directing subsidies to better (more compact, walkable and transit-served) locations.

References

Abt Associates Inc. (2010). A Methodological Review of the Center for Neighborhood Technology's Housing + Transportation Affordability Index.

Badoe, D. A. & Miller, E. J. (2000). Transportation–land-use interaction: Empirical findings in North America, and the implications for modeling. *Transportation Research D*, *5*(4), 235-263.

Belsky, E. S., Goodman, J., & Drew, R. (2005, June). Measuring the nation's rental housing affordability problems. *The Joint Center for Housing Studies*, Harvard University. http://www.jchs.harvard.edu/publications/rental/rd051_measuring_rental_affordability05.pdf

Bogdon, A. S., & Can, A. (1997). Indicators of local housing affordability: Comparative and spatial approaches. *Real Estate Economics*, *25*(1), 43-60.

Brownstone, D. (2008). Key relationships between the built environment and VMT. *Transportation Research Board*, 7.

Cao, X., Mokhtarian, P. L., & Handy, S. L. (2009). Examining the impacts of residential self-selection on
travel behaviour: A focus on empirical findings. *Transport Reviews*, *29*(3), 359-395.

Center for Neighborhood Technology and Surface Transportation Policy Project (2005). *Driven to Spend:Pumping Dollars out of Our Households and Communities*, Washington, D.C.

Center for Transit-Oriented Development and Center for Neighborhood Technology, (2006) *The Affordability Index: A New Tool for Measuring the True Affordability of a Housing Choice*. Brookings Institution, Washington, D.C.

Cervero, R., & Kockelman, K. (1997). Travel Demand and the 3Ds: Density, Diversity, and Design.*Transportation Research Part D: Transport and Environment*, *2*(3), 199-219.

Cervero, R. (2003). The built environment and travel: Evidence from the United States. *European Journalof Transport and Infrastructure Research*, *3*(2), 119-137.

Chatman, D. & Voorhoeve, N. (2010). The Transportation-Credit Mortgage: A Post-Mortem**.** *Housing Policy Debate.* 20(3), 355-382.

Combs, E. R., Combs, B. A., & Ziebarth, A. C. (1994). Housing affordability: A comparison of measures. *Consumer Interests Annual*, *41*, 188-194.

Crane, R. (2000). The influence of urban form on travel: An interpretive review. *Journal of Planning Literature*, *15*(1), 3-23.

Dietz, R. (1993). A Joint Model of Residential and Employment Location in Urban Areas. *Journal of Urban Economics*, Vol. 44, pp. 197–215

Econsult Corporation and Penn Institute for Urban Research, (2012). Review of the Center for Neighborhood Technology's Housing and Transportation Affordability Index (H+T® Affordability Index).

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment. *Transportation Research Record,, 1780*, 87-114.

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment:A Meta-Analysis. *Journal of the American Planning Association*, *76*(3), 265-296.

Ewing, R. & Hamidi, S. (2014) Measuring Urban Sprawl and Validating Sprawl Measures, *Technical Report Prepared for the National Cancer Institute, National Institutes of Health, the Ford Foundation, and Smart Growth America*. http://gis.cancer.gov/tools/urban-sprawl (Accessed January 5, 2015).

Handy, S. L. (2005). *Critical assessment of the literature on the relationships among transportation, land use, and physical activity. (Special Report 282: Does the built environment influence physical activity?Examining the evidence*.) Washington, DC: Transportation Research Board and Institute of MedicineCommittee on Physical Activity, Health, Transportation, and Land Use.

Greene WH (2012) *Econometric Analysis*. New York: Prentice Hall

Heath, G. W., Brownson, R. C., Kruger, J., Miles, R., Powell, K. E., Ramsey, L. T., & the Task Force on Community Preventive Services. (2006). The effectiveness of urban design and land use and transport policies and practices to increase physical activity: A systematic review. *Journal of Physical Activity and Health*, *3*(1), 55-76.

Hilbe JM (2011) *Negative Binomial Regression.* Cambridge: Cambridge University Press.

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D., & Haas, P. (2002). Location efficiency: Neighborhood and socio-economic characteristics determine auto ownership and use-studies in Chicago, Los Angeles and San Francisco. *Transportation Planning and Technology*, *25*(1), 1-27.

