THE ROLE OF URBAN SPATIAL STRUCTURE
IN REDUCING VMT AND GHG EMISSIONS

BY

SUNGWON LEE

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Regional Planning
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2015

Urbana, Illinois

Doctoral Committee:
- Associate Professor Bumsoo Lee, Chair and Director of Research
- Associate Professor Brian Deal
- Assistant Professor Bev Wilson
- Professor Geoffrey Hewings

ABSTRACT

The aim of this study is to uncover the role of urban spatial structure in greenhouse gas (GHG) mitigation and to understand how sustainable urban form can better reduce climate change. Until now, a great number of studies have focused on the links between urban spatial structure and travel behavior, but little is known about spatial structure impacts on residential energy consumption. Most previous studies applied the use of neighborhood scale spatial structure to understand greenhouse gas emissions. However, such studies are too narrow to explain total urban spatial influences. This dissertation research therefore focuses on regional scale spatial structure (urban area level) in order to decrease GHGs and mitigate climate change.

In doing so, this dissertation research consists of the three specific topics to scrutinize the role of sustainable urban spatial structure. The first topic (chapter 2) empirically examines whether and to what extent spatial structure affects the amount of household sector greenhouse gas emissions in U.S. urbanized areas. The study covers the comprehensive impacts of spatial structure not only on travel behavior, but also on residential energy consumption. Therefore, we can trace the overall impacts of urban spatial structure on all sources of GHG in the US household sector. The second topic (chapter 3) focuses on the impact of multiple geographic scales of sustainable built-environment to mitigate GHGs. In the study, the impacts of neighborhood level characters and regional level urban form elements are compared. The final topic (chapter 4) compares land-use policy with price policy to effectively reduce GHGs, and empirically shows how both policies can support GHG mitigation.

1) The influence of urban form on greenhouse emissions in the household sector

This study comprehensively investigates the diverse paths through which urban form influences an individual household's carbon dioxide emissions in the 125 largest urbanized areas in the U.S. This research takes a consolidated approach in investigating all energy consumption in the household sector: CO_2 emissions from heating, cooling and transportation. The result of the multilevel structure equation model (multilevel SEM) analyses shows 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. The impacts of a centralized population and a polycentric structure have only a moderate impact in the analyses, but overall population centrality increase and polycentricity decrease are good for reducing CO_2. In reality, however, the majority of US urban spatial structure have developed in the opposite direction of sustainability from 2000 to 2010; both population density and population-weighted density have

decreased by about 3.5% for last 10 years in the largest 121 urban areas. In addition, population centrality has decreased by about 16%, while polycentricity has increased by 7%. The result also shows that doubling per capita transit subsidies is associated with a nearly 46% lower VMT and 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 research findings corroborate the notion that urban land use and transportation policies to build more compact and transit friendly cities should be a crucial part of any strategic efforts to mitigate GHG emissions and stabilize climate at all levels of government.

2) Sustainable urban form at local and regional scales

The link between urban form and travel behavior is recognized as a key role in understanding the role of sustainable urban development in reducing greenhouse gas emissions in the transportation sector. Many recent studies have found that urban form variables—such as density, land use diversity, street design, destination accessibility, and distance to transit (the "5Ds")—significantly influence travel behavior including mode choice, trip frequency, trip distance, and ultimately vehicle miles traveled (VMT), and they are regarded as the fundamental principles for land use policies to promote more sustainable transportation. In previous study, the 5 element impacts on VMT (VMT elasticity w.r.t. 5Ds) are significant, but not large. The reason seems to come from the small geographic unit of analysis (census tract, census block group or TAZ level). According to the NHTS (2009), more than 85% Americans still use automobile when they travel, and the average one-way trip distance by auto is about 9 miles, while the average radius of census tract and census block group is only about 0.5 and 0.3 miles, respectively. Moreover, many sustainable urban form studies have focuses on neighborhood character based on residence or working place, but home based work (HBW) is less than 10%, and there are various trip purposes, so there are diverse origins and destinations in each travel. Ironically, however, most studies suggest that coupling sustainable urban structure with supporting neighborhood structures decreases VMT, but most people use cars for travel for trips beyond the geographic unit of analysis.

To fill the gap in the literature, this study investigates the influences of urban form at both geographical scales on travel behavior and carbon dioxide emissions using a multilevel analysis (3 level analysis; individual household, neighborhood, and urbanized area). The results show that the influence of regional level urban form is higher than that of neighborhood level on VMT. Regional level variables such as population weighted density (PWD), population centrality, jobs-to-housing ratio, and transit service supply significantly reduce VMT and CO_2 from transportation sector. Most 5D elements at the neighborhood level also significantly diminish VMT and CO_2, but the coefficient of regional level variables are higher than that of neighborhood level urban form elements. Moreover, the empirical outputs indicate that the positive effects of sustainable urban elements (5Ds) at the neighborhood level to reduce GHGs are increased under more high-density, high-centralized, and high job accessible UAs than auto-oriented UAs. For instance, when we double the compactness level at the neighborhood level, VMT decreases by about 50% in the average PWD UAs such as St. Louis. However, the influence can intensify by about 75% when the UA density (PWD) arrives at the New York level.

3) Complementarity between land use planning and pricing in VMT reduction

To effectively reduce VMT, there seems to be no majority consensus. There is a wide gap between advocates of pricing policies and advocates of land use planning. Advocates of each approach underestimate the role and impacts of the other approach. In particular, skepticism still remains concerning the potential for more sustainable urban form and development patterns in reducing VMT and carbon emissions. The majority planners, on the other hand, emphasize that "getting prices right" policies cannot be effective in the absence of alternatives to automobile usage in many U.S. cities. However, land use planning and pricing approaches are complementary and potentially synergetic rather than competing and conflicting. Further, all possible policy options should be fully employed to achieve climate-stabilizing GHG reduction targets. Thus, policy analysts and decision makers should understand the complex interactions between various policy instruments to mitigate policy conflicts and maximize synergetic effects. Nonetheless, empirical research on the policy synergy between different approaches in transportation planning is extremely rare.

To enhance the understanding of the policy synergy between pricing and land use planning approaches, this study examines the interaction effects between fuel prices and land use (urban form) variables in reducing VMT in 115 UAs for 10 years from Jan. 2002 to Dec. 2011 (monthly data). To find the both policy impacts, diverse empirical analyses are conducted from simple comparative analysis, to regression analysis, panel analysis, and panel type locally weighted smoothing (P-LOESS). The results show that there are synergic effect between land use policies and fuel price policies. Under the high fuel price, VMT reducing impacts of most compact urban form variables (UA level) are estimated to be stronger. When PWD doubles, VMT is reduced by about 19% under around 1 dollar per gallon ($ 2005), but the impact increases to about 27% under about $2.5 /gallon. However, the complementary relations do not seem constant as gasoline price increases. With gasoline price increases, the elasticities of VMT dramatically increases below $2.5 per gallon. However, the elasticities remain at around 27%, even when the fuel price increases beyond $2.5 to $4 per gallon. The elasticities of urban compactness and centrality also show a similar pattern, in which they stabilize at a certain level.

The implications of all findings from the three topics may greatly add to sustainable land use policy and transportation planning. While current federal- and state-level climate change policies mainly depend on technology solutions, the first study gives strong evidence for the importance of land use planning, as GHG mitigation strategies must alter travel behavior as well as energy consumption behavior. The comparison between local and regional level built environment impacts in the second topic highlight an essential issue of whether the state and/or regional governance can effectively reduce GHGs. The study shows that scattered and fragmented development of compact neighborhoods is not sufficient to moderate auto-oriented travel behavior. Instead, the study implies that strategic regional level coordination of smart growth policies can effectively foster sustainable travel behavior such as urban growth boundaries, balanced jobs-housing development, and transit oriented development. The final study underlines how both land use and fuel price policies generates synergic effects, which is largely overlooked by planners. The study empirically shows the adequate range of fuel prices to stimulate increasing effectiveness of sustainable land use policy, so the results can provide great evidence for the actual implementation of synergic activities.

To My Parents, Wife, and Katherine

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

Our planet is warming. The global mean temperature (GMT) is projected to rise, with the lowest and highest projections being respectively 1.1°C and 6.4°C by 2100, if greenhouse gas (GHG) emissions from human activities are not curbed (Intergovernmental Panel on Climate Change, 2007; Smith et al., 2008). Over the last 55 years, CO_2 concentrations have risen from 315 ppm in 1958 to 400 ppm in 2013. Climatologists warn that humans may face disastrous consequences when the CO_2 concentration passes 450 ppm[1] (Jones, 2013; Showstack, 2013; Stults, Wagner-Cremer & Axsmith, 2011); they suggest the GMT level be maintained under "the 2°C guardrail"[2] (Hansen et al., 2008).

[1] Many climatologists argue that the warm period of Pliocene (almost 3.6 million years ago) provides a potential analogue for the future climate change and impacts. Studies in paleoclimatology show that the concentrations of carbon dioxide ranged from about 380 to 450 ppm in the period of the middle Pliocene. The global mean temperature (GMT) was about 3°C warmer than now and the sea level lapped coasts 5 meters or higher. Many species became extinct in the Pliocene era.

