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Development of an Integrated Model System of Transport and Residential Energy Consumption

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Abstract

The energy footprint of households is inextricably tied to the amount of travel undertaken by households. The travel energy footprint of a household is dependent on the mix of vehicles owned and used by members of the household, and the extent to which different vehicles in a household are driven. Integrated models of activity-travel demand and transport energy consumption often do not consider the mix of vehicle types owned and used by households, thus making it difficult to assess the energy implications of shifting vehicle/fuel type choices – particularly in a rapidly evolving marketplace. More importantly, integrated models of activity-travel demand and transport energy consumption do not consider the residential energy consumption implications of travel. If people travel more (and spend more time outside home), they may consume more travel energy, but consume less in-home residential energy. Thus, an integrated model system that tightly connects activity-travel demand, travel energy consumption (sensitive to vehicle fleet/fuel type), and residential energy consumption (sensitive to activity-travel choices) is needed to obtain a holistic picture of household energy footprint. This paper describes an integrated transport – energy model system that connects these three entities. The model is developed by fusing information between two survey data sets, namely, the National Household Travel Survey (NHTS) data set and the Residential Energy Consumption Survey (RECS) data set. The integrated model system is applied to a synthetic population of a few selected counties in New York to illustrate the efficacy of the model system.

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Keywords: integrated models; transport energy; residential energy; household energy footprint; transport and energy modeling; data fusion and imputation

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1. Introduction

The US Environmental Protection Agency (EPA) estimates that the nation's transportation, commercial, and residential sectors contributed 29, 19, and 21 percent respectively, of the total greenhouse gas (GHG) emissions in 2016 (EIA, 2017), thus demonstrating the role of human activity in shaping the carbon footprint of a community. It is therefore of considerable importance to quantify the consumption of energy that is attributable to each of these sectors, as the energy consumption patterns directly translate into GHG emissions that contribute to global climate extremes. This paper focuses on the estimation of the energy footprint of a household. Within the scope of this paper, household energy footprint is assumed to comprise of two main components. The first component is the transport energy consumption and the second component is the residential energy consumption that stems from electricity, natural gas, and other utility expenditures. The transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which each of the different vehicles in a household is driven.

The residential energy footprint primarily stems from the consumption of electricity and natural gas, although other fuel sources may also contribute to a household's utility expenditure pattern. The scope of analysis of residential energy footprint can be very broad depending on the extent of the supply chain that is considered and the extent to which embedded energy is included in the accounting system. For purposes of quantifying and characterizing the residential energy footprint in this paper, only the actual operational energy consumption (utility expenditures) is included within its scope. The total household (operational) energy footprint may then be viewed as a sum of the transport energy consumption and residential energy consumption. Both components account only for the operational energy consumption within the respective domains. The residential energy consumption may be posited, however, as being influenced by activity-travel characteristics of household members. If household members travel extensively and spend a lot of time outside home, then the residential energy consumption may get reduced if the households take necessary energy saving precautions when they are not at home. Such households may have large transportation energy footprints (if they travel long distances) and smaller residential energy footprints. Conversely, households that spend a lot of time at home may have smaller transport energy footprints, but larger residential energy footprints. The estimation of the total energy footprint of a household should take into account the potential relationship that may exist between transport and residential energy footprint.

Despite considerable work in this area, an integrated model of household energy footprint that accounts for the relationship between transport and residential energy consumption remains elusive. This paper aims to fill this critical gap by presenting a comprehensive integrated model system and energy analysis tool that can be used to quantify the total household energy footprint, including the separate transport and residential energy consumption components. The model system is developed through a multi-step process that involves fusing information contained in the 2017 National Household Travel Survey (NHTS) data set (which includes detailed vehicle and travel information) and the 2015 Residential Energy Consumption Survey (RECS) data set (which includes detailed residential energy-related information). The model system involves computing the transport energy footprint based on household vehicle mix and miles of travel, and then computing both electricity and natural gas consumption separately while accounting for the influence that activity-travel behavior may have on the residential energy consumption patterns.

The remainder of this paper is organized as follows. The next section offers a brief overview of the work in this topic area. The third section presents a brief overview of the two data sets used and fused in this study. The fourth section offers a detailed description of the integrated modeling framework and methodology. The fifth section presents an illustrative application of the model system to a synthetic population in selected counties of New York. The sixth and final section offers concluding remarks

2. Understanding and Quantifying the Residential and Transport Energy Footprint

There is a vast body of literature devoted to analyzing and quantifying energy consumption patterns of various entities. However, modeling tools developed thus far do not explicitly account for inter-dependencies among constituent energy consumption components that are vital to forecasting the energy footprint in response to changes in population characteristics and built environment conditions, technology, transportation network attributes, and policy interventions.

A number of studies have focused on analyzing residential energy consumption patterns. A few studies have reported that spatial configuration and land use pattern are important determinants of residential energy consumption (e.g., Wang et al, 2016). Fan et al (2017) studied the impact of urbanization on residential energy consumption in China, and found that urbanization accounted for 15.4 percent of the increase in residential energy consumption between 1996 and 2012. The study reported, however, that urbanization is good for energy conservation as urbanization is associated with a reduction in coal consumption and increase in oil and gas consumption. Other studies (e.g., Longhi, 2015) have explored the influence of dwelling unit characteristics, household characteristics, and household behaviors on per capita energy consumption. Any model of residential energy consumption needs to incorporate these factors. More recently, Zhang et al (2018) applied a microsimulation-based approach to estimate residential energy consumption. The study involved the fusion and synthesis of data across energy and census data sets to estimate a model of residential energy consumption at the level of the individual household. The work in this paper is inspired by that work, but extends it in very significant ways by integrating transportation energy consumption to obtain a holistic household energy footprint estimation model system.