Jain R. & Brecher, C. (2014). Housing Affordability Versus Location Affordability. Prepared for Citizens Budget Commission.
http://www.cbcny.org/sites/default/files/REPORT_HousingAffordabilityVsLocation_08122014.pdf

Linneman, P. D., & Megbolugbe, I. F. (1992). Housing affordability: Myth or reality? *Urban Studies*, *29*(3), 369-392.

Lipman, B. J. (2006). A Heavy Load. The Combined Housing and Transportation Burdens of Working Families. Technical report prepared for Center for Housing Policy, Washington, D.C.

Litman, T. (2009). Transportation cost and benefit analysis. *Victoria Transport Policy Institute*, 1-19.

McMillan, T. E. (2005). Urban form and a child's trip to school: The current literature and a framework for future research. *Journal of Planning Literature, 19*(4), 440-456.

McMillan T. E. (2007). The relative influence of urban form on a child's travel mode to school. *Transportation Research A*, *41*(1), 69-79.

Pont, K**.**, Ziviani, J., Wadley, D., Bennett, S., & Abbott, R. (2009). Environmental correlates of children's active transportation: A systematic literature review. *Health & Place*, *15*(3), 827-840**.**

O'Dell, W., Smith, M. T., & White, D. (2004). Weaknesses in current measures of housing needs. *Housing and Society*, *31*(1), 29-40.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Sage Publication.

Raudenbush SW, Bryk AS, Cheong YF, et al. (2010) *HLM 7: Hierarchical Linear and Nonlinear Modeling*. Chicago, IL: Scientific Software International.

Robinson, M., Scobie, G. M., & Hallinan, B. (2006). Affordability of housing: concepts, measurement and evidence. *MONTH*, *6*, 04.

Saelens, B. E., Sallis, J. F., & Frank, L. D. (2003). Environmental correlates of walking and cycling: Findings from the transportation, urban design, and planning literatures. *Annals of Behavioral Medicine*, *25*(2), 80-91.

Stead, D., & Marshall, S. (2001). The relationships between urban form and travel patterns. An international review and evaluation. *European Journal of Transport and Infrastructure Research, 1*(2), 113-141.

Tegeler, Phillip (2011). Transportation and Fair Housing Part 1: We Need a Better Measure of Opportunity. Shelterforce: The Journal of Affordable Housing and Community Building.

U.S. Department of Housing and Urban Development. (2006, January). *Housing impact analysis.* Washington, DC: U.S. Government Printing Office.

Yip, N. M., & Lau, K. Y. (2002). Setting rent with reference to tenants' affordability: Public housing rent policy in Hong Kong. *Journal of Housing and the Built Environment*, *17*(4), 409-418.

Appendix A

Percentage of HUD affordable properties in U.S metropolitan areas

#	MSA name	# affordable	Total properties	% affordable
1	Akron, OH Metro Area	34	89	38.2
2	Albany-Schenectady-Troy, NY Metro Area	47	77	61.0
3	Albany, GA Metro Area	0	16	0.0
4	Albuquerque, NM Metro Area	33	60	55.0
5	Alexandria, LA Metro Area	0	14	0.0
6	Allentown-Bethlehem-Easton, PA-NJ Metro Area	41	46	89.1
7	Altoona, PA Metro Area	4	16	25.0
8	Amarillo, TX Metro Area	12	14	85.7
9	Ames, IA Metro Area	4	4	100.0
10	Anderson, IN Metro Area	8	19	42.1
11	Anderson, SC Metro Area	3	12	25.0
12	Ann Arbor, MI Metro Area	29	31	93.6
13	Anniston-Oxford, AL Metro Area	0	10	0.0
14	Appleton, WI Metro Area	6	7	85.7
15	Asheville, NC Metro Area	3	38	7.9
16	Athens-Clarke County, GA Metro Area	3	13	23.1
17	Atlanta-Sandy Springs-Marietta, GA Metro Area	63	246	25.6
18	Auburn-Opelika, AL Metro Area	7	11	63.6
19	Augusta-Richmond County, GA-SC Metro Area	3	45	6.7
20	Austin-Round Rock-San Marcos, TX Metro Area	67	72	93.1
21	Bakersfield-Delano, CA Metro Area	0	22	0.0
22	Baltimore-Towson, MD Metro Area	188	281	66.9
23	Bangor, ME Metro Area	6	23	26.1
24	Baton Rouge, LA Metro Area	4	56	7.1
25	Battle Creek, MI Metro Area	0	10	0.0
26	Bay City, MI Metro Area	0	7	0.0
27	Beaumont-Port Arthur, TX Metro Area	1	39	2.6
28	Bellingham, WA Metro Area	9	11	81.8
29	Bend, OR Metro Area	13	13	100.0
30	Bethesda-Rockville-Frederick, MD Metro Division	125	141	88.7
31	Billings, MT Metro Area	13	17	76.5
32	Binghamton, NY Metro Area	4	13	30.8
33	Birmingham-Hoover, AL Metro Area	14	86	16.3
34	Bismarck, ND Metro Area	5	5	100.0
35	Blacksburg-Christiansburg-Radford, VA Metro Area	12	21	57.1
36	Bloomington-Normal, IL Metro Area	11	11	100.0