[2] The IPCC (2007) recommended that the GMT should be kept within a maximum of 2°C above pre-industrial levels to prevent potentially catastrophic consequences for human society and natural ecosystems (Smith et al., 2009). This goal was also endorsed by the Copenhagen Climate Summit (Richardson et al., 2009; UNFCCC, 2009)

In response to the scientists' warning, the Obama Administration set an ambitious goal of reducing GHG emissions to 17 % below the 2005 levels by 2020 and to 83 % thereof by 2050 (U.S. Department of State, 2010). Most of the current and proposed policy measures to meet the climate-stabilizing reduction target in the U.S. depend on technology and pricing solutions, including fuel economy standards, low-carbon fuels, and carbon taxes (Chapman, 2007; Ewing et al., 2008; Pacala & Socolow, 2004). Many studies, however, show that technology and market solutions alone, without involving energy demand moderation, cannot achieve the GHG emissions reduction goals (Boies et al., 2009; Grazi & van den Bergh, 2008; Johansson, 2009; Kromer, Bandivadekar & Evans, 2010; Morrow et al., 2010). Moreover, technology is not likely to develop at a sufficient rate to meet the challenge (Johansson, 2009), and even potential GHG savings from improved energy efficiency can be partially offset by rebounded energy consumption (Greening, Greene & Difiglio, 2000; Sorrell, Dimitropoulos & Sommerville, 2009). To fill this gap, additional steps will be needed. Reducing individual energy consumption through shifts in behavior presents one such opportunity to affect GHG emissions, and this study mainly focuses on the role of sustainable urban spatial structure to mitigate GHG emissions.

The purpose of this dissertation is to uncover how sustainable urban spatial structure mitigates GHG emissions and stabilizes climate change. Over the last several decades, urban spatial structure has been steadily changing to a more decentralized, polycentric, and dispersed one. This trend can have negative impacts on global warming due to increased travel distances, traffic congestion, residential energy consumption, and so on. In addition, the change of built environments can leave long-lasting effects on individual travel and residential energy consumption behaviors because of the durability of the built environment.

Thus, many scholars realize the magnitude of the problem and have conducted a proliferation of empirical studies to discover the connections between specific land-use elements and sustainable travel behaviors in U.S. cities. They found that the links are statistically significant, but the size of the impacts is generally smaller than scholars and planners had expected. However, most of these studies focus on small scale geography, investigating the variations of neighborhood characteristics within a regional boundary. Thus, it is likely that the impacts of urban form change are underestimated in previous studies. Urban residents' average one-way trip distance is nearly ten miles in the U.S. Thus, land use characteristics at the neighborhood level may not significantly influence people's travel decisions and studies focusing on small scale variations in urban form may not disclose the profound relationships between urban form and travel behavior, resulting in an underestimating of the role of sustainable urban form. For this reason, this dissertation focuses on urban area level spatial structure—population-weighted density, population centrality, and polycentricity—and its role in GHGs reduction.

1.1. Urban spatial structure at the UA level

Classic theoretical urban economic models describe monocentric urban spatial structure, in which land price, employment and population all decline with the distance from Central Business District (CBD) (Alonso, 1964; Mills, 1967; Muth, 1969). Over the second half of the last century, however, jobs and population have been constantly decentralizing, significant portion of which have re-concentrated in new job centers in U.S. metropolitan areas. These changes of urban structure have had profound influences on travel behavior and residential energy consumption. In an effort to analyze the decentralizing and polycentrizing trends, Giuliano & Small (1991), Bogart & Ferry (1999), McMillen (2001), Craig & Ng (2001), McMillen & Smith (2003), and Lee (2007) have recently developed new methods to quantify urban spatial structure.

There are two dimensions of urban area-level spatial structure—*centralized* versus *decentralized* and *clustered* versus *dispersed*—as shown in Figure 1.1 (Anas, Arnott & Small, 1998; Galster et al., 2001; Meijers & Burger, 2010). The centralization dimension (x-axis) quantifies the proximity of population or employment to the major job center at the urban core location, CBD, while the concentration dimension (y-axis) measures how disproportionately jobs or population are clustered in a few locations over the urban area.

This study focuses on two major spatial dimensions, population centrality and employment polycentricity, the latter of which is a combined outcome of metropolitan wide decentralization and local concentration—decentralized concentration. Population centrality measures the degree of population concentration near the CBD, whereas polycentricity measures the extent to which jobs and urban activities are clustered around subcenters as opposed to the CBD (Anas, Arnott & Small, 1998; Galster et al., 2001; Lee & Lee, 2014). It is well known that polycentric structure may reduce the average commute distance, but is less supportive of public transit than monocentric urban areas (Lee & Lee, 2014).

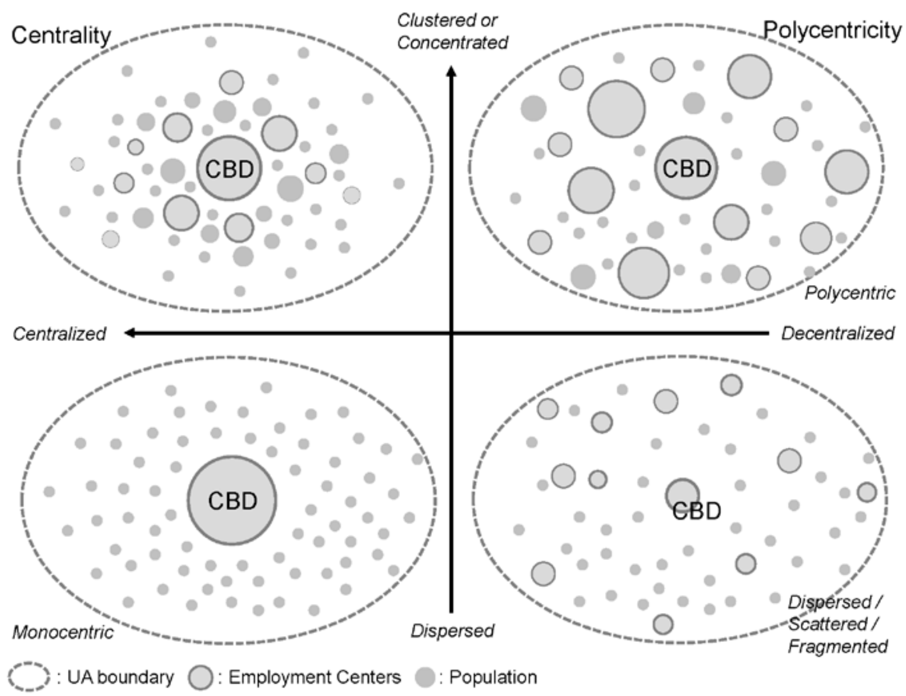


Figure 1.1. The classification of urban spatial structure with two dimensions.

To identify employment centers in a metropolitan area, a geographical weighted regression (GWR) procedure developed by Lee (2007) is applied. The primary quality of employment centers is a significantly higher employment density than in the surrounding areas. First, two employment density surfaces are estimated using the GWR—one with a small window size (10 neighboring census tracts) and the other with a large window size (100 census tracts). Those census tracts where small window GWR estimates have statistically significantly higher density than large window GWR estimates are defined as center candidates. In the second screening step, I defined the clusters of identified density peaks as employment centers when they have more jobs than an employment size threshold that ranges from 3,000 to 10,000 jobs, depending on metropolitan population size. I used census tract level employment data from Census Transportation Planning Packages (CTPP) in 2000, and Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) in 2010.

I developed various indices of population centrality and polycentricity at the urbanized area level based on 1) the locations of subcenters, 2) the number of identified subcenters, 3) employment shares in subcenters, and 4) census tract level population in relation to the distance from the CBD (Table 1.1). To estimate population centrality, several different indices were used, focusing on the CBD's population share, population density gradient, area-based or weighted area-based population density gradient, and so on. I used a principal component analysis (PCA) to summarize all these indices into one population centrality index. I also took several approached to estimating polycentricity indices based on subcenters' employment share, the number of subcenters, and intra-urban rank-size distribution of employment centers, and then summarized them by using a PCA.

Table 1.1. List of centrality and polycentricity indices.

Index	Source	Formula
Population Centralization Index: the 1st factor of CPS, MWI, ACI & WADI, WUAD and PDG (results of PCA)		
CBD Pop. Share (CPS)	Lee (2007)	$CPS = p_{CBD} \Big/ \sum_{i=1}^{n} p_i$, The share of urbanized area population in the CBD.
Modified Wheaton Index (MWI)	Wheaton (2004); Lee (2007)	$MWI = \dfrac{(\sum_{i=1}^{n} P_{i-1} DCBD_i - \sum_{i=1}^{n} P_i DCBD_{i-1})}{DCBD^*}$
Area Based Centralization Index (ACI)	Massey & Denton (1988); Lee (2007)	$ACI = \sum_{i=1}^{n} P_{i-1} A_i - \sum_{i=1}^{n} P_i A_{i-1}$, 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.
Weighted Average Distance from the CBD (WADI)	Galster et al. (2001)	$ADC = \sum_{i=1}^{n} p_i DCBD_i \Big/ E$
Ratio of Weighted to Unweighted Average Distance (WUAD)	Cutsinger et al. (2005)	$WUAD = \left(\dfrac{\sum_{i=1}^{n} p_i DCBD_i}{E} \right) \Big/ \left(\dfrac{\sum_{i=1}^{n} DCBD_i}{N} \right)$, 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 (PDG)	Lee & Lee (2014)	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 Index: the 1st Factor of SUB, NES, SRSD, Primacy, and CSR (Result of PCA)		
Subcenters' Share of Center Emp. (SUB)	Lee (2007)	Subcenters' Share of Centers Employment: $SUB = e_{SUB} / (e_{CBD} + e_{SUB})$
The number of extra subcenters (NES)	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 (SRSD)	Meijers & 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). I use "rank – ½" rather than actual rank in the regression to reduce a bias due to small samples (Gabaix & 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, I 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 (CSR)	Lee & Lee (2014)	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. I 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.; DCBD*: urbanized area radius; n: number of zones.