There is a vast body of work dedicated to measuring and quantifying transport energy consumption. Recently, Ding et al (2017) explored the impacts of the built environment on vehicle miles of travel (VMT) and energy consumption, and found that vehicle energy consumption is inversely related to employment density and street connectivity. Liu and Shen (2011) estimate a structural equations model to examine the effects of urban land use characteristics on household travel and energy consumption in the Baltimore metropolitan area. Interestingly they find that urban form does not have a direct effect on vehicle miles of travel or energy consumption; rather urban form has an indirect effect by affecting travel speeds. Other efforts aimed at quantifying transport energy consumption include those by Tirumalachetty et al (2013) and Das and Parikh (2004). Derrible et al (2010) developed a macroscopic model of GHG emissions for municipalities (called MUNTAG) which is sensitive to land use signals, public transport changes, and other policy interventions. More recently, Garikapati et al (2017) developed a framework to estimate household energy footprint at the traffic analysis zone (TAZ) level through an interface with a standard metropolitan travel demand model. They note that any travel energy footprint calculation that does not account for variation in vehicle fleet mix distribution across space is likely to not only be erroneous, but also fail to provide the policy sensitivity that may be desired for analyzing alternative fuel vehicle scenarios (owing to evolution of technology, changes in the marketplace, or incentives and disincentives instituted through public policy interventions).

Overall, given the enormous interest in this space in many different disciplines, the outlook for the field is very bright. In fact, a few studies have attempted a more holistic and integrated approach to energy analysis; for example, Holden and Noland (2005) studied the relationships between land use characteristics and four distinct consumption categories, including energy use for heating, everyday travel use energy, and long leisure-time travel by plane and car. Ding et al (2017) investigated the direct and indirect effect of household consumption activities on energy consumption in China while taking into account the perspective of consumers' lifestyles. But, despite these and many other advances (e.g., Sheppard et al, 2017; Auld et al, 2018) in the development of energy modeling tools, an integrated model system that considers the inter-relationship between transport and residential energy consumption in computing a household energy footprint remains elusive; this effort is intended to fill this gap.

3. The Travel and Energy Survey Data Sets

An integrated transport and residential energy analysis tool requires information from two major survey data sets as explained in the previous section. Transportation, activity participation, and vehicle fleet related information need to come from a travel survey data set and residential energy consumption information needs to come from an energy survey data set. For the development of this tool, the two data sets used are the 2017 National Household Travel Survey (NHTS) data set and the 2015 Residential Energy Consumption Survey (RECS) data set.

The National Household Travel Survey (NHTS) data set is derived from a large scale travel survey that is conducted about every 8-10 years by the US Department of Transportation to understand and quantify travel undertaken by people on a daily basis. Respondent households are asked to furnish detailed information about household and person level socio-demographic characteristics, vehicles owned or leased by the household, and trips undertaken by each member of the household on a specific travel day. Thus the NHTS is a rich source of information about vehicle ownership and fleet composition for households, which is precisely the information needed to compute the transport energy consumption of households. For developing the household vehicle fleet composition and utilization (VFCU) model in this study, four vehicle types were considered: car, van, SUV, and truck. These four vehicle types were further subdivided according to age based on whether the vehicle is less than or equal to eight years old. Thus there are a total of eight vehicle type categories; in addition, the motorcycle is added as a ninth vehicle category. A multiple discrete continuous extreme value (MDCEV) model of vehicle fleet composition and utilization is developed in this effort to determine the mix of vehicle types that a household may own, together with the amount of mileage that each vehicle will be driven by the household on an annual basis. Information about vehicle type and mileage is available in the NHTS, thus making it possible to estimate such a model.

In addition, the NHTS provides detailed activity-travel information for each member of the household for a specific travel survey day. The detailed activity-travel information provides data on every trip undertaken by the household members and includes a range of attributes including trip origin and destination, trip purpose, vehicle occupancy, travel party composition, trip start and end times, travel mode, and travel distance and time. These variables can be used to derive the total time that an individual spends outside home at various activity locations, time spent traveling, and time spent in home (although in-home activities are not explicitly recorded). By aggregating information about travel and activity records across individuals within a household, it will be possible to derive the total time spent outside home (for different activities), inside home, and traveling (for various purposes) for a household.

The Residential Energy Consumption Survey (RECS) data set is derived from a large scale energy consumption survey that is conducted about every six years. The most recent edition of the RECS data set is of 2015 vintage, and used in this study. Although the sample size is reasonably large (by survey design standards), the sample is rather small when compared with the sample size for the NHTS. The sample size comprises 5,686 households (with complete information) distributed throughout the country. Similar to the NHTS, the RECS includes information about the household that responded to the survey, along with detailed information about energy consumption that can be used to estimate models of residential electricity and natural gas consumption.

