The Influence of Urban Form on GHG Emissions in the U.S. Household Sector

Sungwon Lee
Department of Urban and Regional Planning
University of Illinois at Urbana-Champaign

Bumsoo Lee*
Department of Urban and Regional Planning
University of Illinois at Urbana-Champaign

*Corresponding author
M206 Temple Buell Hall, MC-619
Champaign, IL 61820, USA
+ 1 217 333 3601
bumsoo@illinois.edu

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Abstract

To better understand the role of sustainable urban development in greenhouse gas (GHG) mitigation, this study examines the paths by which urban form influences an individual household's carbon dioxide emissions in the 125 largest urbanized areas in the U.S. Our multilevel SEM analyses show that doubling population-weighted density is associated with a reduction in CO_2 emissions from household travel and residential energy consumption by 48% and 35%, respectively. Centralized population and polycentric structures have only a moderate impact in our analyses. The results also show that doubling per capita transit subsidies leads to a nearly 46% lower vehicle miles traveled (VMT) and an 18% reduction in transportation CO_2 emissions. Given that household travel and residential energy use account for 42% of total U.S. carbon dioxide emissions, these findings highlight the importance of smart growth policies to build more compact and transit friendly cities as a crucial part of any strategic efforts to mitigate GHG emissions and stabilize climate.

Keywords: Greenhouse gas emissions, urban form, household sector

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1. Introduction

Experts widely agree that the global mean temperature (GMT) should be kept within a maximum of 2°C above preindustrial levels to prevent potentially catastrophic consequences for human society and natural ecosystems (Smith et al., 2009). In response to "the 2°C guardrail" endorsed by the Copenhagen Climate Summit (Richardson et al., 2009; UNFCCC, 2009), the U.S. federal government set a goal of reducing greenhouse gas (GHG) emissions by 17% below 2005 levels in 2020 and by 83% in 2050 (U.S. Department of State, 2010). Most of the current and proposed policy measures to meet the climate stabilizing GHG reduction target in the U.S. rely on technology and pricing solutions: stricter fuel economy standards, promoting low-carbon fuels, and cap and trade systems or carbon taxes (Chapman, 2007; Ewing et al., 2008a; Pacala and Socolow, 2004). Many studies, however, show that technology and market solutions alone, without moderating energy demand, cannot achieve these GHG reduction goals (Boies et al., 2009; Grazi and Van den Bergh, 2008; Johansson, 2009; Kromer et al., 2010; Morrow et al., 2010). Moreover, technology may not develop at a sufficient rate to meet the challenge (Johansson, 2009), and the potential GHG savings from improved energy efficiency are likely to be (at least partially) offset by 'rebounded' energy consumption (Greening et al., 2000; Sorrell et al., 2009).

To fill this gap, additional steps are needed. Reducing individual energy consumption through shifts in behavior represents one opportunity to mitigate GHG emissions. This option is compelling given that households, as an end-user sector, account for 42% of total U.S. carbon dioxide emissions from fossil fuel combustion, combining emissions from residential buildings (22%) and passenger travel (20%) (U.S. Environmental Protection Agency, 2012). While various factors such as energy price, income, and weather affect household energy consumption, a growing body of literature has linked compact urban development to more carbon-efficient lifestyles, including less driving and more energy efficient housing choices (Ewing et al., 2008a; Ewing et al., 2008b). Nevertheless, researchers disagree about the magnitude of urban form effects. Some argue that more sustainable urban form and transportation network can more effectively reduce carbon emissions than replacing all gasoline with corn ethanol (Marshall, 2008). Others question whether urban form matters at all (Echenique et al., 2012). Therefore, more empirical research is necessary to systematically assess the potential of smart growth policies to mitigate household sector carbon emissions.

This study investigates the paths by which urban form influences household sector carbon dioxide emissions in the 125 largest urbanized areas (UAs) in the U.S. We estimate individual household carbon emissions from travel and home energy use by processing household surveys, including the census and quantify spatial structure of urbanized areas in several dimensions beyond a simple population density measure. Using this data, combined with a multilevel structural equation model (SEM), we demonstrate that shifting toward more compact urban form can significantly reduce energy consumption and CO_2 emissions in the household sector. Our analysis shows that increasing population-weighted density by 10% leads to a reduction in CO_2 emissions by 4.8% and 3.5% from household travel and residential building energy use, respectively. The effects of other spatial variables are estimated to be small.

2. Urban form and GHG emissions

Connections between urban form and GHG emissions have been studied in the fields of transportation and building energy research. In the transportation sector, research has typically focused on the influence of the built environment on travel demand, often measured in vehicle miles traveled (VMT). In the absence of adequate emissions data at individual and even urban area levels, emissions are often assumed to be a function of VMT, given the current or a target fuel efficiency and fuel carbon content (Mui et al., 2007). Despite earlier skepticism (Boarnet and Crane, 2001; Boarnet and Sarmiento, 1998), many recent empirical studies have found that urban form variables significantly influence travel behavior, including mode choice, trip frequency, trip distance, and, ultimately, VMT. These variables include density, land use diversity, street design (3Ds; Cervero and Kockelman, 1997), destination accessibility, and distance to transit (additional 2Ds; Cervero et al., 2009). A growing body of literature shows that residents in more compact and transit-friendly neighborhoods drive considerably less than those living in sprawling neighborhoods. Moreover, the travel impacts of neighborhood characteristics are found to be significant, even after controlling for the effects of residential self-sorting by preferences and environmental attitudes (Cao et al., 2009; Mokhtarian and Cao, 2008).

However, research on urban form and travel connections mostly focuses on neighborhood level effects, despite the continually reported significance of urban area level spatial structure. Several studies show that variables such as job accessibility (the 4th D) and distance to downtown have larger impacts on VMT reduction (with a typical elasticity of -0.2) than neighborhood level attributes, whose elasticities typically range between -0.04 and -0.12 (Cervero and Duncan, 2006; Ewing and Cervero, 2010; Kockelman, 1997; Naess, 2005; Sun et al., 1998). These results suggest that the location and distribution of developments within a metropolitan region may be more important determinants of travel behavior than neighborhood level density and land use mix at given locations. Nonetheless, few studies have examined the impacts of urbanized or metropolitan area level spatial form (Bento et al., 2005; Cervero and Murakami, 2010; Ewing et al., 2003), primarily due to the lack of appropriate measures of urban area level spatial structure.

Some research has extended urban form and travel connections to study the impacts on energy consumption and GHG emissions. A study of California households finds that 40% higher residential density is associated with a 5.5% fuel use reduction, with 3.8% coming from less driving and 1.7% derived from vehicle choice (Brownstone and Golob, 2009). Other studies show that households in denser urban areas are less likely to own and drive low fuel-efficiency vehicles such as SUVs and pickup trucks (Bhat and Sen, 2006; Bhat et al., 2009; Fang, 2008; Liu and Shen, 2011). These findings suggest that vehicle choice in terms of fuel-efficiency, as well as VMT, should also be taken into account when measuring the effects of urban form on GHG emissions from household travel.

Urban form also affects energy consumption, and hence GHG emissions in residential buildings, through two paths: housing choices—sizes and types—and, potentially, urban heat island (UHI) effects. Households in multifamily housing units, characterized by shared walls and typically smaller floor space, consume less energy for space heating, cooling, and all other purposes than do households in detached single-family homes, when controlling for the age of housing structures as a proxy of construction technology (Brown and Southworth, 2005; Holden and Norland, 2005; Myors et al., 2005; Perkins et al., 2009). An analysis of the U.S. Residential Energy Consumption Survey (RECS) data shows that single-family home residents consume 54% more energy for home heating and 26% more energy for home cooling than do comparable multifamily housing units (Ewing and Rong, 2008). The same study also shows that doubling home size is associated with the use of 16% more energy for heating and 13% more energy for cooling. However, research in this area is still too thin to derive a generalizable elasticity between residential energy use and development density.

UHI effects, another potential path between urban form and residential energy use, are known to raise surface temperatures by 0.5 to 5°C in urban areas, compared with surrounding rural regions (Navigant Consulting, 2009; Rosenfeld et al., 1995; Stone, 2007). Thus, UHI effects significantly affect the energy demand for home cooling and heating by changing the number of cooling degree days (CDDs) and heating degree days (HDDs) in large urban areas. While many studies indeed show the negative consequence of UHI effects in sun-belt cities such as Phoenix, AZ (Baker et al., 2002; Guhathakurta and Gober, 2007), potential heating energy savings in the winter, especially in frost-belt cities, remain understudied. A national scale study is needed to adequately assess this potential trade-off. The potential relationship between the intensity of UHI effects and urban development patterns also require further research.

Although UHI intensity is found to increase with urban population size (Arnfield, 2003; Oke, 1973), little is known about the effects of urban form—including population density and polycentric structure—on heat island formation. Because increased heat storage capacity and limited evapotranspiration of constructed urban fabrics are the main causes of UHI (Oke et al., 1991), urban form would affect UHI intensity to the extent that it alters the thermal properties of urban surfaces. A study of the Atlanta (GA) region shows that lower density residential areas with large lots generate more radiant heat energy than do higher density developments (Stone and Rodgers, 2001). On the contrary, a county level cross-sectional study shows that the UHI effect is more intense in compact counties, with increased CDDs and decreased HDDs (Ewing and Rong, 2008). Further empirical studies are therefore necessary.

Researchers have recently begun to take a more comprehensive and systematic approach to inventorying metropolitan carbon footprints. They associate the variation in newly estimated metropolitan level carbon emissions with population densities and public transportation systems, as well as with other variables such as weather and electricity prices (Brown et al., 2009; Glaeser and Kahn, 2010; Zhou and Gurney, 2011). These studies of metropolitan level carbon footprints should be extended to examine the impact of other dimensions of spatial structure beyond simple density, including polycentricity and centrality. Household level analysis is also much more effective than aggregate scale examinations in isolating pure urban form effects from the effects of other socioeconomic and demographic variables.