Another basic but important element of urban spatial structure is population density. The conventional population density, however, has many shortcomings and is very sensitive to the boundary changes of census geographies over years. For instance, this conventional measure presents the Los Angeles urbanized area as having higher density than the New York UA although most people believe New York to be far denser than Los Angeles. The disconnect can be overcome by using population-weighted density (PWD)—the weighted mean of census block group level density within an UA, with each block group's population being used as the weight. The PWD of New York is significantly higher than that of LA, which is consistent with our intuition. Several studies indicate that the PWD captures the density that an average urban resident experiences in daily life better than a conventional density (Lee & Lee, 2014; Transportation Research Board, 2009). Therefore, this study uses PWD as one of major regional-level land-use variables.

As a preliminary analysis, spatial structure variables of the 125 largest UAs with more than 250 thousand residents as of 2000 are presented in Table 1.2-1.3 and Figure 1.2-1.7. During the period between 2000 and 2010, urban areas became more clustered and polycentric in terms of employment distribution (Table 1.2) while population further decentralized across the board (Table 1.3). The CBDs of largest urban areas somewhat lost their employment shares by approximately 0.4 percent points, but most urban areas have gained clustered jobs in both the CBD and suburban job centers. CBD employment share slightly increased from 10.8 percent to 11.1 percent on average, and it increased by 1.5 percent in small UAs having less than 1 million people over ten years. Subcenters have also shown steady growth as the role of job centers, and their growth overwhelms the upturn of CBDs. Subcenter employment share has escalated by 3.7 percent on average, and the polycentricity index also increased by 7.3 percent.

However, population has decentralized by about 16 percent in terms of the centrality index, on average, and both conventional population density and the population-weighted density (PWD) decreased as well (Table 1.3). Large urban areas in the East and West coasts still maintain higher population density than other small UAs (Figure 1.5). While population densities have decreased in most UAs for the 10 year period, some UAs such as Portland, Washington, D.C., and Miami have experienced an increase in population density.

Figure 1.3 shows a negative association between population centrality and polycentricity in the 25 largest UAs. In general, most UAs moved in the direction from the fourth to the second quadrant in the 2000s, indicating decentralization and polycentrizing trends. For instance, both population density and PWD in the Chicago UA dropped by about 10% and 9%, respectively, while the number of subcenters has increased from 19 to 30 (Table 1.2). Polycentricity index upsurged by about 7%, but population centrality index fell by about 9% (Table 1.3).

The negative association between population centrality and polycentricity is also found in the full sample as shown in Figure 1.4. In general, population centrality is relatively high in older UAs in the Eastern Coast (Figure 1.6), while urban areas in the Sunbelt region are more polycentric (Figure 1.7).

Table 1.2. Number of subcenters and employment shares of job centers in the largest 125 UAs.

	No. of Subcenters			Employment Shares (%)								
				All Centers (C=A+B)			CBD (A)			Subcenters (B)		
	2000	2010*	Diff.	2000	2010*	Diff (%p)	2000	2010*	Diff (%p)	2000	2010*	Diff (%p)
New York	28	32	**4**	23.4	27.5	**4.1**	12.0	10.0	**−2.0**	11.4	17.5	**6.1**
Los Angeles	45	50	**5**	39.4	35.4	**−3.9**	3.7	4.4	**0.7**	35.6	31.0	**−4.7**
Chicago	19	30	**11**	21.1	27.1	**6.0**	7.6	11.5	**3.9**	13.5	15.6	**2.2**
Miami	9	17	**8**	22.1	29.0	**6.9**	5.3	2.9	**−2.4**	16.8	26.1	**9.3**
Philadelphia	13	18	**5**	17.8	17.4	**−0.4**	9.6	8.0	**−1.6**	8.2	9.4	**1.2**
Dallas	11	23	**12**	28.0	31.2	**3.2**	5.4	6.1	**0.6**	22.6	25.2	**2.6**
Houston	12	16	**4**	30.3	33.4	**3.1**	9.4	8.1	**−1.2**	21.0	25.3	**4.3**
Washington	15	20	**5**	29.9	35.3	**5.4**	12.7	11.6	**−1.1**	17.2	23.7	**6.5**
Atlanta	6	20	**14**	20.6	34.1	**13.5**	8.6	8.1	**−0.6**	12.0	26.0	**14.0**
Boston	6			16.7			10.9			5.8		
Population Size**												
higher than 2.5 million	14.4	20.5	**6.1**	26.6	29.8	**3.3**	8.8	8.4	**−0.4**	17.7	21.4	**3.6**
1 million - 2.5 million	5.0	6.8	**1.8**	25.7	29.6	**3.9**	11.3	11.8	**0.4**	14.4	17.9	**3.5**
less than 1 million	2.5	3.5	**0.9**	29.2	35.0	**5.8**	14.8	16.3	**1.5**	14.4	18.7	**4.3**
Total (125 UAs)	**4.6**	**6.3**	**1.7**	**27.0**	**31.0**	**4.0**	**10.8**	**11.1**	**0.3**	**16.2**	**19.9**	**3.7**

* Notes: LODES data is used to estimate the indices for Centrality and Polycentricity, but they don't cover the state of Massachusetts. Thus, the three UAs—Boston, MA-NH-RI, Springfield, MA-CT, and Worcester, MA-CT—are not accounted for all indices as of 2010.

** There are 16 UAs (higher than 2.5 million UAs), 25 UAs (1 million-2.5 million), and 84 UAs (less than 1 million).

Table 1.3. The urban spatial structure comparison between 2000 and 2010 in the largest 125 UAs.

	Conventional Population density			Population-weighted density (block group level)			Population Centrality			Polycentricity		
	2000	2010	delta	2000	2010	delta	2000	2010*	Delta*	2000	2010*	Delta*
New York	5,337	5,319	**−0.3%**	37,140	36,712	**−1.2%**	151	147	**−2.7%**	72	94	**30.7%**
Los Angeles	7,088	6,999	**−1.3%**	14,368	14,108	**−1.8%**	75	69	**−7.6%**	168	153	**−8.6%**
Chicago	3,921	3,524	**−10.1%**	11,898	10,853	**−8.8%**	132	120	**−9.1%**	97	103	**7.0%**
Miami	4,424	4,442	**0.4%**	7,898	8,754	**10.8%**	61	60	**−1.8%**	115	145	**26.1%**
Philadelphia	2,872	2,746	**−4.4%**	10,296	9,624	**−6.5%**	114	107	**−6.7%**	79	92	**16.5%**
Dallas	2,957	2,879	**−2.6%**	6,123	5,631	**−8.0%**	65	59	**−9.2%**	131	138	**4.7%**
Houston	2,978	2,978	**0.0%**	5,910	5,748	**−2.7%**	93	80	**−13.5%**	107	124	**15.3%**
Washington	3,417	3,470	**1.6%**	8,475	9,118	**7.6%**	121	93	**−22.6%**	86	117	**36.0%**
Atlanta	1,789	1,707	**−4.6%**	2,955	2,925	**−1.0%**	110	99	**−10.5%**	93	128	**38.2%**
Boston	2,334	2,232	**−4.4%**	9,838	10,099	**2.7%**	130			53		
Population Size**												
higher than 2.5 million	3,685	3,636	**−1.6%**	10,177	9,989	**−2.4%**	100	89	**−10.3%**	107	119	**11.1%**
1 million - 2.5 million	2,974	2,839	**−4.8%**	5,384	5,216	**−3.2%**	97	84	**−13.2%**	88	102	**15.6%**
less than 1 million	2,272	2,183	**−3.4%**	4,220	4,057	**−3.9%**	114	93	**−17.9%**	98	102	**4.0%**
Total (125 UAs)	**2,598**	**2,508**	**−3.5%**	**5,240**	**5,078**	**−3.5%**	**108**	**91**	**-16.2%**	**97**	**104**	**7.3%**

* Notes: LODES data is used to estimate the indices for Centrality and Polycentricity, but they don't cover the state of Massachusetts. Thus, the three UAs—Boston, MA-NH-RI, Springfield, MA-CT, and Worcester, MA-CT—are not accounted for both indices between Population Centrality and Polycentricity as of 2010.