It is entirely possible to estimate a transport energy consumption model based on NHTS and a residential energy consumption model based on RECS. These two independent model systems could be applied to, say, a synthetic population to derive transport energy consumption and residential energy consumption separately, and then compute total household energy footprint as a sum of the values. However, such an approach does not recognize the potential impact of transport energy consumption and activity-travel engagement patterns on residential energy consumption. Hence the proposed framework in this study involves imputing vehicle fleet composition and utilization information and activity-travel duration information derived from the NHTS to the household records in RECS. The enhanced RECS data set can then be used to estimate residential energy consumption models that are sensitive to activity-time allocation patterns, vehicle fleet mix and utilization, and transport energy consumption.

To facilitate some consistency in the data fusion process, a random sample of size equal to the RECS was extracted from the NHTS (this is really not necessary, but was done to ease computational intensity of model estimation). Table 1 presents a summary of the two household samples. A slightly larger percent of households in the RECS rent their home compared to the sample in the NHTS. The household income categories do not line up exactly between the two surveys; in the NHTS, nearly 30 percent of households make less than $35,000, while in the RECS, nearly 40 percent of households make less than $40,000. Over 75 percent of households in both data sets reside in urban areas. The distribution of the sample from a geographic perspective suggests there are some differences in the spatial distribution of the samples across the United States, but the differences do not have any adverse effect on the model development effort described in this paper. Similarly, the two samples exhibit noticeable differences in the household size distribution, distribution of number of adults and number of children, and distribution by dwelling unit type (which was derived for the 2017 NHTS sample using a model estimated on the older 2009 NHTS sample). While these differences are noteworthy and merit some additional investigation for future work and model development efforts, they are not likely to have an adverse effect on the data fusion/imputation process because model predictions will generally account for such differences.

Table 1. Description of Household Characteristics

2017 National Household Travel Survey (NHTS) Household Characteristics (N = 5,686)		**2015 Residential Energy Consumption Survey (RECS) Household Characteristics (N = 5,686)**	
Variable	Value (%)	Variable	Value (%)
Home ownership		*Home ownership*	
Own	76.6	Own	69.1
Rent	23.4	Rent	30.9
Annual Household income		*Annual Household income*	
Low (less than $35,000)	29.4	Low (less than $40,000)	39.6
Medium ($35,000 to $99,999)	42.9	Medium ($40,000 to $99,999)	37.8
High ($100,000 or more)	27.7	High ($100,000 or more)	22.6
Household in urban/rural area		*Household in urban/rural area*	
Urban	77.6	Urban	79.6
Rural	22.4	Rural	20.4
Census Division		*Census Division*	
New England	1.6	New England	4.4
Middle Atlantic	14.2	Middle Atlantic	9.5
East North Central	12.0	East North Central	14.7
West North Central	4.4	West North Central	8.6
South Atlantic	22.2	South Atlantic	18.6
East South Central	0.9	East South Central	6.5
West South Central	20.2	West South Central	10.2
Mountain	3.5	Mountain	8.3
Pacific	20.9	Pacific	19.1
Household Size		*Household Size*	
One	32.7	One	22.9
Two	42.6	Two	36.9
Three or more	24.7	Three or more	40.2
Number of Adult household members (Age ≥ 18 years)		*Number of Adult household members (Age ≥ 18 years)*	
One	35.5	One	27.8
Two	54.7	Two	54.4
Three or more	9.8	Three or more	17.7
Number of Young household member (Age ≤ 17 years)		*Number of Young household member (Age ≤ 17 years)*	
Zero	93.1	Zero	67.6
One	4.8	One	13.9
Two or more	2.1	Two or more	18.4
*Household unit type**		*Household unit type*	
Detached	72.0	Detached	69.5
Attached	23.6	Attached	8.9
Apartment	4.4	Apartment	21.6

***Note**: Derived housing unit type from 2009 NHTS

4. Model Development and Estimation Results

This section of the paper provides a summary of the model development and estimation process. The effort undertaken in this study can be broken down into two distinct enterprises. First, there is the model development phase in which information is fused between two data sets and models are estimated so that they can be applied to any region's population to quantify the household energy footprint. Thus, there is the data fusion and model estimation phase. Second, there is the model application phase. In this phase, the efficacy of the model is demonstrated by applying the model system developed in the first phase to a real-world case study. These two distinct phases were undertaken as part of this research effort.

An integrated model of transport and residential energy consumption should include components capable of estimating and quantifying:

- Transport energy consumption due to vehicle ownership, fleet mix, and vehicle miles of travel
- Electricity consumption due to household operations
- Natural gas consumption due to household operations

The *first* step of the development process is to estimate a vehicle fleet composition and utilization (VFCU) model system on the NHTS data set. The VFCU model system estimated and implemented here is similar to that developed previously (You et al, 2014). The model system includes a number of components. They are as follows:

a) A household mileage budget prediction model: The MDCEV model essentially allocates a continuous household mileage to different vehicle alternatives, thus creating a vehicle fleet composition and mileage profile for each household. To accomplish this, a budget prediction model is needed. The mileage reported in the NHTS data is used to estimate a log-linear regression model of mileage.
b) A MDCEV model of vehicle fleet composition: The MDCEV model explicitly recognizes that households may choose to own and consume multiple vehicles of different types. A total of nine vehicle type alternatives are considered in this study, and the MDCEV model is estimated for this choice set. The model is capable of accounting for diminishing marginal utility (satiation effects) and zero consumption (corner solutions) wherein some vehicle alternatives may not be chosen by a household at all.
c) Ordered Probit models of vehicle counts by type: The MDCEV model is able to predict the types of vehicles that a household owns (consumes), but it does not explicitly provide the number of vehicles within each type that a household may own. For example, a household may own two cars that are less than eight years old. While the MDCEV model is able to predict that the household owns cars less than eight years old, it does not explicitly provide a count of the number of cars within that vehicle class. The ordered probit models of vehicle counts by type help establish the number of vehicles that are owned within each class of vehicles that the MDCEV predicts that a household owns.