37	Bloomington, IN Metro Area	13	14	92.9
38	Boise City-Nampa, ID Metro Area	31	32	96.9
39	Bremerton-Silverdale, WA Metro Area	1	27	3.7
40	Bridgeport-Stamford-Norwalk, CT Metro Area	77	81	95.1
41	Brownsville-Harlingen, TX Metro Area	0	11	0.0
42	Buffalo-Niagara Falls, NY Metro Area	24	145	16.6
43	Burlington-South Burlington, VT Metro Area	23	27	85.2
44	Camden, NJ Metro Division	35	70	50.0
45	Canton-Massillon, OH Metro Area	18	34	52.9
46	Cape Coral-Fort Myers, FL Metro Area	0	33	0.0
47	Carson City, NV Metro Area	3	3	100.0
48	Casper, WY Metro Area	8	10	80.0
49	Cedar Rapids, IA Metro Area	18	19	94.7
50	Champaign-Urbana, IL Metro Area	20	20	100.0
51	Charleston-North Charleston-Summerville, SC Metro Area	9	44	20.5
52	Charleston, WV Metro Area	5	22	22.7
53	Charlotte-Gastonia-Rock Hill, NC-SC Metro Area	42	137	30.7
54	Charlottesville, VA Metro Area	18	18	100.0
55	Chattanooga, TN-GA Metro Area	0	48	0.0
56	Cheyenne, WY Metro Area	11	11	100.0
57	Chicago-Joliet-Naperville, IL Metro Division	596	693	86.0
58	Chico, CA Metro Area	0	15	0.0
59	Cincinnati-Middletown, OH-KY-IN Metro Area	90	260	34.6
60	Clarksville, TN-KY Metro Area	0	12	0.0
61	Cleveland-Elyria-Mentor, OH Metro Area	75	262	28.6
62	Cleveland, TN Metro Area	2	15	13.3
63	College Station-Bryan, TX Metro Area	0	12	0.0
64	Colorado Springs, CO Metro Area	25	34	73.5
65	Columbia, MO Metro Area	7	10	70.0
66	Columbia, SC Metro Area	10	58	17.2
67	Columbus, GA-AL Metro Area	4	25	16.0
68	Columbus, IN Metro Area	19	19	100.0
69	Columbus, OH Metro Area	82	204	40.2
70	Corpus Christi, TX Metro Area	9	34	26.5
71	Crestview-Fort Walton Beach-Destin, FL Metro Area	0	6	0.0
72	Cumberland, MD-WV Metro Area	3	7	42.9
73	Dallas-Plano-Irving, TX Metro Division	60	212	28.3
74	Danville, IL Metro Area	8	13	61.5
75	Davenport-Moline-Rock Island, IA-IL Metro Area	36	45	80.0
76	Dayton, OH Metro Area	26	124	21.0
77	Decatur, AL Metro Area	0	9	0.0