** There are 16 UAs (higher than 2.5 million UAs), 25 UAs (1 million-2.5 million), and 84 UAs (less than 1 million).

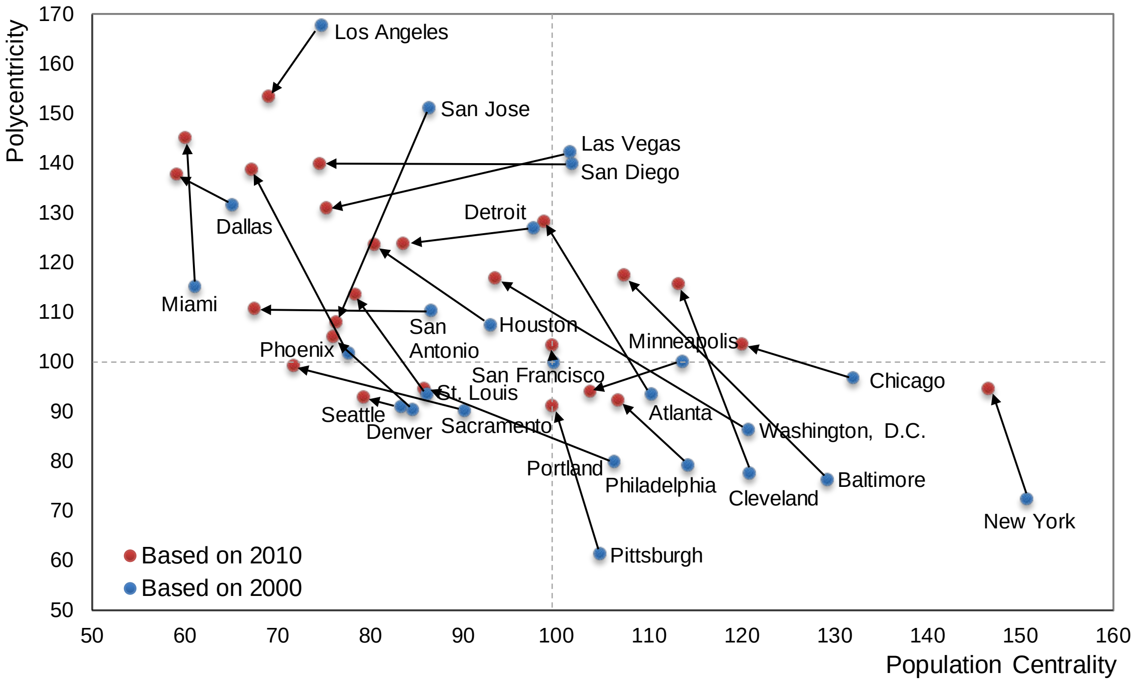


Figure 1.2. The change of urban spatial structure from 2000 to 2010 in the largest 25 UAs.

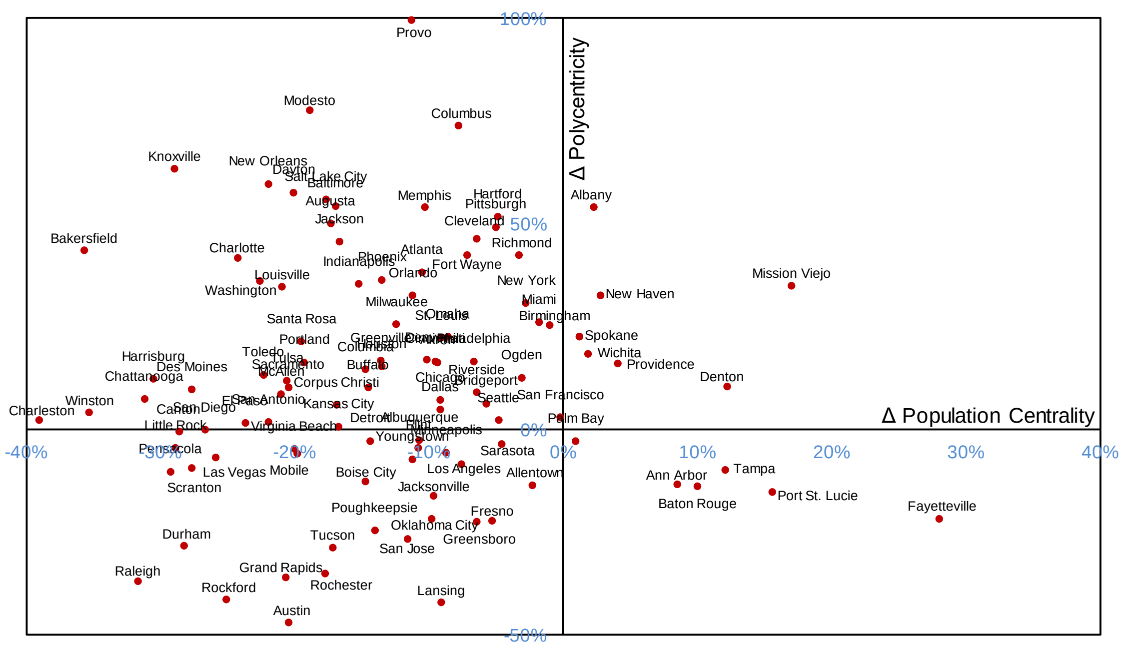


Figure 1.3. The change of urban spatial structure from 2000 to 2010 in the largest 125 UAs.

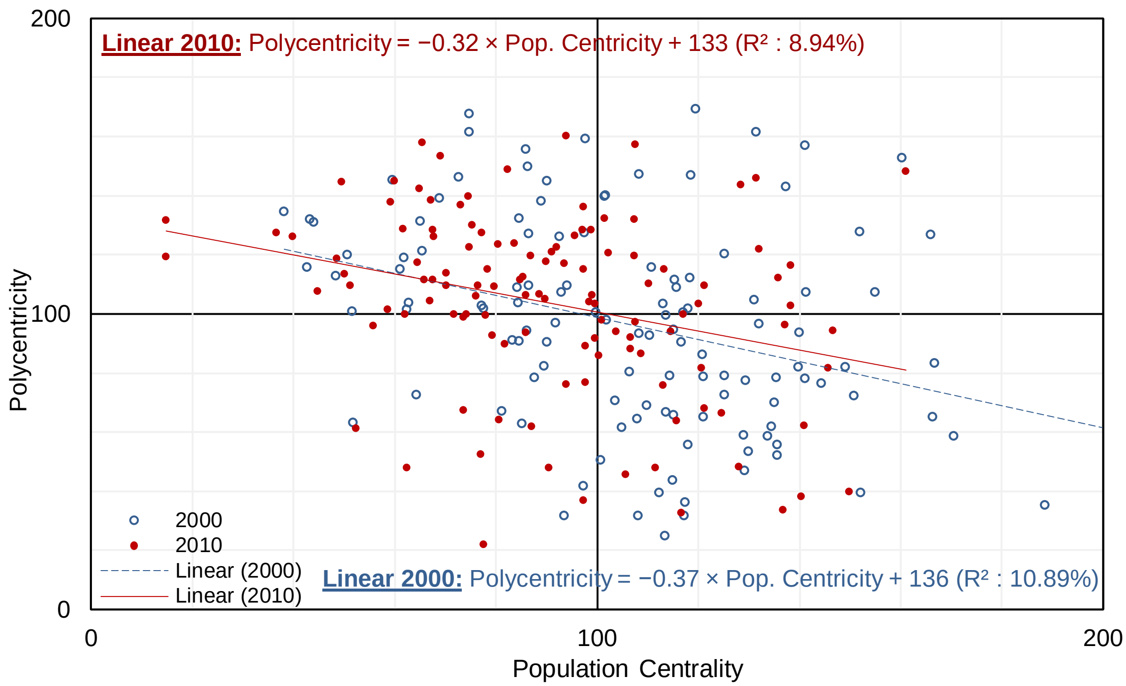


Figure 1.4. The relations between population centrality and polycentricity, and the change from 2000 to 2010 in the largest 125 UAs.

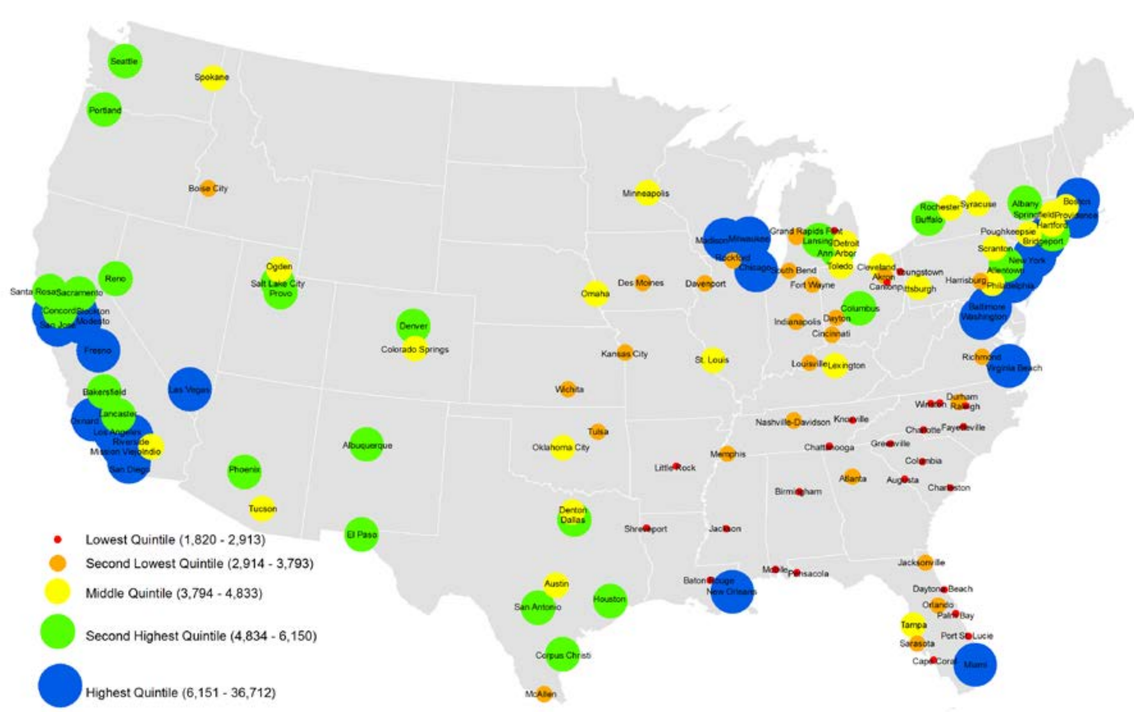


Figure 1.5. Population-weighted density in the largest 125 UAs (2010).