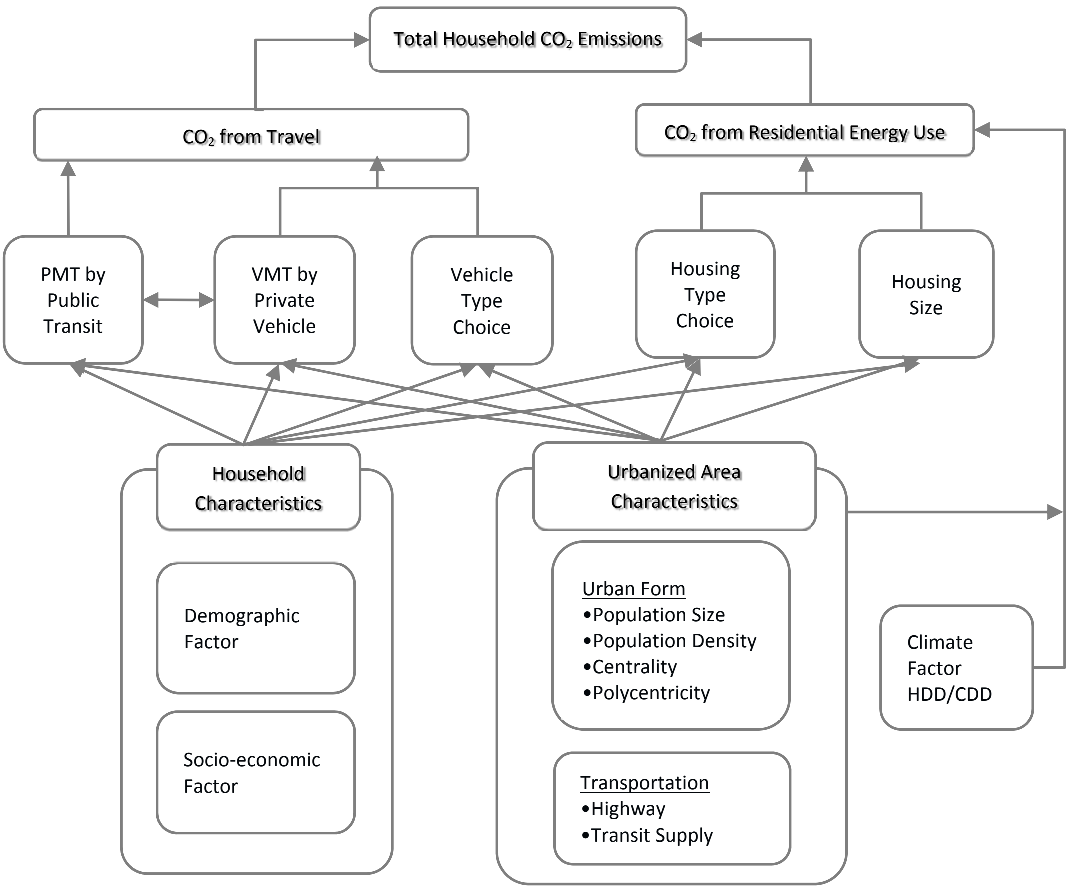

Fig. 1. Conceptual framework and key relationships among main variables.

In sum, previous studies have explored the mechanisms by which urban form influences household sector GHG emissions and have provided meaningful data on certain aspects of this connection (e.g., the elasticities of VMT with respect to neighborhood level urban form indices). However, existing research is largely single-sector driven and focuses mostly on urban form effects at the neighborhood scale. Single-sector research cannot address the potential tradeoffs between transportation and residential emissions. For example, polycentric development may potentially mitigate UHI effects by preserving more natural surfaces between urban centers within a metropolitan region, as demonstrated by the Green Heart (*Groene Hart*), in Randstad, Holland. However, such development is likely to increase VMT, as a monocentric region can be better served by public transportation. Thus, this study examines the effects of urbanized area level urban form on individual household level carbon dioxide emissions, accounting for both transportation and residential energy uses.

The conceptual framework of the research, shown in Figure 1, summarizes the key relationships between our main variables. The chain of causal relationships begins with exogenous variables grouped at two levels: household and urbanized area. Spatial structure variables at the urbanized area level, as well as other transportation infrastructure variables, affect transportation CO_2 emissions via choice of public transit use, VMT, and the choice of vehicle type (in terms of fuel efficiency), after controlling for household level demographic and socioeconomic factors. Two travel behavior variables that are endogenous to the model, public transit use and VMT, are negatively correlated. Urban development patterns also influence an individual household's energy use, and hence CO_2 emissions at home, by affecting available options for housing type and size. The UHI effect is also a potential link between urban form and residential energy consumption that should be further explored.

3. Research methods

3.1. Model specification

Our basic approach is a multilevel structural equation model (SEM), which simultaneously tests multiple causal relations between urban spatial structure and household CO_2 emissions. SEM is an increasingly popular statistical method in various disciplines, including travel behavior research. As a confirmatory analysis method, SEM can be used to examine a system of causal relationships covering both direct and indirect effects when, as is the case with this study, a suggested analytical framework has many endogenous variables (Golob, 2003). However, our data set has a hierarchical structure, with individual households being nested within an urbanized area (UA). Thus, a conventional SEM may lead to false inferences because the data violate the assumption of independent and identical distribution (*iid*). While many studies have opted to do an aggregate level analysis to avoid false inferences, the aggregate approach leads to substantial loss of statistical power and information, and, further, can be subject to an ecological fallacy (Bryk and Raudenbush, 1992).

Multilevel SEM, introduced by Muthén (1994), combines the strengths of the multilevel linear model (MLM) with SEM. As demonstrated by Preacher et al. (2011; 2010), Multilevel SEM has many advantages over MLM, including reduced bias and increased statistical power when analyzing clustered data. The parameters of our Multilevel SEM are estimated by the Weighted Least Squares Estimation with Missing Variable (WLSMV) method, which was developed for the unbiased and efficient estimation of multilevel models with non-normal variables, such as discrete endogenous variables (Hox, 2010; Preacher et al., 2011). Housing type is a categorical endogenous variable in the current research, and its presence merits the WLSMV over maximum likelihood estimation (MLE). We will use the WLSMV procedure available in Mplus® 5.21.

The effects of urban form on CO_2 emissions from household travel and residential energy use are estimated in separate models because of data limitations. To our knowledge, no single data source contains information on travel behavior, residential energy consumption, and sub-state level location variables. We use the 2000 Census Public Use Microdata Sample (PUMS) for residential carbon emission models and the 2001 National Household Travel Survey for analyzing CO_2

emissions from travel. The unit of analysis in both models is individual households nested within the 125 largest urbanized areas in the United States.

The path diagram in Figure 2 summarizes the structure of the transportation CO_2 emissions model, showing the chain of relationships among key variables with expected signs. The model includes two endogenous variables: VMT and the amount of travel related CO_2 emissions. Key predictors of interest—urbanized area level spatial structure variables, including population density, population centrality, and polycentricity—influence household CO_2 emissions via direct and indirect paths. The indirect effect includes all impacts through changes in VMT. For example, households in more compact UAs with a higher density and more centralized population are expected to drive less because of more frequent use of alternative modes of transportation and proximity to trip destinations. Hence, such households tend to emit less CO_2 than comparable households in more automobile-oriented UAs with a lower density. In addition, studies have shown that residents in high density cities tend to drive more fuel-efficient vehicles. Further, carbon emissions per passenger mile by public transit should also be lower in compactly developed urban areas, because of higher average passenger loads in general. The impacts of lower CO_2 emissions per vehicle mile and passenger mile will thus be captured by the direct path from population density to transportation CO_2 emissions.

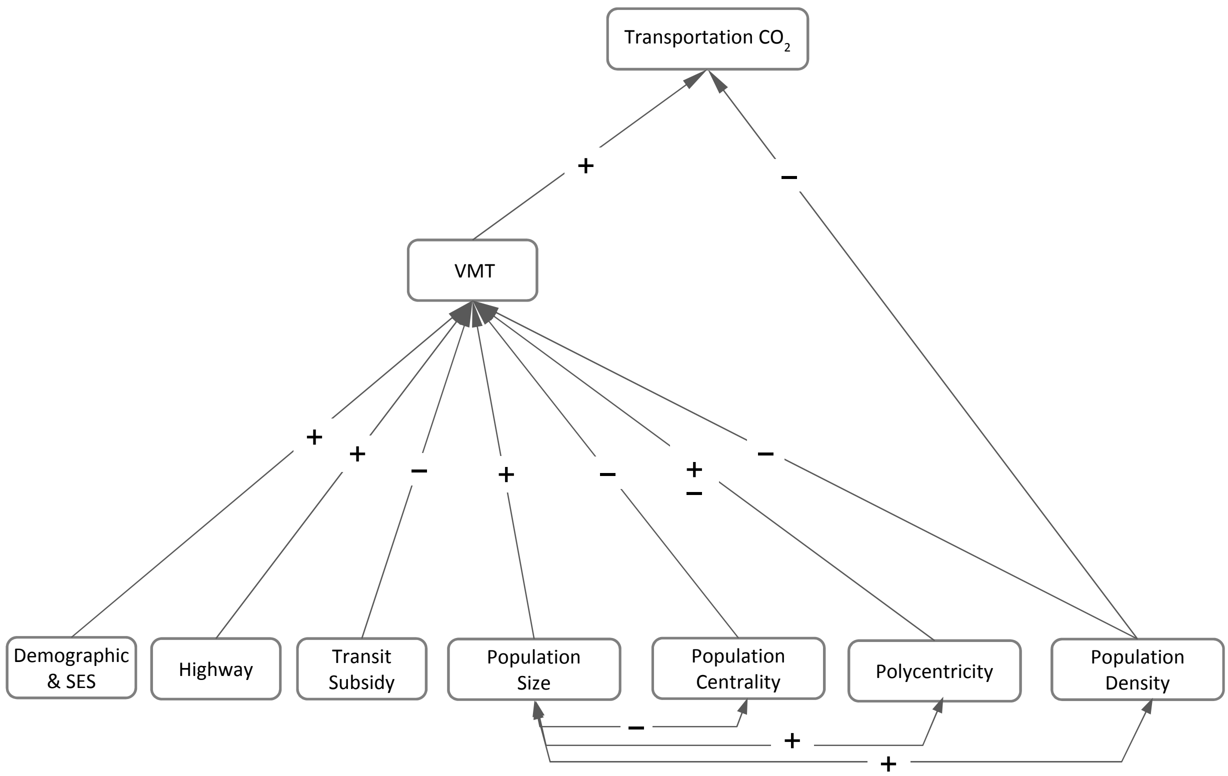

Fig. 2. Path diagram for transportation CO_2 emissions with expected signs.