78	Decatur, IL Metro Area	14	17	82.4
79	Deltona-Daytona Beach-Ormond Beach, FL Metro Area	0	20	0.0
80	Denver-Aurora-Broomfield, CO Metro Area	220	233	94.4
81	Des Moines-West Des Moines, IA Metro Area	33	39	84.6
82	Detroit-Livonia-Dearborn, MI Metro Division	48	208	23.1
83	Dothan, AL Metro Area	1	10	10.0
84	Dubuque, IA Metro Area	5	6	83.3
85	Duluth, MN-WI Metro Area	18	37	48.7
86	Durham-Chapel Hill, NC Metro Area	21	43	48.8
87	Eau Claire, WI Metro Area	17	25	68.0
88	Edison-New Brunswick, NJ Metro Division	31	118	26.3
89	El Centro, CA Metro Area	0	13	0.0
90	El Paso, TX Metro Area	2	40	5.0
91	Elkhart-Goshen, IN Metro Area	0	18	0.0
92	Elmira, NY Metro Area	0	9	0.0
93	Erie, PA Metro Area	5	42	11.9
94	Eugene-Springfield, OR Metro Area	34	37	91.9
95	Evansville, IN-KY Metro Area	21	44	47.7
96	Fargo, ND-MN Metro Area	15	18	83.3
97	Farmington, NM Metro Area	0	6	0.0
98	Fayetteville-Springdale-Rogers, AR-MO Metro Area	1	24	4.2
99	Fayetteville, NC Metro Area	0	34	0.0
100	Flagstaff, AZ Metro Area	0	7	0.0
101	Flint, MI Metro Area	0	33	0.0
102	Florence-Muscle Shoals, AL Metro Area	2	20	10.0
103	Fond du Lac, WI Metro Area	3	7	42.9
104	Fort Collins-Loveland, CO Metro Area	21	23	91.3
105	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL Metro Division	24	56	42.9
106	Fort Smith, AR-OK Metro Area	0	15	0.0
107	Fort Wayne, IN Metro Area	14	34	41.2
108	Fort Worth-Arlington, TX Metro Division	15	95	15.8
109	Fresno, CA Metro Area	1	30	3.3
110	Gadsden, AL Metro Area	0	13	0.0
111	Gainesville, FL Metro Area	1	24	4.2
112	Gainesville, GA Metro Area	3	6	50.0
113	Gary, IN Metro Division	2	61	3.3
114	Glens Falls, NY Metro Area	1	3	33.3
115	Goldsboro, NC Metro Area	0	8	0.0
116	Grand Forks, ND-MN Metro Area	17	18	94.4
117	Grand Junction, CO Metro Area	15	18	83.3

118	Grand Rapids-Wyoming, MI Metro Area	5	51	9.8
119	Great Falls, MT Metro Area	11	14	78.6
120	Greeley, CO Metro Area	12	16	75.0
121	Green Bay, WI Metro Area	12	13	92.3
122	Greensboro-High Point, NC Metro Area	1	56	1.8
123	Greenville-Mauldin-Easley, SC Metro Area	8	46	17.4
124	Greenville, NC Metro Area	5	11	45.5
125	Gulfport-Biloxi, MS Metro Area	0	21	0.0
126	Harrisburg-Carlisle, PA Metro Area	13	30	43.3
127	Harrisonburg, VA Metro Area	1	5	20.0
128	Hartford-West Hartford-East Hartford, CT Metro Area	80	161	49.7
129	Hattiesburg, MS Metro Area	0	18	0.0
130	Hickory-Lenoir-Morganton, NC Metro Area	0	33	0.0
131	Hinesville-Fort Stewart, GA Metro Area	0	7	0.0
132	Holland-Grand Haven, MI Metro Area	4	15	26.7
133	Houma-Bayou Cane-Thibodaux, LA Metro Area	0	12	0.0
134	Houston-Sugar Land-Baytown, TX Metro Area	46	240	19.2
135	Huntington-Ashland, WV-KY-OH Metro Area	0	36	0.0
136	Huntsville, AL Metro Area	12	19	63.2
137	Idaho Falls, ID Metro Area	9	9	100.0
138	Indianapolis-Carmel, IN Metro Area	43	195	22.1
139	Iowa City, IA Metro Area	8	8	100.0
140	Ithaca, NY Metro Area	3	5	60.0
141	Jackson, MI Metro Area	7	18	38.9
142	Jackson, MS Metro Area	1	56	1.8
143	Jackson, TN Metro Area	2	11	18.2
144	Jacksonville, FL Metro Area	15	96	15.6
145	Jacksonville, NC Metro Area	0	9	0.0
146	Janesville, WI Metro Area	7	14	50.0
147	Jefferson City, MO Metro Area	11	11	100.0
148	Johnson City, TN Metro Area	2	29	6.9
149	Johnstown, PA Metro Area	2	7	28.6
150	Jonesboro, AR Metro Area	0	13	0.0
151	Joplin, MO Metro Area	0	11	0.0
152	Kalamazoo-Portage, MI Metro Area	3	41	7.3
153	Kankakee-Bradley, IL Metro Area	13	13	100.0
154	Kansas City, MO-KS Metro Area	164	208	78.9
155	Kennewick-Pasco-Richland, WA Metro Area	9	24	37.5
156	Killeen-Temple-Fort Hood, TX Metro Area	0	7	0.0
157	Kingsport-Bristol-Bristol, TN-VA Metro Area	2	28	7.1
158	Kingston, NY Metro Area	7	14	50.0