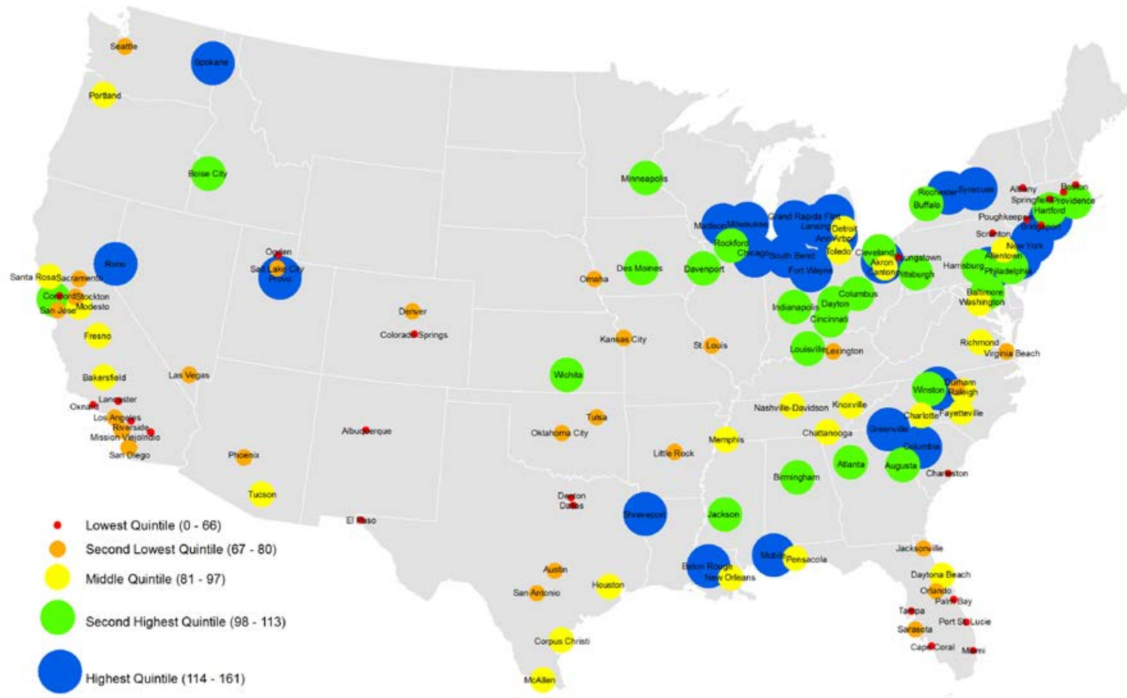


Figure 1.6. Population centrality index in the largest 125 UAs (2010).

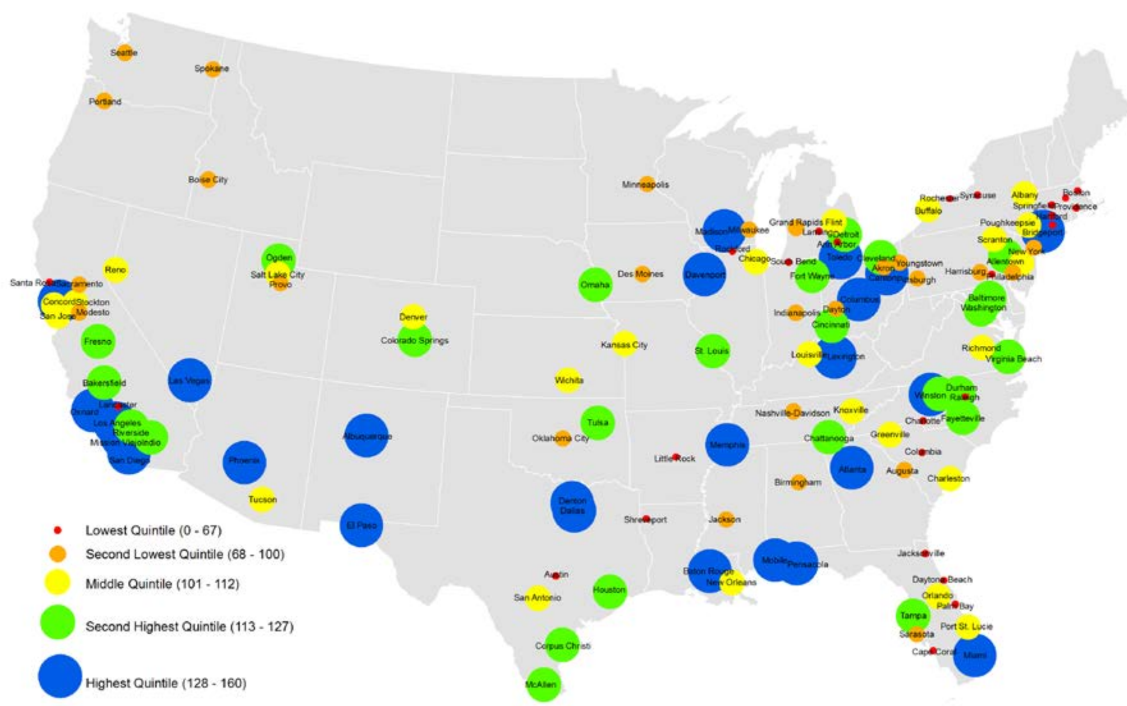


Figure 1.7. Polycentricity index in the largest 125 UAs (2010).

1.2. Three empirical studies

Many scholars in planning and related fields have studied the role of sustainable urban form in moderating energy consumption and mitigating GHG emissions. The primary research question has been how land use planning in line with growth management and smart growth principles would reduce automobile dependency, thereby mitigating GHG emissions. In practice, such studies have made significant contributions by offering important guidance toward more sustainable development. However, several issues still remain regarding the role of sustainable urban form.

First, the impacts of urban form on residential energy consumption have been relatively understudied while the connections between urban form and travel behavior are increasingly elucidated in recent years. Residential energy consumption is another significant source of GHG emissions and is also considerably influenced by urban form through many paths. The level of household energy consumption is apparently a function of housing type and size and available housing options are largely determined by how we develop urban areas. Urban footprint is also connected to urban heat island (UHI) effects that are believed to be affected by spatial development patterns. Thus, a comprehensive approach is required to account for both transportation and residential energy consumptions, since single-sector research cannot address the potential tradeoffs between transportation and residential sector emissions. In Chapter 2, I will investigate the various paths via which urban form influences household GHG emissions in residential and transportation sectors.

Second, many of the existing studies primarily focus on the effects of neighborhood level characteristics. A growing body of literature provides important guidance for more sustainable development such as the 5 Ds—Density, Diversity, Design, Destination, and Distance to transit. However, some recent studies indicate that regional level spatial structure may have more important implications on people's travel behavior. Chapter 3 will examine how urban form elements at two spatial scales, urbanized area and neighborhood levels, interact to influence VMT and GHGs. It is assumed that smart growth policies at each level has a positive and reciprocal influence on promoting more sustainable travel behaviors.

Finally, both scholars and policy makers undervalue the complementary nature of pricing policies and land use approaches to mitigate climate impacts in urban areas. Although many empirical studies have found that sustainable urban form can lead to lower vehicle miles traveled (VMT) and hence reduced GHG emissions, many economists are still skeptic about the magnitude of the urban form effects. They believe that *getting-the-right-price* policies such as increased fuel prices or road pricing can moderate the demand for private vehicle use in a more effective and efficient way by internalizing the environmental externalities of driving. The long standing disagreement between advocates of pricing policies and proponents of land use planning approach has often manifested itself in an unproductive way by underestimating the role of the other approach. In Chapter 4, I demonstrate that the two groups of policy approaches are not conflict or substitute for each other, but complementary to each other. Both policies should be fully employed to achieve climate-stabilizing GHG reduction targets. A key hypothesis of the chapter is that the fuel price elasticity of VMT is higher in compactly developed urbanized areas (UAs) than in sprawling regions, and increasing fuel prices will also reinforce the impacts of compact development on VMT reduction.