Centrality is assumed to decrease VMT by promoting transit use, while population size is assumed to be positively associated with VMT. However, we assume that polycentricity has mixed effects on VMT: it reduces commuting distances, given the decentralized population in U.S. urbanized areas, but it discourages public transit use. The direction of the net effect on VMT is an empirical question. Our model also considers the potential associations between population size and urban form variables.

Different levels of transportation supply among UAs should also be controlled to estimate the unbiased effects of urban-form variables on travel behavior and carbon emissions. Per capita highway lane miles and public transportation subsidy are included. We use the level of per capita subsidy to transit services as a proxy for public transportation policies. This is because the actual level of public transit services such as vehicle operation miles is likely to be endogenous to travel demand. In addition to the statistical controls at the urbanized area level, the transportation CO_2 model includes 23 household level covariates, such as household size, income, age, race and education of household head, life cycle stage, and number of workers. Many of these covariates are used as dummy variables in considering the nonlinearity of the expected relationships. In general, socioeconomic status (SES) is assumed to be positively associated with VMT and carbon dioxide emissions.

Figure 3 presents the more complex structure of the residential carbon emissions model. Urban spatial structure variables are assumed to influence individual household energy consumption at home, and hence carbon dioxide emissions, by affecting housing choices and UA level urban heat island (UHI) effects. Households in compactly developed UAs are more likely to live in energy efficient small and attached units. Thus, two housing choice variables, housing type and number of rooms, are used as intermediate variables between population density and residential energy consumption. The links between urban form and UHI effects are less established in the literature, as seen above. While density, given population size, is assumed to intensify UHI effects, following the results by Ewing and Rong (2008), we hypothesize that polycentric structure will lessen the formation of UHIs by allowing more natural surface within an urbanized area.

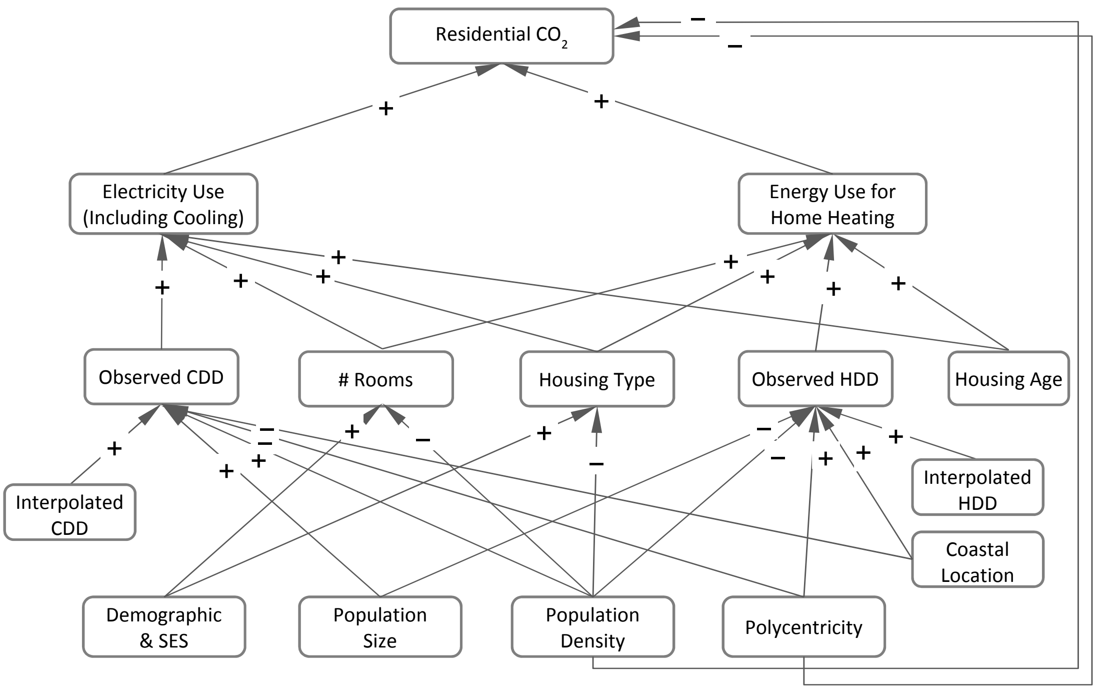

Fig. 3. Path diagram for residential CO_2 emissions with expected signs.

We estimate the impacts of urban form variables on UHI effects by treating observed (actual) annual cooling degree days (CDD) and heating degree days (HDD), which have direct effects on energy use for home heating and cooling, as endogenous to the model. These actual degree days are modeled as a function of corresponding interpolated degree days and UA level exogenous variables, including population size, urban form, and coastal location indicator that are assumed to affect UHI intensity. Since interpolated degree days are expected to be unaffected by urbanization, the effects of UA variables on observed degree days and energy consumption, after controlling for interpolated degree days, can be interpreted as the impacts via UHI. We interpolate (or extrapolate for some coastal areas) observed temperature of surrounding rural stations from U.S. Historical Climatology Network (USHCN) data into degree days in urbanized areas, using a kriging method. We apply an ordinary kriging, using a spherical model with a 3.5° radius (about 300 miles), 1.2° ranges (about 100 miles), and 2° sill (about 150 miles). Actual annual degree days are derived from daily temperature data of the Global Historical Climatology Network (GHCN) by the National Climatic Data Center (NCDC).

The residential CO_2 model includes housing age as a proxy for energy efficiency of the housing structure in addition to all household level exogenous variables used in the transportation CO_2 model.

3.2. Estimation of household level CO_2 emissions

Researchers have recently begun to take a more comprehensive and systematic approach to estimating metropolitan carbon footprints. The Vulcan project completed an inventory of the total fossil fuel CO_2 emissions on a 10km ×10km grid that can be aggregated at the urban area or county scale (Gurney et al., 2009; Parshall et al., 2010). Although representing significant progress in regional level CO_2 accounting, the resulting aggregate data sets have limited utility for studying individual household behavior. Further, the Vulcan project, a production-based study, traces where fossil fuels are burned instead of identifying the source of energy demand. In contrast, Glaeser and Kahn (2010) estimate carbon footprints for a standardized household in different regions by using household survey data. Carbon footprint estimations based on self-reported surveys, which are designed for purposes other than studying energy use, may not be as accurate as estimations based on observed data. Nonetheless, carbon footprint data estimated at the household level can be very useful in studying household energy consumption and GHG emission behaviors.

We take an approach similar to that of Glaeser and Kahn (2010) to estimate household level CO_2 emissions from travel and residential energy consumption in the 125 largest urbanized areas in the U.S. (areas with more than .2 million people). Carbon dioxide emissions from driving are estimated using annual VMT and fuel efficiency (mpg) variables from the 2001 National Household Transportation Survey (NHTS) data. We first estimate annual gasoline consumption for each vehicle as the product of VMT and gallons of fuel per mile and then aggregate to the household level. We then convert household level annual gasoline consumption to CO_2 emissions by multiplying by an emission factor of 23.46 lbs/gallon (19.56 lbs/gallon plus 20% additional emissions for refining and distribution), as suggested by Glaeser and Kahn (2010).

Although private vehicle use is the major source of household CO_2 emissions, emissions from public transit should also be included for full transportation carbon accounting. As shown below, public transit can generate more carbon emissions per person mile than an average private vehicle when transit vehicle occupancy rate is low, which is the case in many U.S. urbanized areas (UAs). To estimate the carbon emissions from transit rides of individual households, we use annual frequency of public transit use from the 2001 NHTS and UA level characteristics of passenger trips by public transit derived from the 2001 National Transit Database. We estimate the average passenger trip length in each urbanized area by dividing total passenger miles by unlinked passenger trips. UA level emission factors per passenger mile are estimated by using transit agency level annual energy consumption by various sources (electricity, diesel, gasoline, LPG, methanol, ethanol, CNG, bunker, biodiesel, and others) and modes (bus and rail), total passenger miles, and CO_2 emission factors by energy source.[1]

- CO_2 Private vehicle use = Annual VMT / Fuel efficiency (mpg) * Emission factor 23.46 (lbs/gallon).
- CO_2 Public transit ride = Household annual transit rides * UA average passenger trip length * UA specific emission factor per passenger mile.

[1] http://www.eia.gov/oiaf/1605/coefficients.html#tbl2.