159	Kokomo, IN Metro Area	8	10	80.0
160	La Crosse, WI-MN Metro Area	8	12	66.7
161	Lafayette, IN Metro Area	21	23	91.3
162	Lafayette, LA Metro Area	0	23	0.0
163	Lake Charles, LA Metro Area	4	17	23.5
164	Lake County-Kenosha County, IL-WI Metro Division	51	58	87.9
165	Lakeland-Winter Haven, FL Metro Area	1	16	6.3
166	Lancaster, PA Metro Area	14	19	73.7
167	Lansing-East Lansing, MI Metro Area	8	39	20.5
168	Laredo, TX Metro Area	0	10	0.0
169	Las Vegas-Paradise, NV Metro Area	0	67	0.0
170	Lawrence, KS Metro Area	8	8	100.0
171	Lawton, OK Metro Area	3	13	23.1
172	Lebanon, PA Metro Area	1	6	16.7
173	Lewiston, ID-WA Metro Area	7	16	43.8
174	Lexington-Fayette, KY Metro Area	30	49	61.2
175	Lima, OH Metro Area	18	20	90.0
176	Lincoln, NE Metro Area	31	31	100.0
177	Little Rock-North Little Rock-Conway, AR Metro Area	13	74	17.6
178	Longview, TX Metro Area	1	16	6.3
179	Longview, WA Metro Area	7	7	100.0
180	Los Angeles-Long Beach-Glendale, CA Metro Division	763	787	97.0
181	Louisville/Jefferson County, KY-IN Metro Area	48	143	33.6
182	Lubbock, TX Metro Area	0	15	0.0
183	Lynchburg, VA Metro Area	6	26	23.1
184	Macon, GA Metro Area	1	30	3.3
185	Madera-Chowchilla, CA Metro Area	1	4	25.0
186	Madison, WI Metro Area	56	56	100.0
187	Manchester-Nashua, NH Metro Area	46	48	95.8
188	Mansfield, OH Metro Area	4	16	25.0
189	McAllen-Edinburg-Mission, TX Metro Area	0	33	0.0
190	Medford, OR Metro Area	8	21	38.1
191	Memphis, TN-MS-AR Metro Area	1	111	0.9
192	Merced, CA Metro Area	0	10	0.0
193	Miami-Miami Beach-Kendall, FL Metro Division	62	158	39.2
194	Michigan City-La Porte, IN Metro Area	0	14	0.0
195	Milwaukee-Waukesha-West Allis, WI Metro Area	151	205	73.7
196	Minneapolis-St. Paul-Bloomington, MN-WI Metro Area	376	423	88.9
197	Mobile, AL Metro Area	1	67	1.5
198	Modesto, CA Metro Area	1	20	5.0
199	Monroe, LA Metro Area	1	20	5.0