This dissertation research addresses the three closely related issues in the literature by three separate but closely connected empirical studies, each presented in following chapters. Figure 1.8 below depicts how the topics of following three chapters are inter-connected.

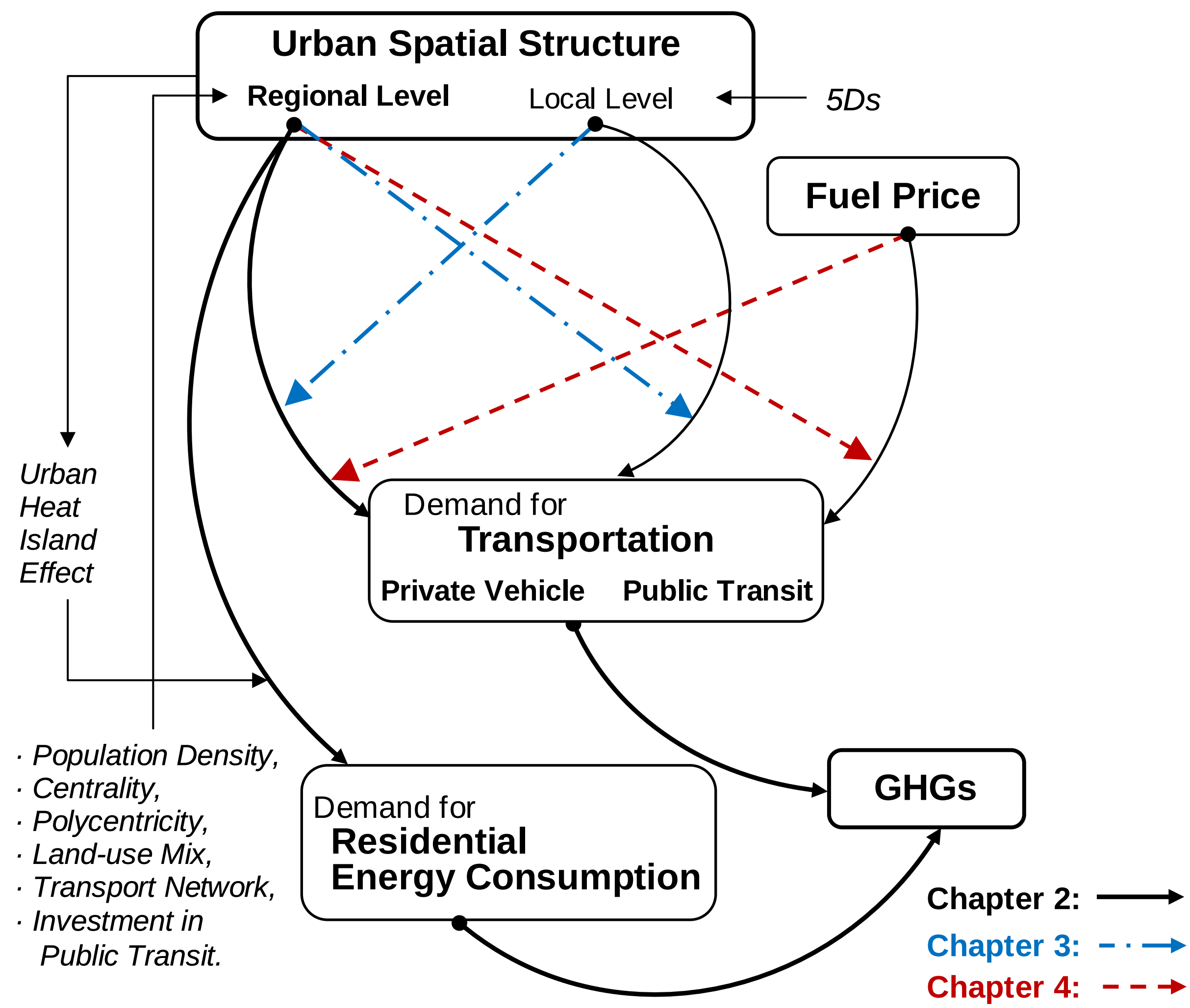


Figure 1.8. Potential linkages of the three papers.

1.3. Bibliography

Alonso, W. (1964). *Location and land use. Toward a general theory of land rent*: Harvard University Press.

Anas, A., Arnott, R., & Small, K.A. (1998). Urban spatial structure. *Journal of Economic Literature, 36*, 1426-1464. Retrieved from http://www.jstor.org/stable/2564805

Bogart, W.T., & Ferry, W.C. (1999). Employment centres in greater Cleveland: Evidence of evolution in a formerly monocentric city. *Urban Studies, 36*(12), 2099. doi:10.1080/0042098992566

Boies, A., Hankey, S., Kittelson, D., Marshall, J.D., Nussbaum, P., Watts, W., & Wilson, E.J. (2009). Reducing motor vehicle greenhouse gas emissions in a non-California state: A case study of Minnesota. *Environmental science & technology, 43*(23), 8721-8729. doi:10.1021/es902019z

Chapman, L. (2007). Transport and climate change: a review. *Journal of Transport Geography, 15*(5), 354-367. doi:10.1016/j.jtrangeo.2006.11.008

Craig, S.G., & Ng, P.T. (2001). Using Quantile Smoothing Splines to Identify Employment Subcenters in a Multicentric Urban Area. *Journal of Urban Economics, 49*(1), 100-120. doi:10.1006/juec.2000.2186

Cutsinger, J., Galster, G., Wolman, H., Hanson, R., & Towns, D. (2005). Verifying the Multi-Dimensional Nature of Metropolitan Land Use: Advancing the Understanding and Measurement of Sprawl. *Journal of Urban Affairs, 27*(3), 235-259. doi:10.1111/j.0735-2166.2005.00235.x

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., & Anderson, G. (2008). Urban development and climate change. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 1*(3), 201-216. doi:10.1080/17549170802529316

Gabaix, X., & Ibragimov, R. (2011). Rank − 1 / 2: A Simple Way to Improve the OLS Estimation of Tail Exponents. *Journal of Business & Economic Statistics, 29*(1), 24-39. doi:10.1198/jbes.2009.06157

Galster, G., Hanson, R., Ratcliffe, M.R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling Sprawl to the Ground: Defining and measuring an elusive concept. *Housing Policy Debate, 12*(4), 681-717. doi:10.1080/10511482.2001.9521426

Giuliano, G., & Small, K.A. (1991). Subcenters in the Los Angeles region. *Regional Science and Urban Economics, 21*(2), 163-182. doi:10.1016/0166-0462(91)90032-I

Grazi, F., & van den Bergh, J.C.J.M. (2008). Spatial organization, transport, and climate change: Comparing instruments of spatial planning and policy. *Ecological economics, 67*(4), 630-639. doi:10.1016/j.ecolecon.2008.01.014

Greening, L.A., Greene, D.L., & Difiglio, C. (2000). Energy efficiency and consumption — the rebound effect — a survey. *Energy Policy, 28*(6–7), 389-401. doi:10.1016/S0301-4215(00)00021-5

Hansen, J., Sato, M., Kharecha, P., Beerling, D., Berner, R., Masson-Delmotte, V., Pagani, M., Raymo, M., Royer, D.L., & Zachos, J.C. (2008). Target atmospheric CO2: Where should humanity aim? *arXiv preprint arXiv:0804.1126*. doi:10.2174/1874282300802010217

Intergovernmental Panel on Climate Change. (2007). *Climate Change 2007: The Physical Science Basis*.

Johansson, B. (2009). Will restrictions on CO2 emissions require reductions in transport demand? *Energy Policy, 37*(8), 3212-3220.

Jones, N. (2013). Troubling milestone for CO2. *Nature Geosci, 6*(8), 589-589. doi:10.1038/ngeo1900

Kromer, M.A., Bandivadekar, A., & Evans, C. (2010). Long-term greenhouse gas emission and petroleum reduction goals: Evolutionary pathways for the light-duty vehicle sector. *Energy, 35*(1), 387-397. doi:10.1016/j.energy.2009.10.006

Lee, B. (2007). "Edge" or "Edgeless" Cities? Urban Spatial Structure in US Metropolitan Areas, 1980 to 2000. *Journal of Regional Science, 47*(3), 479-515. doi:10.1111/j.1467-9787.2007.00517.x

Lee, S., & Lee, B. (2014). The influence of urban form on GHG emissions in the U.S. household sector. *Energy Policy, 68*(0), 534-549. doi:10.1016/j.enpol.2014.01.024

Massey, D.S., & Denton, N. (1988). The dimensions of residential segregation. *Social Forces, 67*, 281-313. doi:10.1093/sf/67.2.281

McMillen, D.P. (2001). Nonparametric employment subcenter identification. *Journal of Urban Economics, 50*(3), 448-473. doi:10.1006/juec.2001.2228

McMillen, D.P., & Smith, S.C. (2003). The number of subcenters in large urban areas. *Journal of Urban Economics, 53*(3), 321-338. doi:10.1016/s0094-1190(03)00026-3

Meijers, E. (2008). Measuring polycentricity and its promises. *European Planning Studies, 16*(9), 1313-1323. doi:10.1080/09654310802401805

Meijers, E.J., & Burger, M.J. (2010). Spatial structure and productivity in US metropolitan areas. *Environment and Planning A, 42*(6), 1383-1402. doi:10.1068/a42151

Mills, E.S. (1967). An aggregative model of resource allocation in a metropolitan area. *The American Economic Review, 57*(2), 197-210. Retrieved from http://www.jstor.org/stable/1821621

Morrow, R.W., Gallagher, K.S., Collantes, G., & Lee, H. (2010). Analysis of policies to reduce oil consumption and greenhouse-gas emissions from the US transportation sector. *Energy Policy, 38*(3), 1305-1320. doi:10.1016/j.enpol.2009.11.006

Muth, R.F. (1969). *Cities And Housing; The Spatial Pattern Of Urban Residential Land Use*. Chicago, US: University of Chicago Press.