We use Public Use Microdata Sample (PUMS) data from the 2000 census to estimate carbon dioxide emissions from residential energy use: heating, cooling, and general electricity. CO_2 emissions from home heating are estimated by using such variables as annual natural gas cost and heating fuel type indicator. This choice is inevitable because the response rate for annual home heating fuel cost variable, an obviously better option, is too low to be used (5%). For households that use natural gas for home heating, we convert the annual natural gas cost to CO_2 emissions by multiplying various factors, as shown below. For households that use different energy sources for home heating, such as electricity and LPG, we take two steps to estimate CO_2 emissions. First, we predict annual energy consumption for home heating (kWh) of each individual household based on a multiple regression analysis for a sample of natural gas using households in the same urbanized area. The amount of energy for home heating is regressed on all available household and housing characteristics. Second, we convert predicted energy consumption (kWh) to CO_2 emissions by multiplying various conversion factors obtained from the U.S. Energy Information Administration (EIA)[2]: LPG .467, kerosene .545, coal or coke .717, wood .035, solar 0, and emission factors for electricity varying by region.

- CO_2 Home heating, natural gas using household = Annual natural gas cost ($) / varying-by-state[3] natural gas price ($/ ft^3) * energy efficiency 0.301 (kWh/ft^3) * emission factor 0.399 (lbs/kWh).

We estimate electricity consumption, including energy use for home cooling, based on the formula shown below. Electricity use for home heating is then subtracted to obtain the net electricity consumption for those households. It should be noted that the amount of carbon dioxide emissions from power generation varies substantially across regions, ranging from 775 to 2,283 lbs/mWh, as of 2000.

- CO_2 Electricity = Annual electricity cost ($) / varying-by-state[4] electricity price ($/mWh) * varying-by-region[5] emission factor (lbs/mWh).

3.3. Urban form indices

We measure UA level spatial form in three distinctive dimensions that are expected to have influences on household sector GHG emissions: population density, centrality, and polycentricity. Population density is one of the most important indicators of urban footprint and, hence, carbon footprint. We use population-weighted density instead of a conventional population density measure. While the latter would simply divide urbanized area population by total land area, the population-weighted density of a UA is estimated as the weighted mean of census block group level densities, with each block group's population being used as the weight. We use this alternative measure because it better captures the population density that typical residents of an urban area experience in their daily lives than do conventional density measures (Transportation Research Board, 2009).

Centrality measures the extent to which a UA population is concentrated near the central location as opposed to being suburbanized toward fringe areas (Anas et al., 1998; Galster et al., 2001). Various indicators have been developed to measure the extent of population (de)centralization (See Lee, 2013 for a survey of indices). Given the pros and cons of different measures, we derive a

[2] http://www.eia.gov/oiaf/1605/coefficients.html.
[3] http://www.eia.gov/dnav/ng /ng_pri_sum_a_EPG0_PRS_DMcf_a.html.
[4] http://205.254.135.24 /FTPROOT/electricity/054000.pdf.
[5] http://www.epa.gov/cleanenergy/energy-resources/egrid/archive.html.

centrality index from the multiple measures listed below, using a standard principal component analysis:

- Central business district's (CBD) population share (Lee, 2007): The share of urbanized area population in the CBD.
- Area-based centrality index (Lee, 2007; Massey and Denton, 1988): $ACI = \sum_{i=1}^{n} P_{i-1}A_i - \sum_{i=1}^{n} P_i A_{i-1}$. ACI measures how fast population cumulates with distance from the CBD compared to land area accumulation. It ranges between -1 and 1, with a larger value indicating a higher degree of centrality.
- Ratio of weighted to unweighted average distance (Cutsinger et al., 2005): $WUAD = \left(\frac{\sum_{i=1}^{n} p_i DCBD_i}{E}\right) / \left(\frac{\sum_{i=1}^{n} DCBD_i}{N}\right)$. The ratio typically ranges from 0 to 1, indicating the concentration of whole population in the CBD and a perfectly even distribution of population throughout the UA, respectively. An index value larger than 1 indicates an exceptional degree of suburbanization beyond even distribution.
- Population density gradient: Density gradient measures the rate of decrease in population density with distance from the CBD. It can be estimated as a parameter β from a monocentric urban density gradient model, $\ln d_i = \alpha + \beta DCBD_i$.

Polycentricity denotes the degree to which the functions of urban centers, which act as a hub of economic, commercial, and recreational activities, are shared between the traditional CBD and subcenters. The number of clustered jobs in urban centers is often used as a proxy of concentrated urban activities. Newer metropolitan areas in the West, such as Los Angeles and San Francisco, are generally more polycentric than their older counterparts in the East, such as Boston and New York (Lee, 2007). As discussed above, a polycentric structure may reduce the average commute distance, but is less supportive of public transit than are monocentric urban areas. The polycentricity index is also derived from several different measures:

- Subcenters' share of center employment (Lee, 2007): $SUB = e_{Sub}/(e_{CBD}+e_{Sub})$.
- The number of extra subcenters (Veneri, 2010): The difference between the number of identified employment subcenters and the number of subcenters predicted as a function of UA population by a Poisson regression analysis.
- Slope of rank-size distribution (Meijers and Burger, 2010; NORDREGIO, 2005): Estimated parameter β of the rank-size distribution of employment centers in each UA, $\ln e_k = \alpha + \beta \ln(rank_k - 0.5)$. We use "rank – ½" rather than actual rank in the regression to reduce a bias due to small samples (Gabaix and Ibragimov, 2011).
- Primacy (Meijers, 2008; NORDREGIO, 2005): The degree by which the largest center in the UA deviates from the rank-size distribution of employment centers. To estimate the primacy index, we omit the largest employment center (the CBD in most cases) from the rank-size regression run and then compare predicted and actual employment sizes of it.
- Commuter shed ratio: This measure compares the commuter shed of all subcenters combined with that of the CBD. The commuter shed of a center is defined as census tracts from which more than 10% of workers commute to the center. We develop two indices by measuring the size of commuter shed in terms of employment and land area.

P_i: cumulative proportion of employment in census tract *i* when all tracts are sorted by the distance from the CBD; A_i: cumulative proportion of land area in tract *i*; p_i: population in tract *i*, CBD_i: the distance of tract *i* from the CBD; E: total UA employment; N: number of census tracts; d_i: population density in tract *i*; e_{CBD}: number of jobs in the CBD; e_{SUB}: number of jobs in subcenters; e_k: number of jobs in employment center k; $rank_k$: the rank of urban employment center k in employment size within a UA.

Building some of the spatial indices, especially the ones involving employment shares in urban centers, requires identifying employment centers in urbanized areas. We rely on employment density approaches to identifying urban centers, derived mainly from the field of urban economics (Giuliano and Small, 1991; McMillen, 2001). Urban centers should have significantly higher employment density than surrounding areas and considerable size of employment to function as loci of urban activities. In the first step, we identify two sets of employment density peaks in each UA by applying two alternative methods, absolute and relative density criteria. We then define those clusters of candidate tracts as employment centers that have cluster employment of more than a minimum employment threshold, ranging from 3,000 to 10,000 jobs depending on total metropolitan employment. See Lee (2007) for a detailed description for the procedure.

4. Results

4.1. Household CO_2 emissions in U.S. urbanized areas

The average annual CO_2 emission of U.S. households in the largest 125 urban areas is estimated at 49,733 lbs, as shown in Table 1, combining emissions from driving, public transit use, home heating, and electricity use. While our estimates are derived from household survey data, they are comparable with the results from production-based carbon accounting. The U.S. Energy Information Administration's (EIA) Monthly Energy Review reports that, in 2000, the average CO_2 emission per household from total energy use in the residential sector was 24,765 lbs, while in 2001 CO_2 emissions from passenger travel were about 23,271 lbs, assuming that passenger travel accounts for about 61% of total emissions in the transportation sector. The small difference can be attributed to several factors. First, because we use a natural gas consumption variable, our home heating energy figure may include energy use for water heating and cooking. Second, the method we use to estimate the frequency of transit use from the NHTS data underestimates transit ridership and hence CO_2 emissions from public transportation use. Finally, our estimation is based on the 125 UA sample, not all households in the United States.

Private vehicle driving is a predominant source (97.5%) of carbon emissions from household travel simply because it is the dominant travel mode (88.2%). Switching from driving to riding public transit has a good potential for reducing carbon emissions. Our data show that average public transit produces about 53% less CO_2 per passenger mile than a single-occupancy private vehicle and 26% less than an average-occupancy vehicle. However, public transit is not cleaner than private vehicles in all cities. In 91 out of the 125 urbanized areas in our sample, public transit emits more CO_2 per passenger mile—the result of low occupancy rates of transit modes in small and medium sized cities.[6] This does not mean that we should discourage public transportation in small and medium sized cities. Rather, it implies an even larger potential in GHG reduction of switching from driving to transit riding when threshold passenger loads are ensured by supporting land use and transportation policies.

Regarding residential energy consumption, it should be noted that more CO_2 is produced from electricity consumption (including electricity for home cooling) than from home heating, even as home heating accounts for double the energy use. In other words, on average, the current portfolio of power generation relies on much dirtier energy sources than does individual residential home heating. It is also notable that there is wide variation in the resources mix, and the relative carbon intensity of power generation, across the Emissions and Generation Resource Integrated Database (eGRID) subregions. The amount of CO_2 emissions per MWh of electricity ranges from 775 lbs in

[6] An analysis of the National Transit Database shows that a typical 40-passenger diesel bus is more carbon efficient than the average single-occupancy vehicle when it carries a minimum of 7 passengers on board (Hodges, 2010).

the SERC Tennessee Valley to 2,283 lbs in the Southwest Power Pool (SPP) North. These results imply that electricity use for home heating should be discouraged, especially in those regions where power generation is particularly carbon intense. It also suggests that switching to an alternative resource mix from coal in power generation should be a priority in warmer regions where the demand for home cooling is high.