200	Monroe, MI Metro Area	0	2	0.0
201	Montgomery, AL Metro Area	7	33	21.2
202	Mount Vernon-Anacortes, WA Metro Area	0	3	0.0
203	Muncie, IN Metro Area	8	13	61.5
204	Muskegon-Norton Shores, MI Metro Area	2	19	10.5
205	Myrtle Beach-North Myrtle Beach-Conway, SC Metro Area	0	6	0.0
206	Naples-Marco Island, FL Metro Area	3	6	50.0
207	Nashville-Davidson--Murfreesboro--Franklin, TN Metro Area	11	96	11.5
208	Nassau-Suffolk, NY Metro Division	107	109	98.2
209	New Haven-Milford, CT Metro Area	86	127	67.7
210	New Orleans-Metairie-Kenner, LA Metro Area	18	82	22.0
211	New York-White Plains-Wayne, NY-NJ Metro Division	686	756	90.7
212	Newark-Union, NJ-PA Metro Division	144	204	70.6
213	North Port-Bradenton-Sarasota, FL Metro Area	5	32	15.6
214	Norwich-New London, CT Metro Area	13	29	44.8
215	Oakland-Fremont-Hayward, CA Metro Division	160	181	88.4
216	Ocala, FL Metro Area	0	15	0.0
217	Odessa, TX Metro Area	4	8	50.0
218	Oklahoma City, OK Metro Area	7	58	12.1
219	Olympia, WA Metro Area	9	9	100.0
220	Omaha-Council Bluffs, NE-IA Metro Area	50	88	56.8
221	Orlando-Kissimmee-Sanford, FL Metro Area	1	76	1.3
222	Oshkosh-Neenah, WI Metro Area	6	27	22.2
223	Owensboro, KY Metro Area	6	11	54.6
224	Oxnard-Thousand Oaks-Ventura, CA Metro Area	15	17	88.2
225	Palm Bay-Melbourne-Titusville, FL Metro Area	0	29	0.0
226	Panama City-Lynn Haven-Panama City Beach, FL Metro Area	1	15	6.7
227	Parkersburg-Marietta-Vienna, WV-OH Metro Area	1	14	7.1
228	Pensacola-Ferry Pass-Brent, FL Metro Area	0	1	0.0
229	Peoria, IL Metro Area	26	50	52.0
230	Philadelphia, PA Metro Division	205	261	78.5
231	Phoenix-Mesa-Glendale, AZ Metro Area	5	191	2.6
232	Pine Bluff, AR Metro Area	0	14	0.0
233	Pittsburgh, PA Metro Area	57	321	17.8
234	Pocatello, ID Metro Area	9	11	81.8
235	Port St. Lucie, FL Metro Area	0	9	0.0
236	Portland-South Portland-Biddeford, ME Metro Area	1	80	1.3
237	Portland-Vancouver-Hillsboro, OR-WA Metro Area	197	220	89.6

238	Poughkeepsie-Newburgh-Middletown, NY Metro Area	3	22	13.6
239	Providence-New Bedford-Fall River, RI-MA Metro Area	161	267	60.3
240	Pueblo, CO Metro Area	7	13	53.9
241	Punta Gorda, FL Metro Area	0	8	0.0
242	Racine, WI Metro Area	22	23	95.7
243	Raleigh-Cary, NC Metro Area	50	51	98.0
244	Rapid City, SD Metro Area	5	20	25.0
245	Reading, PA Metro Area	9	11	81.8
246	Redding, CA Metro Area	2	12	16.7
247	Reno-Sparks, NV Metro Area	16	18	88.9
248	Richmond, VA Metro Area	71	101	70.3
249	Riverside-San Bernardino-Ontario, CA Metro Area	11	129	8.5
250	Roanoke, VA Metro Area	9	26	34.6
251	Rochester, MN Metro Area	18	18	100.0
252	Rochester, NY Metro Area	34	78	43.6
253	Rockford, IL Metro Area	22	41	53.7
254	Rocky Mount, NC Metro Area	0	18	0.0
255	Rome, GA Metro Area	0	5	0.0
256	Sacramento--Arden-Arcade--Roseville, CA Metro Area	68	117	58.1
257	Saginaw-Saginaw Township North, MI Metro Area	0	15	0.0
258	Salem, OR Metro Area	18	27	66.7
259	Salinas, CA Metro Area	0	18	0.0
260	Salt Lake City, UT Metro Area	66	75	88.0
261	San Angelo, TX Metro Area	5	10	50.0
262	San Antonio-New Braunfels, TX Metro Area	18	133	13.5
263	San Diego-Carlsbad-San Marcos, CA Metro Area	117	145	80.7
264	San Francisco-San Mateo-Redwood City, CA Metro Division	156	156	100.0
265	San Jose-Sunnyvale-Santa Clara, CA Metro Area	94	94	100.0
266	San Luis Obispo-Paso Robles, CA Metro Area	7	8	87.5
267	Santa Ana-Anaheim-Irvine, CA Metro Division	83	83	100.0
268	Santa Barbara-Santa Maria-Goleta, CA Metro Area	14	15	93.3
269	Santa Cruz-Watsonville, CA Metro Area	20	20	100.0
270	Santa Fe, NM Metro Area	16	16	100.0
271	Santa Rosa-Petaluma, CA Metro Area	34	35	97.1
272	Scranton--Wilkes-Barre, PA Metro Area	13	47	27.7
273	Seattle-Bellevue-Everett, WA Metro Division	134	186	72.0
274	Sheboygan, WI Metro Area	4	9	44.4
275	Sherman-Denison, TX Metro Area	0	5	0.0
276	Shreveport-Bossier City, LA Metro Area	0	58	0.0