This entire VFCU model stream was estimated on the NHTS sample for this study and the model was subjected to extensive testing and validation. Some additional procedures explained in You et al (2014) were also implemented to ensure that the model predictions matched real world vehicle fleet composition and utilization patterns.

The *second* step of the process involved estimating a MDCEV model of activity time allocation (ATA). The activity time allocation model essentially allocates a budget of 1440 minutes to various activity categories including out-of-home mandatory activity time, out-of-home non-mandatory activity time, in-home time, and travel time. The sum of these four components of time should be equal to the budget of 1440 minutes. The activity-travel diary information in the NHTS is used to compute these time durations for each household in the sample. The household time budget is assumed to equal 1440 × number of adults in the household. This budget is then allocated through a multiple discrete continuous choice process to the different activity categories. Because the budget is predetermined in the activity time allocation context, there is no need for a model component dedicated to estimating the budget. The MDCEV model of activity time allocation is estimated on the NHTS data set, and predicted time allocation patterns are compared against actual patterns in the data to validate the model. The model was found to perform quite well in replicating distributions of activity time allocation and was hence deemed appropriate to be used for imputing activity time allocation patterns to households in the RECS data set.

The *third* step involved the application of the MDCEV model of vehicle fleet composition and utilization to the RECS data set to predict, impute, and append vehicle ownership information to the household records in the RECS data set. The MDCEV model that was estimated in the first step was applied and predicted vehicle fleet mix and annual mileage values (for each vehicle) were appended to the RECS data set. The *fourth* step is a very similar step, in that the MDCEV model of activity time allocation was applied to the household records in the RECS data set to estimate and append the amount of time that each household devoted to various activity categories identified previously. It should be noted that all records in the RECS data set are household level records; hence the time allocation pattern predicted and appended corresponds to activity durations at the household level (for example, the time spent traveling corresponds to the total time spent traveling by all adult household members).

At the end of the third step, each RECS household record has a vehicle fleet composition and corresponding annual mileage values. The *fifth* step involved converting these vehicle mileage values into energy consumption estimates. Fuel economy data published by the US Environmental Protection Agency (2018) was used to convert vehicle mileage values to annual energy consumption values. Using the energy conversion factors, the total BTU of transport energy consumption was computed for each household and appended to the household records in RECS data set. It should be noted that vehicle body type and age are explicitly considered in the computation of the transportation energy footprint. Pure electric vehicles were assumed to have no transportation energy footprint, but were assumed to contribute to residential energy footprint by virtue of charging at home.

The fully enhanced RECS data set contains all of the information about the household and housing unit (original variables contained in RECS), together with vehicle fleet composition and utilization information, transport energy consumption information, and household activity time allocation information. In the *sixth and final step*, this enhanced data set was used to estimate a seemingly unrelated regression (SUR) equation model of residential electricity and natural gas consumption (these variables are native to the RECS data set). The SUR model recognizes the presence of error correlation between the two linear regression equations embedded in the model system and incorporates transport energy consumption and activity time allocation variables as explanatory factors, thus capturing the potential inter-dependency between residential energy consumption on the one hand, and transport energy consumption and activity time allocation on the other. Estimation results for the SUR model are presented in Table 2.

Table 2. Seemingly Unrelated Regressions (SUR) Equation Model Estimation Results

Electricity Consumption Regression Equation		***Natural Gas Regression Equation***	
Explanatory Variable	Coef (t-stat)	Explanatory Variable	Coef (t-stat)
Constant	9.36 (360.2)	Constant	9.59 (168.8)
Out of Home Mandatory Activity Time (‘000s min)	-0.025 (-1.56)	In Home Time (‘000s min)	0.017 (1.14)
Medium Income Household (≥ \$40,000, < \$100,000)	-0.043 (-2.18)	Low Income Household (<\$40,000)	0.112 (2.90)
Number of Adult members ≥2 (age ≥ 18)	0.130 (4.85)	High Income Household (≥\$100,000)	-0.075 (-2.01)
Number of Young members ≥2 (age ≤ 17)	0.124 (4.79)	Number of Adult members ≥2 (age ≥ 18)	-0.077 (-1.89)
Home Location = Rural	0.044 (1.25)	Number of Young members ≥2 (age ≤ 17)	0.062 (1.58)
Detached housing unit type	0.053 (23.97)	Detached housing unit type	0.593 (16.44)
Division = Middle Atlantic	-0.083 (-2.61)	Home ownership = owned	0.285 (7.90)
Division = South Atlantic	0.328 (10.62)	Division = Middle Atlantic	0.361 (8.31)
Division = East North Central	-0.126 (-5.10)	Household Travel Energy (in thousands, BTU)	0.005 (7.00)
Household Travel Energy (in thousands, BTU)	0.004 (10.63)		
Number of Observations 3,302 R-squared 0.343		Number of Observations 3,302 R-squared 0.239	

The model estimation results are quite plausible and consistent with expectations, potentially suggesting that the data imputed to RECS is not inconsistent with patterns of energy consumption and household activity time allocation that one would expect to see in the real world. In the electricity consumption regression equation, it is found that out of home mandatory activity time (time spent outside home at work and school activities) negatively impacts electricity consumption (although the coefficient is not quite statistically significant, it has been retained for its intuitiveness). Medium income households show a lower electricity consumption; it is possible that low income households experience higher electricity consumption (relative to medium income households) by virtue of residing in less energy efficient homes and using less energy efficient appliances. Variables depicting the presence of a larger number of adults and children in the household contribute positively to electricity consumption. Rural homes consume more energy as do detached housing units. These tend to be larger homes, and hence these positive coefficients are reasonable. It is seen that household travel energy consumption is positively related to residential electricity consumption, suggesting that there is more a complementary relationship between transport energy consumption and residential energy consumption.

