

HOW AFFORDABLE IS HUD AFFORDABLE HOUSING?

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 for renewal when HUD contracts expire for these properties, based on location and hence on transportation affordability.

Keywords: *Affordable housing, HUD rental assistance program, transportation costs, affordability*

Introduction

The United States 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% 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, 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). The HUD Section 8 New Construction and Substantial Rehabilitation Program, and other Section 8 privately owned rental housing programs, pay owners the difference between a fair market rent and 30 percent of tenant adjusted income.¹ These are the programs we focus on in this paper. We can assume, therefore, that housing costs alone are affordable for households participating in these HUD rental assistance programs. But is the housing under these programs still affordable when taking into account the transportation costs?

¹ HUD's adjusted income, as defined in 24 CFR 5.611, means a family's annual income minus a number of mandatory deductions. The mandatory deductions include amounts for: dependents; status as an elderly or disabled family; unreimbursed childcare expenses; unreimbursed medical expenses (elderly/disabled family only); unreimbursed disability assistance expenses.

HUD has no way of knowing since transportation costs fall outside its purview and regulations.² But transportation cost, after housing, is the second biggest expense 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. **Despite a recent dip in gasoline prices, the Energy Information Administration predicts a rise in real fuel costs in the years ahead, consuming progressively larger shares of income (EIA 2014).**

Previous studies show that there is a clear tradeoff between the housing and transportation expenses of **families with one or more working members**. 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 and 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

² A proposed regulation would require program participants to analyze transit access data in pursuit of fair housing goals. http://www.huduser.org/portal/affht_pt.html

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, enable us to draw effectiveness conclusions about HUD rental assistance programs.

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. Department of Housing and Urban Development (HUD) 2006, Yip & Lau 2002). The main providers of affordability indexes in the US are real estate institutes and government agencies. The National Association of Realtors, for example, publishes a Housing Affordability Index for existing single-family homes by metropolitan area. The NAR affordability index, for example, 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 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 consume 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 its 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 that measured true housing affordability called the "Housing + Transportation Affordability Index." 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 (Center for Transit-Oriented Development and Center for Neighborhood Technology, 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 due 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.

Later in 2010-13, the Departments of Transportation and Housing and Development funded the development of refined H+T-like index, called the Location Affordability Index. 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 TOD advocates. However, it has also received criticism (Abt Associates 2010; Econsult Corporation and Penn Institute for Urban Research 2012, and Tegeler, 2011).

The first problem with these models is the limited characterization of the built environment. The model of auto use (VMT) only accounts for variations in two built environmental 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 and 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 the 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 socio-demographic 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 reading 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 shortcoming, we estimate models that have greater validity and reliability because they are based on more robust data and a more accurate methodology. Our models accounts 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 and Cervero 2010—also see literature reviews by 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).

Methods

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

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

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 are 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 geo-locate more than 34,000 rental housing assistance properties in HUD's Multifamily Portfolio Dataset. The subsequent analysis, however, focuses on the 8,857 HUD Section 8 New Construction and Substantial Rehabilitation Program, and other Section 8 privately owned rental housing programs, because for these programs housing cost is affordable by definition. The properties in this final database provide a complete

set of variables from which we can estimate transportation costs. We 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 (see Ewing et al. 2014 for more information on the databases). At present, we have consistent datasets for 15 regions. The resulting combined database consists of 62,011 households in the 15 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 environmental variables based on the precise location of households. NHTS provides geocodes (identifies households) only at the census tract level.

[Table 1 about here]

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 15 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 socio-demographic 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 1/4, 1/2, and 1-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 (MPOs).

Variables extracted from these datasets and used in subsequent modeling are shown in Table 2. The table only makes reference to ½ mile buffers, but data for ¼ 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 about here]

Statistical Methods

As shown in Table 2, our data structure is multi-level with households “nested” within regions. This creates a dependence among households in the same region, which violates the independence assumption of ordinary least squares (OLS) regression and leads to inefficient and biased regression coefficients and standard error estimates (Raudenbush and 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 multi-level 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 region 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 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 χ^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 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, and Congdon, 2010). HLM 7 allows the estimation of multi-level 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 a 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 about here]

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 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 4-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 about here]

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 about here]

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 with a quarter mile of a household, and design of the environment around a household, intersection density and percentage of four way intersections within half mile of households' 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 about here]

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 home. It has long been speculated that mixed-use areas would generate more transit trips because 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 does not appear to depend on transit service variable, transit frequency. It is as if once households make a decision to use transit, their frequency of use is determined only by socio-demographics and the built environment.