Table 1

Average annual CO_2 emission per household in the largest 125 U.S. urbanized areas.

	Transportation CO_2		Residential CO_2		Total
	Private Vehicle	Public Transit	Heating	Electricity	
CO_2 emissions per household (lbs)	21,155 (44.6%)	538 (1.1%)	11,160 (23.5%)	14,615 (30.8%)	47,468 (100%)
Household travel					
Annual miles traveled per household[a]	19,706	211			
CO_2 Emissions per VMT (lbs)[b]	1.07				
CO_2 Emissions per PMT (lbs)[b]	0.69	0.51			
Residential energy use					
Energy Consumption (kWh)			24,528 (67.3%)	11,934 (32.7%)	36,462 (100%)
CO_2 Emissions per kWh (lbs)			0.45	1.22	

[a] Vehicle miles traveled (VMT) for private vehicle use and person miles traveled (PMT) for public transit use.
[b] The average occupancy rate of 1.56 per private vehicle and fuel efficiency of 20.96 mpg from the 2001 NHTS are applied to convert VMT to CO_2 emissions.

The geographic pattern of urbanized area carbon footprints shown in Fig. 4 is consistent with previous studies (Brown et al., 2008; Glaeser and Kahn, 2010). The average household carbon dioxide emissions are considerably lower in UAs of the West Coast and Florida, with good climatic conditions, and Northeastern cities that are transit dependent. Many UAs in the Midwest and Southeast that are automobile-oriented and/or carbon intense in power generation have the largest carbon footprints per household.

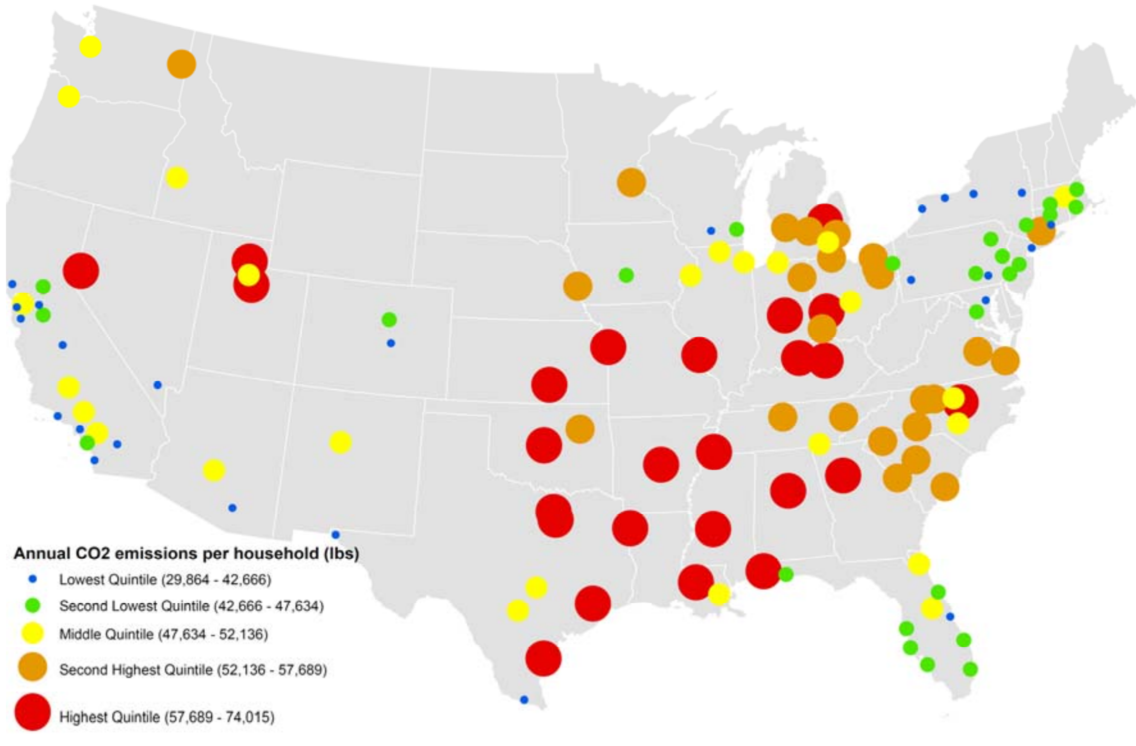

Fig. 4. The geography of carbon footprints in U.S. urbanized areas.

Fig. 5 presents the negative relationship between average annual household CO_2 emissions and population-weighted density, the most basic urban form indicator. The estimated elasticity of CO_2 emissions with regard to density is about 17.34% at the aggregate level when no other covariates are included. However, population density explains only 18% of the variation in average carbon dioxide emissions at the aggregate level. In the following section, we will investigate the true relationship between urban form and CO_2 emissions after controlling for demographic and socioeconomic conditions at the individual household level, along with other UA level characteristics such as climatic conditions and transportation infrastructure.

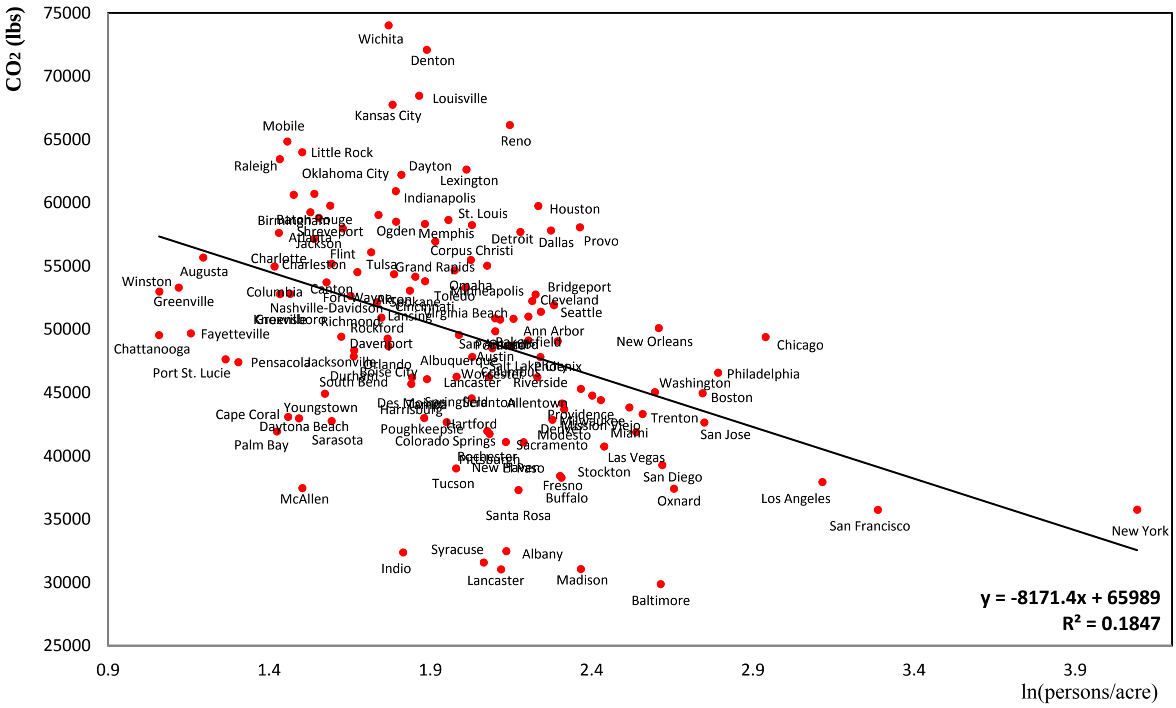

Fig. 5. The relationship between population-weighted density and annual household CO_2 emissions.

4.2. Influence of urban form on household CO_2 emissions

As explained above, we model carbon dioxide emissions from travel and residential energy consumption separately, using a multilevel structural equation model (MSEM). For each sector, we estimate two alternative models, one with a conventional population density and the other with a population-weighted density. Table 2 summarizes several indices of overall goodness-of-fit that are recommended in the literature (Chou and Bentler, 1995; Fan et al., 1999; Kaplan, 1995). The second column of the table shows a rule of thumb threshold value that represents a reasonable fit for each index. Most estimated statistics indicate that both transportation and residential models have a good or reasonable fit. Only the standard root mean square residual (SRMR) cut-off is not satisfied in some of the estimated models. The interclass correlation (ρ), the proportion of total variance explained by hierarchical grouping, ranges between 0.07 and 0.12, which indicates that multilevel modeling is appropriate.

The next section will discuss estimated parameters for selected urbanized area level variables. Full estimation results, including the parameters for household level variables, are shown in Tables A1 and A2 in the appendix. Overall, when compared with previous studies, the results show relatively larger effects of population density on household CO_2 emissions but less significant and marginal effects of other spatial variables such as centrality and polycentrality. We also found that the amount of carbon emissions is more sensitive to urban form variables in transportation than in the residential sector.

Table 2

Goodness-of-fit measures for estimated models.

	General Criteria	Transportation CO_2		Residential CO_2	
		Model 1	Model 2	Model 3	Model 4
CFI	higher than 0.90	0.939	0.947	0.980	0.981
TLI	higher than 0.90	0.908	0.922	0.949	0.949
RMSEA	lower than 0.06	0.050	0.045	0.036	0.037
SRMR (Within)	lower than 0.08	0.009	0.009	0.229	0.229
SRMR (Between)	lower than 0.08	0.021	0.120	0.124	0.113
Interclass correlation (ρ)	-	0.092	0.078	0.113	0.116

[a] Models 1 and 3 use a conventional population density measure, and models 2 and 4 use population-weighted density.
[b] CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; SRMR: Standard root mean square residual.
[c] Interclass correlation (ρ): the ratio of between-group variance to the total variance: $\rho = \frac{\sigma_B^2}{\sigma_B^2+\sigma_W^2}$.