The equation for natural gas consumption also offers behaviorally intuitive interpretation. Although not statistically significant, in-home time allocation affects natural gas consumption with a positive coefficient; the variable is retained in the model in view of the behaviorally intuitive relationship. In the case of natural gas consumption, it is found that low income households have a higher natural gas consumption while high income households have a lower natural gas consumption. A deeper investigation of these relationships reveals that the higher energy efficiency of higher income households and their appliances is contributing to lower natural gas consumption relative to households that are lower income and residing in less energy efficient households. As the number of children increases, the natural gas consumption increases. All other coefficients are positive, suggesting that they contribute positively to natural gas consumption. Once again, it is found that household transport energy consumption has a complementary relationship with natural gas consumption. The complementary relationship is plausible in that households that tend to be active and consume more transport energy are likely to engage in activities and adopt lifestyles that are more energy intensive at home as well.

At the end of these six steps, a model of transport and residential energy consumption that can be applied to a population of agents (households) in any region of the United States is obtained. The suite of models that comprise the integrated transport and residential energy analysis tool constitute the following:

1) MDCEV model of household vehicle fleet composition and utilization (mileage)
2) MDCEV model of household daily activity time allocation
3) Transport energy computation model utilizing energy intensity tables that provide conversion factors (EPA, 2018) to translate miles of household travel by various vehicles to equivalent energy consumption
4) Residential energy consumption model (SUR model) of electricity and natural gas consumption

It should be noted that both NHTS and RECS are national data sets, and hence caution should be exercised when applying models estimated on national samples to local regions. Unfortunately, the RECS data set is not quite large enough to support localized model estimation efforts. Hence, in this study, the entire national sample is used for model estimation and development purposes.

5. Illustrative Case Study

The case study involved applying the tool (model system) to a synthetic population generated for New York City, and computing and mapping energy footprint per household across the traffic analysis zones (TAZs) in the region. The mapping could also have been done by census tract, block group, or block; but the illustration here uses the TAZ as the spatial unit of analysis because the synthetic population was generated at the level of the TAZ.

The case study region of New York City includes 335 TAZs and encompasses a population of 1,610,697 persons residing in 776,333 households in 2015. The total employment in the case study region is 2,385,364. A synthetic population was generated for the region using a software package called PopGen (Konduri et al, 2016). Complete details about the algorithms embedded within PopGen can be found in Konduri et al (2016), and hence only a brief overview is provided here. PopGen creates a synthetic population for a region by weighting and expanding a sample data set such that the weighted sample is representative of the true population with respect to marginal distributions on a number of control variables of interest such as household size, household income, number of workers, number of children, person age, person gender, and person employment status. The marginal control distributions representing true population characteristics are typically obtained from census or from regional agencies that may have such data for TAZs as part of their modeling enterprise. The American Community Survey (ACS) Public Use Microdata Sample (PUMS) data serves as the sample which will be weighted and expanded to match the marginal control distributions. For each TAZ, the sample is weighted to match marginal control distributions on variables of interest, and then households are drawn according to weight-based probabilities to create a synthetic population that matches true population numbers. PopGen embeds an iterative proportional fitting (IPF) algorithm to obtain population-level joint distributions of control variables of interest at the TAZ level, and an iterative proportional updating (IPU) algorithm that computes weights for sample households such that the weighted sample is representative of the control totals estimated through the IPF step. Once the weights are computed, households are drawn probabilistically to generate a synthetic population on a TAZ by TAZ basis. Synthetic populations for all TAZs are compiled together to form the regional synthetic population of households and persons. As the sample records drawn into the synthetic population are derived from PUMS, the records are rich with information necessary to apply a model of the nature described in this paper.

The entire suite of models described in the previous section is applied to the synthetic population. First, the MDCEV model of vehicle fleet composition and utilization is applied; this provides the vehicle ownership and mileage for each household. Second, the MDCEV model of activity time allocation is applied; this provides the time spent by each household (as a whole) in various activity categories including in-home, out-of-home mandatory activities, out-of-home non-mandatory activities, and travel time. Note that the application of the MDCEV models requires that they be exercised in forecasting mode; the procedures described in Pinjari and Bhat (2011) are used to accomplish this. By the end of this step, each synthetic population household is appended with a vehicle fleet composition and an activity time allocation pattern. After that, the energy intensity conversion factors are used to compute the transport energy consumption for each household. Finally, the SUR model of residential energy consumption is applied to compute residential electricity and natural gas consumption as a function of various factors, while accounting for the potential relationship that may exist between residential energy consumption and transport energy consumption.

After the energy footprints are computed for each household in the synthetic population, summaries can be derived and aggregate measures of energy consumption can be calculate at the TAZ level. Figure 1 shows the spatial distribution of energy consumption for TAZs in the New York City region.