[Table 7 about here]

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

$$\text{Odds of any transit trips} = \exp(\log \text{ odds any transit trips})$$

$$\text{probability of any transit trips} = \text{odds of any transit trips} / (1 + \text{odds of any transit trips})$$

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

$$\text{number of transit trips (for households with transit trips)} = \exp(\log \text{ of expected number of transit trips})$$

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

$$\text{Number of transit trips (for all households)} = \text{probability of any transit trips} \times \text{number of transit trips (for households with transit trips)}$$

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^{®ii} 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 often categorized as fixed, such as depreciation and insurance, 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 the states and also to the vehicle's make, model and the 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 Ford F-series Pick Up, followed by 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 low income households 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 about here]

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 (OPIS), 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 about here]

Third, we compute 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's transportation costs for each property in our sample, we added up the three transportation cost components. Finally, we calculated the percentage of 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 income limit for typical household with a household size of 3 in our transportation affordability calculation.

Results and Discussion

We found that, on average, a typical low income household, that qualifies for HUD rental assistance **under the Section 8 New Construction and Substantial Rehabilitation and related Section 8 Multifamily programs**, spends **14.65** percent of its budget on transportation which agrees with LAI recommended 15 percent threshold for transportation affordability. Figure 1 shows the frequency distribution of transportation affordability (percentage of income spent for transportation costs) for **8,857** properties in our sample. **A property with the lowest transportation costs is located in California.** A typical low income household, which is qualified for HUD assistance program in downtown Los Angeles, spends only \$1,988 per year on transportation which is less than 3.5% of its budget. The same household in a property in a

distant and inaccessible location in Wheeling, WV-OH spends \$ 10,349 (28 percent of its budget) on transportation.

[Figure 1 about here]

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 of a typical low-income households. As shown in the figure, across the U.S, cities with good public transit service such as Portland, OR have, in general, lower transportation costs particularly in 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 about here]

Figure 3 and 4 show two compact (New York and Chicago) and two sprawling (Phoenix and Detroit-Warren) metropolitan areas. As shown in 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 at the same line with the LAI transportation costs calculator which shows 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 8,857 properties, households in 3,860 properties (44 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. Interestingly, transportation is unaffordable for all

properties in 70 out of 322 metropolitan areas and divisions that supply Section 8 Multifamily rental assistance. Memphis, TN, Orlando, FL, Hickory, NC, and Las Vegas, NV are some of them (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 and Hamidi, 2014). Accordingly, the more compact metropolitan areas are found to have the highest number of affordable housing supplied by HUD (see Table 11). San Francisco, CA has the highest percentage of affordable properties, followed by Denver, CO, Los Angeles, CA, Washington DC, Portland, OR and New York, NY. 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. Another implication could be that properties in sprawling or inaccessible areas need to include a transportation allowance in addition to the existing utility allowance...or that the housing subsidy would need to be higher in inaccessible areas to account for the added transportation costs. Similarly, this analysis could be used to promote small area fair market rents (FMRs) so that assisted households could access housing in more central locations.

[Figure 3 about here]

[Figure 4 about here]

[Table 10 about here]

[Table 11 about here]

This study has limitations. HUD's Section 8 Multifamily Programs are relatively small and thus dwarfed by tenant-based vouchers and low income housing tax credits (LIHTCs). In addition, the programs are mostly in preservation and operation mode, no longer subsidizing new construction/substantial rehabilitation. It begs the question of why focus on these programs

rather than the larger, more active programs. The answer is our findings can be used to qualify properties for renewal when HUD contracts expire, based on location and hence on transportation affordability. The answer is also because the Section 8 Multifamily Programs have historic significance, and our findings can be applied to any rental assistance program. Precise locations of LIHTC properties are available, and precise locations of voucher recipients are available through data licensing agreements. We will in subsequent papers analyze these programs for transportation affordability. Given the nature of our methodology, we will arrive at similar conclusions.

Second, this paper focuses on assessing affordability of HUD housing for low-income households by integrating transportation costs. However, the paper puts its effort into measuring transportation costs, while less attention is paid to why this is an important issue in affordability. Data do not exist on housing costs for most rental assistance properties, and it is certainly possible that under programs other than those analyzed in this paper, properties in outlying areas have rents that are sufficiently lower to more than compensate for the higher transportation costs.

A third related limitation is the failure to account for the simultaneous relationship between of housing costs and vehicle ownership. Thus, we cannot be sure if housing choice and living environment cause the higher transportation costs, or alternatively higher transportation costs affect housing choice and living environment. It is presumably the sum of housing and transportation costs that should be minimized by households, not transportation costs alone.