4.2.1. Results for transportation CO_2 emissions

Table 3 and Figure 6 summarize the results of transportation CO_2 models. Since Model 2, with a population-weighted density, is our final model, the effects of density only are shown for Model 1 results in Table 3. Combining all direct and indirect elasticities, a 10% increase in population-weighted density is associated with a 4.8% reduction in CO_2 emissions from travel, all else being equal. Most of the density effect occurs via the VMT path, as shown by the indirect composite elasticity, -0.398 (-0.986 × 0.404). High density developments reduce household VMT by promoting alternative transportation modes and bringing trip origins and destinations closer together. In addition, people tend to own more fuel efficient vehicles, and public transit is more carbon efficient per passenger mile, due to higher passenger loads in higher density communities. These additional effects are captured by the direct impact of population-weighted density in our model: -0.08.

Table 3

Direct, indirect, and total effects of key urbanized area characteristics on transportation CO_2 emissions.

Paths from selected UA level variables to transportation CO_2	Coefficient		Elasticity[a]
	1)	2)	1) × 2)
Model 1:			
Total effects of conventional population density			**-0.224**
Density →$^{1)}$ VMT →$^{2)}$ Transportation CO_2	-0.371 ***	0.441 ***	-0.164
Density →$^{2)}$ Transportation CO_2		-0.060 **	-0.060
Model 2:			
Total effects of population-weighted density			**-0.478**
Density →$^{1)}$ VMT →$^{2)}$ Transportation CO_2	-0.986 ***	0.404 ***	-0.398
Density →$^{2)}$ Transportation CO_2		-0.080 ***	-0.080
Total effects of population centrality			**-0.092**
Centrality →$^{1)}$ VMT →$^{2)}$ Transportation CO_2	-0.228 ***	0.404 ***	-0.092
Total effects of polycentricity			**0.069**
Polycentricity →$^{1)}$ VMT →$^{2)}$ Transportation CO_2	0.171 **	0.404 ***	0.069
Total effects of transit subsidy			**-0.184**
Transit subsidy →$^{1)}$ VMT →$^{2)}$ Transportation CO_2	-0.456 ***	0.404 ***	-0.184

[a] Elasticity column shows direct, composite indirect, and total elasticities of transportation CO_2 emissions with respect to exogenous urbanized area level variables. The results for the density variable only are shown for model 1 for comparison.
[b] Full model result is reported in Table A1 in the appendix.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Estimated density effects are larger than most estimates in previous studies. While the average elasticity of VMT with respect to local density as one of many urban form indicators is as small as -0.04 on average (Ewing and Cervero, 2010), it is generally accepted that the density effect is as high as -0.3 when used as a proxy for all other compact urban form characteristics, such as land use mix and urban design (Ewing et al., 2008b). This study reveals that VMT is nearly unit elastic with respect to urban area level population density when a better measure—population-weighted density—is used.

This somewhat exceptionally large elasticity (-0.986) merits further discussion. First, urbanized or metropolitan area level development patterns represented by population density generally have larger impacts on people's travel behavior than do neighborhood level density and design variables. A recent study of per capita VMT in 370 urbanized areas shows that direct and net elasticities with respect to UA density are as high as -0.60 and -0.38, respectively (Cervero and Murakami, 2010). Second, the new measure of population-weighted density more accurately reflects the characteristics of the built environment that an average person experiences and thus explains variation in travel behavior better than a conventional density measure. When a conventional urbanized area density is used in Model 1, the elasticity of VMT is much smaller (-0.371) and is almost identical to the density effect estimated by Cevero and Murakami (2010). Because of the small elasticity of VMT, the total effect of conventional density measure on transportation CO_2 emissions (-0.224) is smaller than half that of population-weighted density.

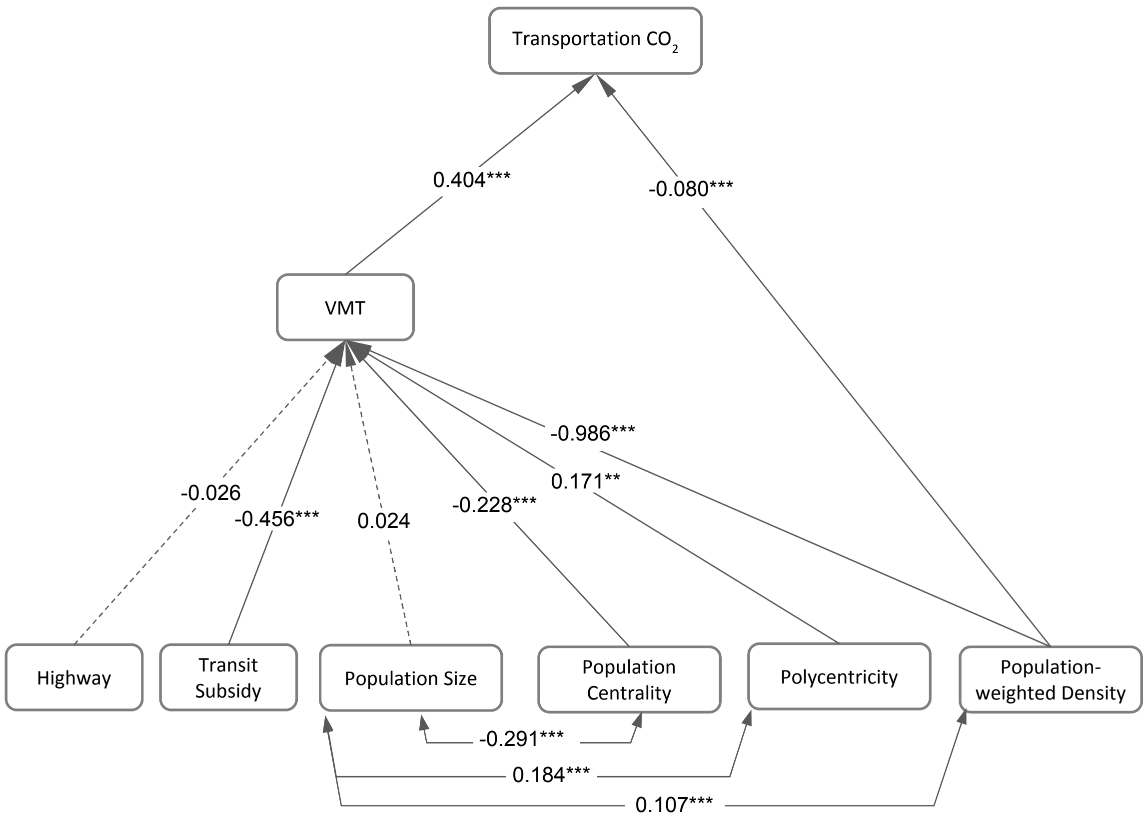

Figure 6. Key results for the transportation carbon dioxide emissions model.

Notes: The results for various household level exogenous variables are suppressed for space reason. They are included in appendix Table A1. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

The impacts of the other two urban form variables are estimated to be moderate. Consistent with our expectation, centralized population distribution, given the same population and density, significantly reduces the amount of vehicle travel, by promoting public transportation and reducing trip distances. The elasticity is estimated at about -0.09. Thus, both overall population density in an urbanized area and the density near the central location are important in reducing carbon dioxide emissions from household travel.

As discussed above, a polycentric structure is expected to have dual effects. On the one hand, it can potentially shorten commute distances, given more decentralized population than employment; on the other, it can make serving urban activities by public transportation more difficult. The net effect is estimated to be moderately positive in this study, suggesting that the effect of discouraging transit use dominates in medium and large U.S. urbanized areas. This finding implies that increasing employment density near the CBD can also be beneficial in terms of CO_2 emission reduction. However, it should be noted that polycentric structure is a spatial adjustment to cope with negative externalities of city size (Fujita and Ogawa, 1982; McMillen and Smith, 2003). Empirical studies have associated polycentric metropolitan structure with higher productivity (Meijers and Burger, 2010), and decentralized employment has often been connected with a shorter average commute time (Crane and Chatman, 2003; Lee, 2006). Thus, developing public transportation networks that can efficiently serve polycentrized urban regions would be a better policy solution (Brown and Thompson, 2008) than discouraging transformation from a monocentric to polycentric urban area.

This policy implication is further articulated by the significance of the transit subsidy variable. Doubling transit subsidy per capita is associated with nearly 46% lower VMT and an 18% reduction in CO_2 emissions. However, the other transportation infrastructure variable, highway lane miles per capita, was insignificant in our results. After controlling for urban form and other urbanized area level characteristics, population size does not exert consistent effects on household level transportation CO_2 emissions—it is significant only in Model 1. In other words, it is not simple population growth but how and where population grows in an urban area that matters for carbon dioxide emissions from household travel.

The results for individual household level demographic and socioeconomic variables are all consistent with our expectations, as shown in Table A1 in the appendix. Higher income, larger household size, more employed workers, and being white are associated with higher CO_2 emissions from travel.

4.2.2. Residential CO_2 emissions

High density development also contributes to energy saving and CO_2 emission reduction in residential buildings. As shown in Table 4, a 10% increase in population-weighted density is associated with a 3.5% reduction in residential CO_2 emissions (the reduction is 3.1% when accounting for only statistically significant path coefficients). While this elasticity is slightly smaller than the impact on transportation CO_2 emissions, it is still a considerable effect that deserves policy attention. The result of Model 1 with a conventional density measure is similar, except that the estimated elasticity is slightly larger, as shown in the top panel of Table 4: -0.375 (-0.351).