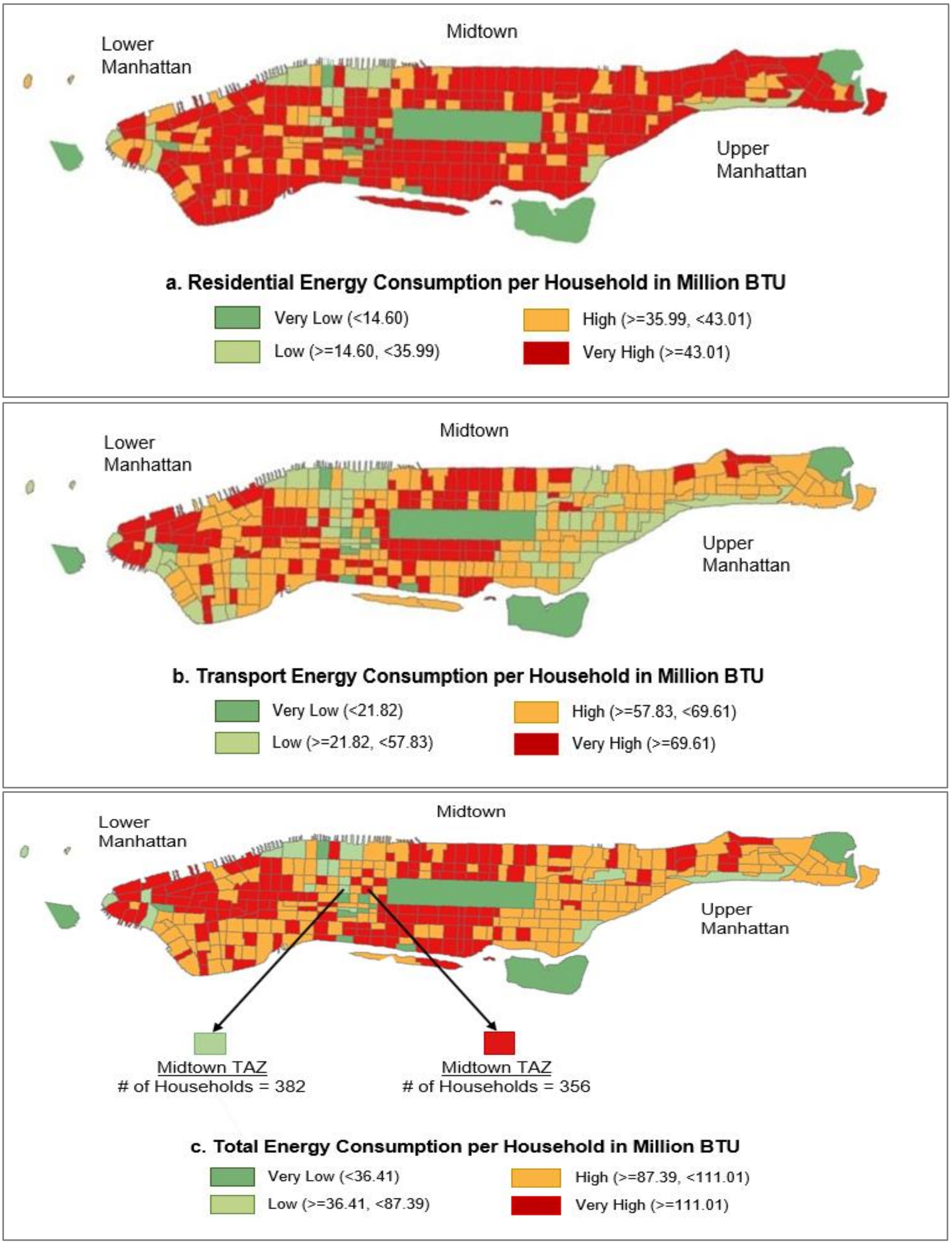

Fig 1. Visualization of Energy Consumption Distribution for Manhattan City

The first picture depicts residential energy consumption (sum of electricity and natural gas consumption, the second graph depicts transport energy consumption, and the third graph constitutes a total energy footprint obtained by adding up the residential and transport energy consumptions. Given that New York City is a diverse and rather mixed/high density area, it is not surprising that no discernible pattern emerges in the maps. Nevertheless, the TAZs can be categorized into one of four blocks, depending on where they fall – on average – compared to the overall average energy footprints per household.

So, four categories of households are created:

- HH: Both residential and transportation energy consumption per household are above the regional averages
- HL: High residential energy consumption and Low transport energy consumption
- LH: Low residential energy consumption and High transport energy consumption
- LL: Low residential energy consumption and Low transport energy consumption

The average energy footprints were computed to be 70,961,927 BTU of residential energy consumption and 81,908,304 BTU of transport energy consumption. These numbers are generally consistent with expectations and measure up quite well to real-world energy consumption estimates (EIA, 2017).

Figure 2 shows a comparison between the HH and LL household segments. It can be seen that there are very clear differences between households that are high consumers of residential and transport energy and households that are low consumers of energy. Because the distributions of energy consumption are skewed, the size of each segment varies. While 25 percent of households fall into the HH segment, 38 percent of households fall into the LL segment. This is consistent with expectations as the average is likely to be impacted by outliers in the energy consumption spectrum. The comparison between the HH and LL segments shows a number of patterns that are very consistent with expectations, suggesting that the integrated energy analysis tool developed in this effort may prove to be a valuable tool in quantifying and assessing energy footprints of households.