Nordregio. (2005). *ESPON 1.1.1: potentials for polycentric development in Europe.* . Retrieved from Stockholm/Luxembourg.: http://www.espon.eu/export/sites/default/Documents/Projects/ESPON2006Projects/ThematicProjects/Polycentricity/fr-1.1.1_revised-full.pdf

Pacala, S., & Socolow, R. (2004). Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies. *Science, 305*(5686), 968-972. doi:10.1126/science.1100103

Richardson, K., Steffen, W., Schellnhuber, H.J., Alcamo, J., Barker, T., Kammen, D.M., Leemans, R., Liverman, D., Munasinghe, M., & Osman-Elasha, B. (2009). *Synthesis Report, Climate Change: Global Risks, Challenges and Decisions*. Retrieved from Copenhagen, Denmark: http://curis.ku.dk/ws/files/14774466/http___climatecongress.ku.pdf

Showstack, R. (2013). Carbon dioxide tops 400 ppm at Mauna Loa, Hawaii. *Eos, Transactions American Geophysical Union, 94*(21), 192-192. doi:10.1002/2013EO210004

Smith, J.B., Schneider, S.H., Oppenheimer, M., Yohe, G.W., Hare, W., Mastrandrea, M.D., Patwardhan, A., Burton, I., Corfee-Morlot, J., Magadza, C.H.D., Füssel, H.-M., Pittock, A.B., Rahman, A., Suarez, A., & van Ypersele, J.-P. (2009). Assessing dangerous climate change through an update of the Intergovernmental Panel on Climate Change (IPCC) “reasons for concern”. *Proceedings of the National Academy of Sciences, 106*(11), 4133-4137. doi:10.1073/pnas.0812355106

Smith, T.M., Reynolds, R.W., Peterson, T.C., & Lawrimore, J. (2008). Improvements to NOAA's historical merged land-ocean surface temperature analysis (1880-2006). *Journal of Climate, 21*(10), 2283-2296. doi:10.1175/2007JCLI2100.1

Sorrell, S., Dimitropoulos, J., & Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy, 37*(4), 1356-1371. doi:10.1016/j.enpol.2008.11.026

Stults, D.Z., Wagner-Cremer, F., & Axsmith, B.J. (2011). Atmospheric paleo-CO2 estimates based on Taxodium distichum (Cupressaceae) fossils from the Miocene and Pliocene of Eastern North America. *Palaeogeography, Palaeoclimatology, Palaeoecology, 309*(3–4), 327-332. doi:10.1016/j.palaeo.2011.06.017

Transportation Research Board. (2009). *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions* (298). Retrieved from Washington, D.C.

U.S. Department of State. (2010). *US Inscription to the UNFCCC on the Copenhagen Accord*. Washington, D.C.

https://unfccc.int/files/meetings/cop_15/copenhagen_accord/application/pdf/unitedstatescphaccord_app.1.pdf.

UNFCCC, E. (2009). *Copenhagen Accord*. Copenhagen: COP 15.

Veneri, P. (2010). Urban polycentricity and the costs of commuting: evidence from Italian metropolitan areas. *Growth and Change*, *41*(3), 403-429. doi:10.1111/j.1468-2257.2010.00531.x

Wheaton, W.C. (2004). Commuting, congestion, and employment dispersal in cities with mixed land use. *Journal of Urban Economics*, *55*(3), 417-438. doi:10.1016/j.jue.2003.12.004

CHAPTER 2
THE INFLUENCE OF URBAN FORM ON GREENHOUSE EMISSIONS IN THE HOUSEHOLD SECTOR[3]

2.1. 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 & Socolow, 2004).

[3] This chapter has been adapted from "Lee, Sungwon, & Lee, Bumsoo (2014). The influence of urban form on GHG emissions in the U.S. household sector. *Energy Policy, 68*(0), 534-549. doi:10.1016/j.enpol.2014.01.024."

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, van den Bergh & van Ommeren, 2008; Johansson, 2009; Kromer, 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, Greene & Difiglio, 2000; Sorrell, Dimitropoulos & Sommerville, 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. I 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), I demonstrate that shifting toward more compact urban form can significantly reduce energy consumption and CO_2 emissions in the household sector. My 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.

2.2. 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 & Crane, 2001; Boarnet & 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 & Kockelman, 1997), destination accessibility, and distance to transit (Added 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, Mokhtarian & Handy, 2009; Mokhtarian & 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 & Duncan, 2006; Ewing & Cervero, 2010; Kockelman, 1997; Næss, 2005; Sun, Wilmot & Kasturi, 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 & Murakami, 2010; Ewing, Pendall & Chen, 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 & 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, Sen & Eluru, 2009; Bhat & Sen, 2006; Fang, 2008; Liu & 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, Southworth & Stovall, 2005; Holden & 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 & 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 & 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 & 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 & 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, Southworth & Sarzynski, 2009; Glaeser & Kahn, 2010; Zhou & 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.

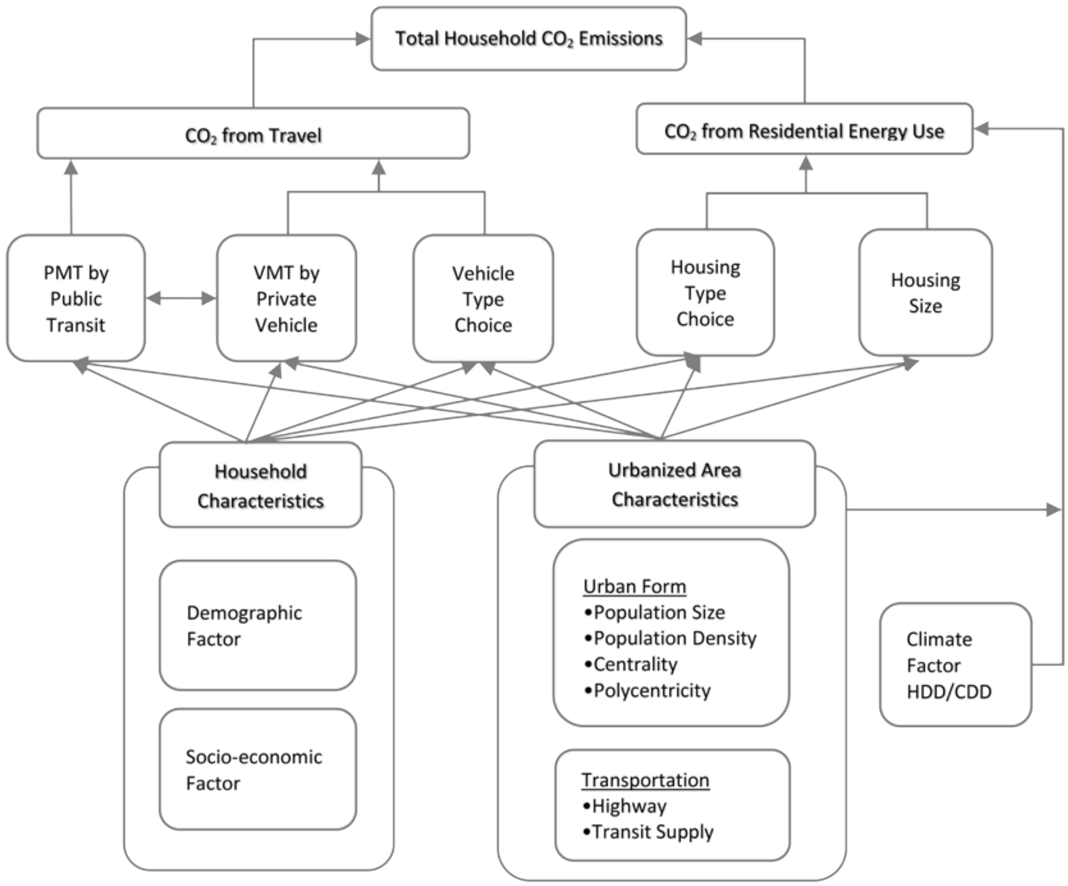


Figure 2.1. Conceptual framework and key relationships among main variables.

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 2.1, summarizes the key relationships between my 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.

2.3. Research methods

2.3.1. Model specification

My 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, my 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 & 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 my 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, Zhang & Zyphur, 2011). Housing type is a categorical endogenous variable in the current research, and its presence merits the WLSMV over maximum likelihood estimation (MLE). I 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 my knowledge, no single data source contains information on travel behavior, residential energy consumption, and sub-state level location variables. I 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 2.2 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.