Our results also show that CO_2 emissions from electricity consumption are more sensitive to population density change (-0.240) than are emissions from home heating (-0.078). This gap in sensitivity can be attributed to several factors. First, a small variation in electricity consumption can lead to a large change in CO_2 emissions, because power generation is 2.7 times more carbon intensive than home heating energy on average. As shown in the housing type path coefficients, the elasticity of home heating energy use with respect to density (-0.245 = -0.362*0.678) is actually larger than that of electricity consumption (-0.158 = -0.362*0.437). However, this order is reversed because CO_2 emissions are more sensitive to electricity than to home heating energy use. Second, there can be measurement errors. The number of rooms, the only available but not the best proxy for housing size, turns out not to have significant effects on home heating energy use. As a result, it may underestimate the impact of urban density on CO_2 emissions from home heating.

The other path from density to CO_2 emissions, the impact of density on the urban heat island (UHI) effect, are found to be statistically insignificant after controlling for urban population size. Consistent with the literature, UHI intensity increases with urban population, with doubling population leading to an 8% increase of CDDs and a 3% decrease of HDDs. The net effect on CO_2 emissions is estimated to be about 1.6% of additional emissions. However, our model does not show any significant impact of urban density given population size on degree days and hence on energy consumption. As discussed above, Ewing and Rong (2008), who took a similar approach to estimating the UHI effect, found that a 1% lower sprawl index (i.e., compact development) is associated with an increase of CDDs by 0.48% and a decrease of HDDs by 0.21%. Further empirical and scientific research is necessary to draw any meaningful conclusion on the potential links between urban density and UHI intensity.

Table 4

Direct, indirect, and total effects of key urbanized area characteristics on residential CO_2 emissions.

Paths from UA level variables to Residential CO_2	Coefficient			Elasticity[a]	
	1)	2)	3)	1) × 2) × 3)	
Model 1:					
Total effects of conventional population density				**-0.375**	**(*-0.351*)**
Through electricity consumption (including home cooling)				**-0.257**	**(*-0.240*)**
Density →[1)] #Rooms →[2)] Electricity →[3)] Residential CO_2	-0.098 ***	1.138 ***	0.865 ***	*-0.096*	
Density →[1)] Housing Type[a] →[2)] Electricity→[3)]Residential CO_2	-0.402 ***	0.413 ***	0.865 ***	*-0.144*	
Density →[1)] CDD →[2)] Electricity →[3)] Residential CO_2	-0.059	0.333 ***	0.865 ***	-0.017	
Through home heating				**-0.092**	**(*-0.111*)**
Density →[1)] #Rooms→[2)] Heating →[3)] Residential CO_2	-0.098 ***	-0.440	0.375 ***	0.016	
Density →[1)] Housing Type[a] →[2)] Heating →[3)] Residential CO_2	-0.402 ***	0.735 ***	0.375 ***	*-0.111*	
Density →[1)] HDD→[2)] Heating →[3)] Residential CO_2	0.012	0.571 ***	0.375 ***	0.003	
Density →[3)] ResidentialCO_2			-0.026	-0.026	
Model 2:					
Total effects of population-weighted density				**-0.355**	**(*-0.306*)**
Through electricity consumption (including home cooling)				**-0.240**	**(*-0.213*)**
Density →[1)] #Rooms →[2)] Electricity →[3)] Residential CO_2	-0.077 ***	1.192 ***	0.851 ***	*-0.078*	
Density →[1)] Housing Type[b] →[2)] Electricity→[3)]Residential CO_2	-0.362 ***	0.437 ***	0.851 ***	*-0.135*	
Density →[1)] CDD →[2)] Electricity →[3)] Residential CO_2	-0.096	0.335 ***	0.851 ***	-0.027	
Through home heating				**-0.078**	**(*-0.093*)**
Density →[1)] #Rooms→[2)] Heating →[3)] Residential CO_2	-0.077 ***	-0.392	0.378 ***	0.011	
Density →[1)] Housing Type[b] →[2)] Heating →[3)] Residential CO_2	-0.362 ***	0.678 ***	0.378 ***	*-0.093*	
Density →[1)] HDD→[2)] Heating →[3)] Residential CO_2	0.016	0.568 ***	0.378 ***	0.003	
Density →[3)] ResidentialCO_2			-0.037	-0.037	
Total effects of polycentricity				**-0.010**	**(*-0.007*)**
Polycentricity →[1)] CDD →[2)] Electricity →[3)] Residential CO_2	-0.025 *	0.335 ***	0.851 ***	*-0.007*	
Polycentricity →[1)] HDD →[2)] Heating →[3)] Residential CO_2	-0.011	0.568 ***	0.378 ***	-0.002	
Polycentricity →[3)] Residential CO_2			-0.001	-0.001	
Total effects of population size				**0.016**	**(*0.016*)**
Population →[1)] CDD→[2)] Electricity →[3)] Residential CO_2	0.083 ***	0.335 ***	0.851 ***	*0.024*	
Population →[1)] HDD→[2)] Heating →[3)] Residential CO_2	-0.034 ***	0.568 ***	0.378 ***	*-0.007*	

[a] Elasticity column shows direct, composite indirect, and total elasticities of transportation CO_2 emissions with respect to exogenous urbanized area level variables. The results for the density variable only are shown for model 1 for comparison.
[b] Although housing type, an important mediating variable, is an ordinal variable, a composite elasticity of CO_2 emissions with respect to population density can still be obtained as the product of comprising path coefficients because a latent continuous variable instead of observed housing type indicators is used when predicting electricity and home heating energy consumption.
[c] Values in italics indicate elasticities of which all comprising coefficients are statistically significant at at least 10%. Values in parentheses are sums of only statistically significant direct and indirect effects.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

The impact of polycentric structure on UHI intensity is only partially identified. Urban polycentricity is found to have a significant effect of reducing cooling degree days and hence reducing electricity consumption and CO_2 emissions, consistent with our expectations. But the size of the effect is too small (-0.007) to have any meaningful policy implications, especially given the negative consequence of polycentric urban structure on VMT and transportation CO_2 emissions.

As shown in Table A2 in the appendix, the residential CO_2 emission model shows expected results for household level demographic and socioeconomic variables. CO_2 emissions from home heating and electricity use increase with household size, income, and education in general, combining all direct and indirect impacts. While newer homes are more energy efficient in home heating, as expected, the age of housing does not significantly affect the amount of electricity consumption.

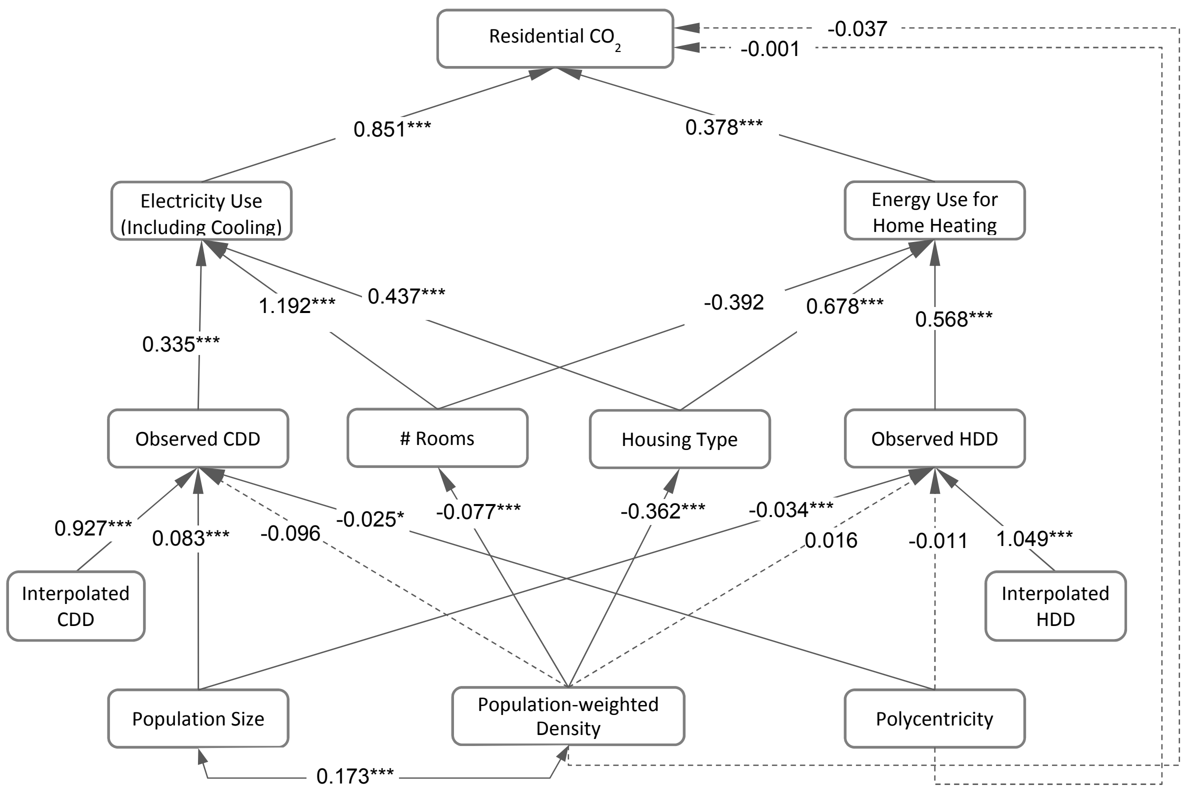

Fig. 7. Key results for the residential carbon dioxide emissions model.
Notes: The results for various household level exogenous variables and location dummy are suppressed to conserve space. They are included in appendix Table A2. Housing type is an ordinal variable (0= multi-family, 1= single attached, and 2= single detached). Coefficients of exogenous variables on housing type are estimated using an ordered probit link function.* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

5. Conclusions

To enhance our understanding of the role of sustainable urban development in GHG mitigation, this study investigated the paths via which urban form influences household carbon dioxide emissions in the 125 largest urbanized areas in the United States. Toward that end, we estimated individual household level CO_2 emissions from travel and residential energy consumption based on the 2001 National Household Travel Survey and the 2000 Census PUMS data. Estimates show that an average U.S. household in large and medium size urban areas annually produces 49,733lbs of CO_2, combining emissions from travel (45.7%) and residential energy consumption (54.3%). It is notable that the carbon intensity of electricity is about 2.7 times that of home heating energy on average and has wide variation from region to region.