The comparison shows that a higher proportion of LL households reside in urban areas lending credence to the belief that urban living contributes a lower energy (carbon) footprint. While 90 percent of households in the HH category own their homes, the corresponding percent for households in the LL category is just 46 percent. Households in the LL category show substantially smaller household sizes, with more than one half of the households in this segment having only one person. Similarly, in terms of income, households that are energy guzzlers have substantially higher income levels than households in the LL category, as expected. In fact, of the households in the HH category, nearly 50 percent fall in the high income bracket. Among households in the HH category, 94 percent reside in detached housing units; the corresponding percent for households in the LL category is just 42 percent. Overall, it can be seen that household structure, composition, location, and income make a real difference in shaping household energy consumption patterns.

In the interest of brevity, the graph comparing HL and LH households is not shown in this paper. However, some interesting differences are seen between these two groups of households as well. The HL segment (high residential and low transport energy consumption) comprises 16 percent of the population, while the LH segment comprises 21 percent of the households in the region. In general, households that have higher transport energy consumption tend to be larger and more affluent, suggesting that these households travel more, participate in activities, and expend more transportation energy.

To further illustrate the efficacy of the modeling tool presented in this paper, two TAZs that have different energy consumption profiles were compared in terms of their profile. The two TAZs that were compared are highlighted in the third panel of Figure 1. One TAZ has a low per household energy consumption while the other has a very large per household energy consumption. What makes one TAZ to be a much higher energy consuming entity than another? Households in the respective TAZs were compared with respect to their attributes and the results are shown in Figure 3. Both TAZs are in close proximity to one another and are located in midtown. The comparison of the profiles of the TAZs shows that they are quite different from one another despite their close proximity. Both TAZs have about an equal number of households in them. The TAZ with high energy consumption (H) has 356 households while the TAZ with low total energy consumption (L) has 382 households. In other words, the energy consumption per household is not necessarily being affected by the number of households in the TAZs. Rather, it is the attributes of the households in these TAZs that contributes to the differences.