277	Sioux City, IA-NE-SD Metro Area	12	24	50.0
278	Sioux Falls, SD Metro Area	31	31	100.0
279	South Bend-Mishawaka, IN-MI Metro Area	17	29	58.6
280	Spartanburg, SC Metro Area	0	21	0.0
281	Spokane, WA Metro Area	27	54	50.0
282	Springfield, IL Metro Area	13	16	81.3
283	Springfield, MO Metro Area	4	25	16.0
284	Springfield, OH Metro Area	6	13	46.2
285	St. Cloud, MN Metro Area	16	21	76.2
286	St. Joseph, MO-KS Metro Area	10	14	71.4
287	St. Louis, MO-IL Metro Area	168	281	59.8
288	State College, PA Metro Area	1	1	100.0
289	Stockton, CA Metro Area	3	22	13.6
290	Sumter, SC Metro Area	0	16	0.0
291	Syracuse, NY Metro Area	13	61	21.3
292	Tacoma, WA Metro Division	10	48	20.8
293	Tallahassee, FL Metro Area	4	19	21.1
294	Tampa-St. Petersburg-Clearwater, FL Metro Area	5	182	2.8
295	Terre Haute, IN Metro Area	5	12	41.7
296	Toledo, OH Metro Area	12	89	13.5
297	Topeka, KS Metro Area	8	25	32.0
298	Trenton-Ewing, NJ Metro Area	2	7	28.6
299	Tucson, AZ Metro Area	3	56	5.4
300	Tulsa, OK Metro Area	3	58	5.2
301	Tuscaloosa, AL Metro Area	0	19	0.0
302	Tyler, TX Metro Area	1	13	7.7
303	Utica-Rome, NY Metro Area	8	25	32.0
304	Vallejo-Fairfield, CA Metro Area	14	19	73.7
305	Vineland-Millville-Bridgeton, NJ Metro Area	2	8	25.0
306	Virginia Beach-Norfolk-Newport News, VA-NC Metro Area	121	155	78.1
307	Visalia-Porterville, CA Metro Area	2	10	20.0
308	Waco, TX Metro Area	1	14	7.1
309	Warren-Troy-Farmington Hills, MI Metro Division	1	147	0.7
310	Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Division	311	353	88.1
311	Waterloo-Cedar Falls, IA Metro Area	3	18	16.7
312	Wausau, WI Metro Area	7	7	100.0
313	West Palm Beach-Boca Raton-Boynton Beach, FL Metro Division	11	41	26.8
314	Wheeling, WV-OH Metro Area	0	17	0.0
315	Wichita Falls, TX Metro Area	2	12	16.7

316	Wichita, KS Metro Area	3	46	6.5
317	Williamsport, PA Metro Area	5	6	83.3
318	Wilmington, DE-MD-NJ Metro Division	55	69	79.7
319	Wilmington, NC Metro Area	0	24	0.0
320	Winchester, VA-WV Metro Area	3	4	75.0
321	Winston-Salem, NC Metro Area	18	46	39.1
322	Yakima, WA Metro Area	8	19	42.1
323	York-Hanover, PA Metro Area	0	13	0.0
324	Youngstown-Warren-Boardman, OH-PA Metro Area	3	61	4.9
325	Yuba City, CA Metro Area	1	10	10.0
326	Yuma, AZ Metro Area	0	7	0.0

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i http://www.locationaffordability.info/ Accessed January 5, 2015.

ii For more information on the regional sprawl index and how it is calculated, see Ewing et al. (2002), "Measuring Sprawl and Its Impacts," available at http://www.smartgrowthamerica.org/resources/measuring-sprawl-and-its-impact/.

iii http://www.edmunds.com/tco.html Accessed January 5, 2015.

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