Fourth, similar to housing costs, vehicle costs involve subjective choice and reflect heterogeneous personal preferences. This subjective choice will definitely influence transit trips and vehicle ownership, and should be measured on the specific household level. However, we simply do not have data in our 15 region database, and cannot estimate the models of housing

costs or vehicle choice that incorporate tenant attitudes and preferences. Even if we had such data and could estimate such models, we could not apply them to HUD rental assistance properties for lack of data on the attitudes and preferences of people living in HUD assisted properties. Our research focuses on the costs of a typical household living in a HUD assisted property, not on the range of transportation costs incurred by the range of rental assistance recipients.

Fifth, 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, and of these, only 8,857 properties participate in the Section 8 Multifamily Housing programs. 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 (LED) data, a key data element for estimating transportation models.

A final 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 in 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 of HUD Section 8 Multifamily programs. 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 multi-level 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 through 7) are available to anyone who might wish to duplicate our results for a specific HUD property or would like to study transportation affordability generally for low-income households. This evidence-based research suggests that these particular 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.

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Table 1. 15-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

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) ¹	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) ²	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
	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 signify great compactness ⁱⁱⁱ (Ewing and Hamidi, 2014)	Regional

¹ The job-population index that measures balance between employment and resident population within a buffer. Index ranges from 0, where only jobs or residents are present within a buffer, not both, to 1 where the ratio of jobs to residents is optimal from the standpoint of trip generation. Values are intermediate when buffers have both jobs and residents, but one predominates .

$$\text{jobpop} = 1 - [\text{ABS}(\text{employment} - 0.2 * \text{population}) / (\text{employment} + 0.2 * \text{population})]$$

ABS is the absolute value of the expression in parentheses. The value 0.2, representing a balance of employment and population, was found through trial and error to maximize the explanatory power of the variable.

² The entropy index measures balance between three different land uses. Index ranges from 0, where all land is in a single use, to 1 where land is evenly divided among the three uses. Values are intermediate when buffers have more than one use but one use predominates. The entropy calculation is:

$$\text{entropy} = -[\text{residential share} * \ln(\text{residential share}) + \text{commercial share} * \ln(\text{commercial share}) + \text{public share} * \ln(\text{public share})] / \ln(3)$$

where ln is the natural logarithm of the value in parentheses and the shares are measured in terms of total parcel land areas.

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				

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
hysize	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				

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
hhsiz	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				

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
hysize	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				

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
hhsz	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				

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	Fullsize Blazer/Tahoe	1,136
14	JEEP	Cherokee	1,088
15	MERCURY	Marquis/Monterey	990

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

Table 10: Fifteen Metropolitan Areas with **Lowest Percentage of Affordable** HUD Assistance
 Properties in Terms of Transportation Costs

MSA name	Number of affordable properties	Total number of properties	% of properties affordable
Memphis, TN-MS-AR	0	59	0
Jackson, MS	0	31	0
Greensboro-High Point, NC	0	27	0
Orlando-Kissimmee-Sanford, FL	0	26	0
Shreveport-Bossier City, LA	0	25	0
McAllen-Edinburg-Mission, TX	0	24	0
Beaumont-Port Arthur, TX	0	21	0
Chattanooga, TN-GA	0	21	0
Huntington-Ashland, WV-KY-OH	0	21	0
Hickory-Lenoir-Morganton, NC	0	20	0
Las Vegas-Paradise, NV	0	20	0
Fayetteville, NC	0	19	0
Wheeling, WV-OH	0	15	0
Flint, MI	0	14	0
Palm Bay-Melbourne-Titusville, FL	0	13	0

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	91	91	100
Denver-Aurora-Broomfield, CO	120	121	99.17
Los Angeles-Long Beach-Glendale, CA	465	482	96.47
Washington-Arlington-Alexandria, DC-VA-MD-WV	155	164	94.51
Portland-Vancouver-Hillsboro, OR-WA	98	104	94.23
New York-White Plains-Wayne, NY-NJ	413	439	94.08
Oakland-Fremont-Hayward, CA	92	98	93.88
Minneapolis-St. Paul-Bloomington, MN-WI	177	189	93.65
Chicago-Joliet-Naperville, IL	271	297	91.25
Kansas City, MO-KS	96	114	84.21
Philadelphia, PA	110	137	80.29
Newark-Union, NJ-PA Metro	89	113	78.76
Milwaukee-Waukesha-West Allis, WI	98	125	78.4
Baltimore-Towson, MD	91	117	77.78
Providence-New Bedford-Fall River, RI-MA	95	146	65.07

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Figure 1. Frequency distribution of predicted Transportation Affordability (percentage of income spent for transportation costs)

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 of a typical low income households.)

Figure 3. Transportation affordability for HUD multifamily properties in New York (left) and Chicago (right)

Figure 4. Transportation affordability for HUD multifamily properties in Phoenix (left) and Detroit-Warren (right)

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

ⁱⁱ <http://www.edmunds.com/tco.html> Accessed January 5, 2015.

ⁱⁱⁱ 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/>.