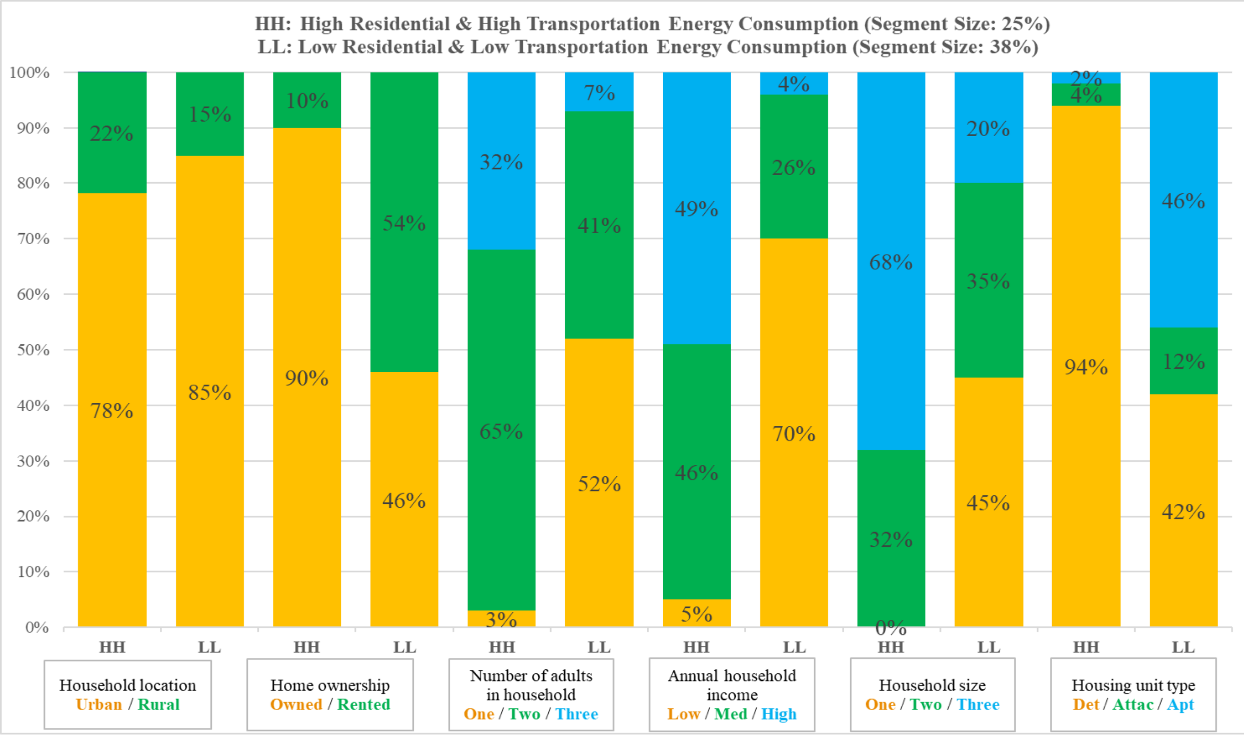

Fig 2. Comparison of Household Profiles Based on their Energy Consumption Bin

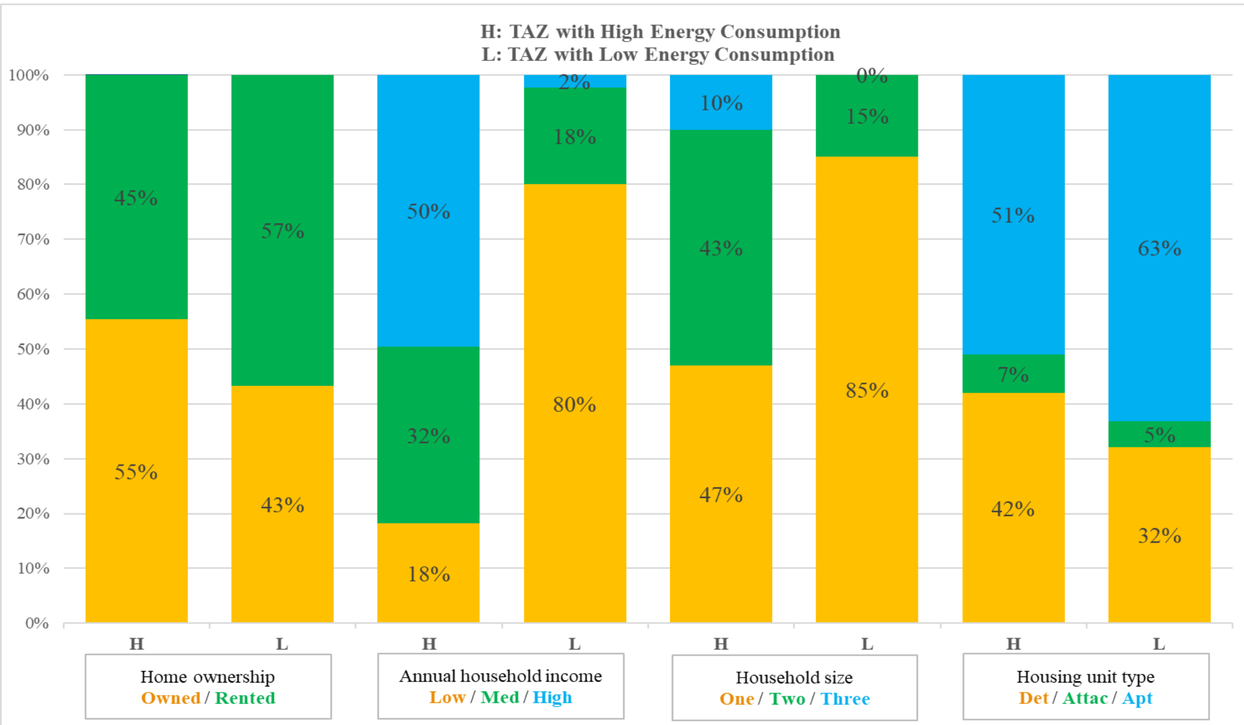

Fig 3. Comparison of Two Zones with Different Energy Consumption Profiles

As expected, a larger proportion of households in the high energy consumption zone are owned (than in the lower energy consumption zone). The disparity in income distribution is extremely stark. While 80 percent of households in the low energy consumption zone are low income, only 18 percent of households in the high energy consumption zone fall into this income category. Low energy consumption zone predominantly has single person households (85 percent) while the high energy consumption zone has a high percent of two and three person households. Similarly, high energy consumption zone has a higher percent of detached single family dwelling units than in the low energy consumption zone. Clearly, the energy consumption model system presented in this paper offers considerable potential for use as a transport planning and energy policy analysis tool.

6. Conclusions

This paper presents an integrated transport and residential energy analysis tool that is capable of quantifying the transport energy consumption and residential energy consumption of an individual household. The motivation to build such a tool stems from the possible inter-relationships that may exist between these two energy consumption footprints. An individual who travels more and spends more time outside the home is likely to have a high transport energy footprint, but may have a lower residential energy footprint and vice versa. Only operational energy consumption is considered within the scope of the tool presented in this paper; energy consumed during travel is transport energy consumption and electricity and natural gas constitute the residential energy consumption footprint.

In order to facilitate an integrated approach to residential and transport energy consumption analysis, detailed activity-travel and vehicle fleet composition and utilization information is modeled using the National Household Travel Survey (NHTS) data set and then applied to the Residential Energy Consumption Survey (RECS) data set to impute transportation related variables in the RECS data set. The enhanced RECS data set is then used to estimate regression equations of electricity and natural gas consumption that incorporate transport and activity time allocation related variables as explanatory factors. In general, it is found that household activity-time allocation patterns can affect residential energy consumption (albeit to a small degree), and residential and transport energy consumption are mutually reinforcing and complementary in nature. This suggests that households that travel more are likely to have lifestyles that also contribute to higher levels of residential energy consumption.

The integrated model system is applied to a synthetic population generated for the New York City region to demonstrate the efficacy of the model. The entire model stream is applied to the synthetic population to estimate transportation and residential energy consumption components for all households in the synthetic population. These computations facilitated the comparison of different energy consumption market segments and the findings are very much aligned with expectations, with larger households, higher income households, households in rural areas, households in detached single family housing, and households owning their home exhibiting higher levels of energy consumption. The tool presented in this paper can be used to analyze the energy footprint implications of alternative urban designs and modal investments.

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Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: S. Sharda, R. Pendyala, S. Khoeini; data collection: S. Sharda, S. Khoeini, T. Kim; analysis and interpretation of results: S. Sharda, R. Pendyala, I. Batur, T. Kim; draft manuscript preparation: S. Sharda, R. Pendyala. All authors reviewed the results and approved the final version of the manuscript.

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