The results of multilevel SEM analyses show that doubling population-weighted density is associated with a reduction in CO_2 emissions from household travel and residential energy consumption by 48% and 35%, respectively. Population density is believed to function as a catchall variable for compact urban form, which may also include land use mix and alternative urban design elements, although several additional UA level urban form variables are included in our models. In any case, our analysis presents considerably larger elasticities than previous estimates by using population-weighted density instead of a conventional density measure. Furthermore, though not included in our analysis, compact urban form can also contribute to reducing energy use and GHG emissions in commercial buildings that may be comparable to carbon savings from residential buildings shown in this study.

The other two urban form variables were only moderately significant: centralized population distribution helps reduce VMT and hence transportation CO_2 emissions, while polycentric structure is associated with an opposite outcome. Perhaps more importantly in terms of policy implications, we also found that public transportation policy can play a significant role in lowering VMT. Doubling the per capita transit subsidy is associated with a nearly 46% lower VMT and an 18% reduction in transportation CO_2 emissions.

Given that household travel and residential energy use account for 42% of total U.S. carbon dioxide emissions, our research findings corroborate that urban land use and transportation policies to build more compact cities should play a crucial part of any strategic efforts to mitigate GHG emissions and stabilize climate at all levels of government. In recent years, smart growth principles aimed at reversing the long-standing trend of sprawled development in U.S. urban areas have been increasingly adopted by urban planners and environmentalists. While these efforts to create more compact, mixed-use and transit-oriented urban areas have produced some evident changes in pioneering regions such as Portland, OR, smart growth still remains an unrealized vision in many other parts of urban America (Downs, 2005). Federal and state level policies and programs are needed to support local and regional efforts to implement smart growth.

The findings of this study also suggest that GHG mitigation strategies should be customized for individual cities or regions to be more effective and efficient, as each region has different characteristics in terms of carbon footprint. For example, electric vehicles and electricity use for home heating are not to be recommended in regions where the carbon intensity of electricity is high (Kennedy, 2011). Switching to alternative power resources should take high priority in warm regions, where the demand for home cooling is high. In low density urban areas with currently high VMT, tighter vehicle fuel efficiency standards and alternative fuel policies are necessary in the short run, while well-coordinated smart growth policies to create sustainable urban environment should follow in the long run.

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Appendix

Table A1.
Full result of transportation CO_2 model (Model 2).

	Between Groups				Within Groups			
	Transportation CO_2		VMT		Transportation CO_2		VMT	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
VMT	0.404	0.000***			0.424	0.000***		
Population-Weighted Density	-0.080	0.005***	-0.986	0.000***				
Population Size			0.024	0.809				
Centrality			-0.228	0.001***				
Polycentricity			0.171	0.025**				
Transit Subsidy			-0.456	0.010***				
Freeway Lane Miles			-0.026	0.933				
Age1 (younger than 21)							-0.483	0.027**
Age2 (21–30)							-0.159	0.207
Age4 (41–50)							0.021	0.836
Age5 (51–65)							0.246	0.031**
Age6 (older than 65)							-0.109	0.331
Race1 (White)							0.728	0.000***
Race2 (African American)							-0.873	0.000***
Education1 (less than high school)							-0.841	0.000***
Education2 (high school)							-0.082	0.569
Education4 (some college)							0.068	0.665
Education5 (4 year university)							0.095	0.508
Education6 (graduate school)							-0.132	0.472
Income1 (less than \$20,000)							-1.918	0.000***
Income2 (\$20,000–\$35,000)							-0.464	0.000***
Income4 (\$55,000–\$80,000)							0.748	0.000***
Income5 (higher than \$80,000)							1.003	0.000***
Life Cycle1 (no children)							-0.359	0.008***
Life Cycle2 (youngest child 0–5)							-0.048	0.708
Life Cycle4 (youngest child 16–21)							-0.236	0.217
Life Cycle5 (retired, no child)							-0.080	0.566
Household Size (# members)							0.209	0.000***
Number of Workers							0.655	0.000***
Goodness of fit								
Comparative fit index (CFI)			0.947					
Tucker-Lewis index (TLI)			0.922					
Root mean square error of approximation (RMSEA)			0.045					
Standard root mean square residual (SRMR), Within			0.009					
Standard root mean square residual (SRMR), Between			0.120					
Interclass correlation (ρ)			0.078					

Notes: Reference categories for dummy variables are as follows: Age3 (household head age 31 – 40); Race3 (all other races); Education3 (technical training); Household annual income3 ($35,000 - $55,000); Life Cycle 3 (youngest child 5–16).
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table A2.
Full result of residential CO_2 model (Model 4).

	Between Groups													
	Residential CO_2		Heating Energy		Electricity Use		# of Rooms		Housing Type		Observed HDD		Observed CDD	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Heating Energy	0.378	0.00***												
Electricity Use	0.851	0.00***												
Observed HDD			0.568	0.00***										
Predicted HDD											1.049	0.00***		
Observed CDD					0.335	0.00***								
Predicted CDD													0.927	0.00***
Population Size											-0.034	0.00***	0.083	0.00***
Weighted Density	-0.037	0.27					-0.077	0.00***	-0.362	0.00***	0.016	0.39	-0.096	0.23
Polycentricity	-0.001	0.95									-0.011	0.17	-0.025	0.06*
Number of Rooms			-0.392	0.43	1.192	0.00***								
Housing Type			0.678	0.00***	0.437	0.00***								
Water Front											0.018	0.43	-0.067	0.17
	Within Groups													
	Residential CO_2		Heating Energy		Electricity Use		# of Rooms		Housing Type					
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value				
Heating Energy	0.448	0.00***												
Electricity Use	0.414	0.00***												
Number of Rooms			0.317	0.00***	0.478	0.00***								
Housing Type			0.455	0.00***	0.369	0.00***								
Sex			-0.085	0.00***	0.024	0.30	0.000	0.96	0.187	0.00***				
Age1 (younger than 21)			0.404	0.00***	0.351	0.00***	-0.205	0.00***	-0.728	0.00***				
Age2 (21–30)			0.201	0.00***	0.089	0.00***	-0.134	0.00***	-0.511	0.00***				
Age4 (41– 50)			-0.043	0.08*	-0.028	0.24	0.065	0.00***	0.199	0.00***				
Age5 (51– 65)			-0.111	0.00***	-0.123	0.00***	0.116	0.00***	0.407	0.00***				
Age6 (older than 65)			-0.130	0.00***	-0.174	0.00***	0.149	0.00***	0.484	0.00***				
Race1 (White)			-0.200	0.00***	-0.083	0.00***	0.163	0.00***	0.361	0.00***				
Race2 (African American)			0.026	0.47	0.015	0.65	0.104	0.00***	0.040	0.48				
Employment Status1			-0.013	0.61	0.040	0.13	0.030	0.01***	-0.014	0.77				
Education1 (less than high chool)			0.177	0.12	0.006	0.95	-0.241	0.00***	-0.387	0.01**				
Education2 (high school)			0.029	0.55	-0.014	0.76	-0.093	0.00***	-0.242	0.00***				
Education4 (some college)			-0.013	0.59	0.006	0.78	0.051	0.00***	0.014	0.72				
Education5 (4 year university)			-0.051	0.06*	-0.033	0.20	0.080	0.00***	0.075	0.07*				
Education6 (Graduate)			0.000	0.99	0.019	0.58	0.124	0.00***	0.002	0.98				
Income1 (less than $17,500)			0.155	0.00***	0.098	0.01***	-0.135	0.00***	-0.438	0.00***				
Income2 ($17,500–$32,300)			0.099	0.00***	0.061	0.04**	-0.094	0.00***	-0.301	0.00***				
Income4 ($56,000–$90,000)			-0.109	0.00***	-0.045	0.15	0.104	0.00***	0.363	0.00***				
Income5 ($90,000–$139,700)			-0.180	0.00***	-0.084	0.03**	0.197	0.00***	0.585	0.00***				
Income6 (higher than $139,700)			0.002	0.96	0.045	0.34	0.297	0.00***	0.588	0.00***				
Household Size			-0.040	0.00***	-0.016	0.03**	0.048	0.00***	0.198	0.00***				
Built Year1 (less than 10 years)			-0.012	0.62	-0.027	0.35								
Built Year3 (21–40 years ago)			0.064	0.01***	0.031	0.23								
Built Year4 (older than 40 years)			0.124	0.00***	0.018	0.53								
Goodness of fit														
Comparative fit index (CFI)							0.981							
Tucker-Lewis index (TLI)							0.949							
Root mean square error of approximation (RMSEA)							0.037							
Standard root mean square residual (SRMR), Within							0.229							
Standard root mean square residual (SRMR), Between							0.113							
Interclass correlation (ρ)							0.116							

Notes: Reference categories for dummy variables are as following: Age3 (household head age 31–40); Employment status0 (unemployed); Race3 (all other races); Education3 (technical training); Household annual income3 ($35,000 - $55,000); Built year (11–20 years).
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.