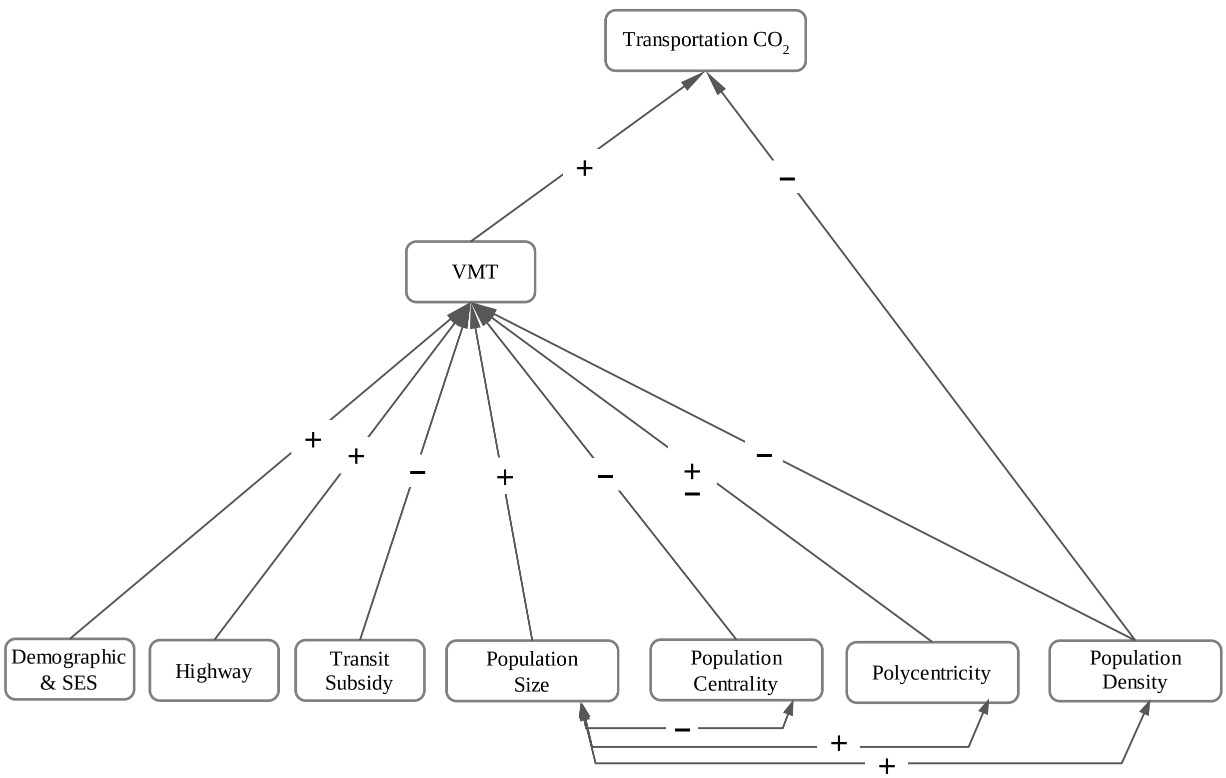


Figure 2.2. Path diagram for transportation CO_2 emissions with expected signs.

Centrality is assumed to decrease VMT by promoting transit use, while population size is assumed to be positively associated with VMT. However, I 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. My 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. I 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 2.3 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), I hypothesize that polycentric structure will lessen the formation of UHIs by allowing more natural surface within an urbanized area.

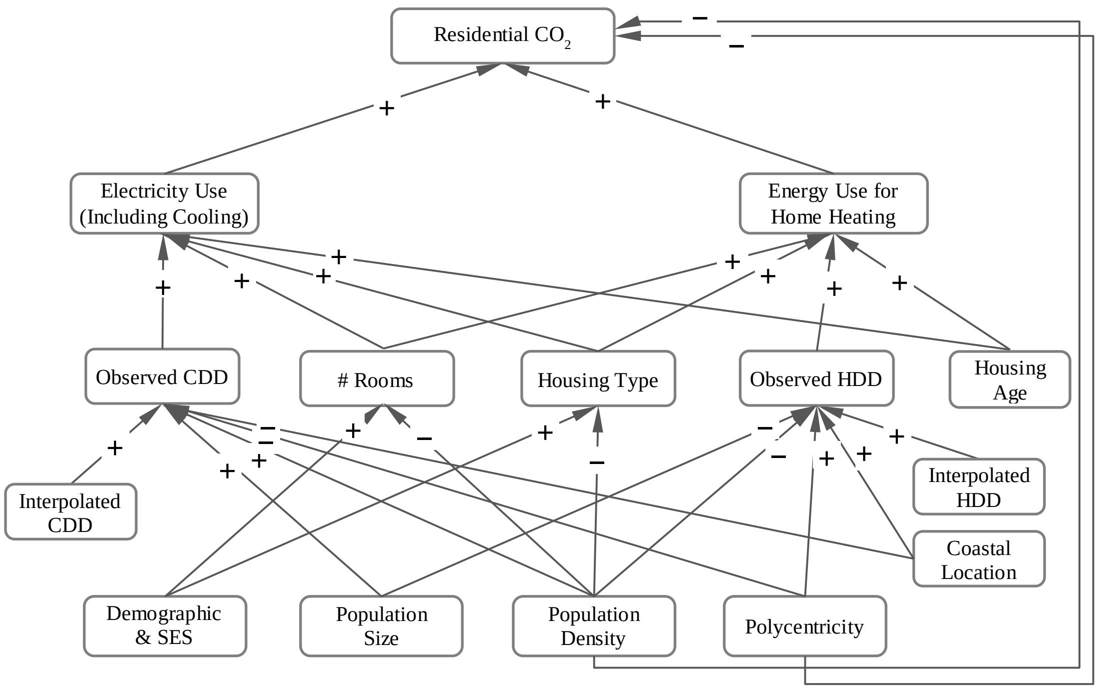


Figure 2.3. Path diagram for residential CO_2 emissions with expected signs.

I 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. I 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. I 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.

2.3.2. 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 & 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.

I take an approach similar to that of Glaeser & 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. I 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. I 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 & 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, I 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. I 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[4].

- 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.

I 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, I 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, I take two steps to estimate CO_2 emissions. First, I 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, I convert predicted energy consumption (kWh) to CO_2 emissions by multiplying various

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

conversion factors obtained from the U.S. Energy Information Administration (EIA) [5]: 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 ($) / varying-by-state [6] natural gas price ($/ ft^3) × energy efficiency 0.301 (kWh/ft^3) × emission factor 0.399 (lbs/kWh).

I 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 ($) / varying-by-state [7] electricity price ($/mWh) × varying-by-region [8] emission factor (lbs/mWh).

In the last step, I add UA location information to household level data sets using GIS. For transportation emissions data, I use zip code of each sample household's residence which is available in a DOT version of the NHTS data. Since Public Use Microsample Areas (PUMAs) in the PUMS data are considerably large, I undergo an

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

individual matching procedure through carful visual inspection of overlaid GIS maps rather than simply assigning PUMAs' centroids to corresponding UAs.

2.3.3. Urban form indices

I 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. I 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. I 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, Arnott & Small, 1998; Galster et al., 2001). Various indicators have been developed to measure the extent of population (de)centralization (See Lee, 2014 for a survey of indices). Given the pros and cons of different measures, I derive a 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 & 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 & Burger, 2010; Nordregio, 2005): Estimated parameter β of the rank-size distribution of employment centers in each UA, $\ln e_k = \alpha + \beta \ln(\text{rank}_k - 0.5)$. I use "rank – ½" rather than actual rank in the regression to reduce a bias due to small samples (Gabaix & 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, I 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. I 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. I rely on employment density approaches to identifying urban centers, derived mainly from the field of urban economics (Giuliano & 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, I identify two sets of employment density peaks in each UA by applying two alternative methods, absolute and relative density criteria. I 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.

2.4. Results

2.4.1. 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 2.1, combining emissions from driving, public transit use, home heating, and electricity use. While my 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 I use a natural gas consumption variable, my home heating energy figure may include energy use for water heating and cooking. Second, the method I 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, my estimation is based on the 125 UA sample, not all households in the United States.

The use of 2000/2001 data was inevitable because the data to build my key urban form variables, the Census Transportation Planning Package, were not available for more recent periods. The EIA data show that CO_2 emissions per household in residential and transportation sectors decreased by about 8% and 9%, respectively, in the 2000s. I surmise that the reduction is due to many reasons including the economic recession and unprecedented oil price increase in the late 2000s. The de-carbonization of electric power generation was also significant during the period, reducing CO_2 emission rate per MWh by about 13% according to the EPA's Emissions and Generation Resource Integrated Database (eGRID). Nonetheless, I do not believe this overall reduction in carbon emissions per household would systematically alter my main analysis results in the next section. I only expect that higher real energy price would have reinforced the impact of compact urban form on carbon efficient lifestyles.

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. My 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 my 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.[9] This does not mean that I 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

[9] 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).

variation in the resources mix, and the relative carbon intensity of power generation, across the eGRID subregions. The amount of CO_2 emissions per MWh of electricity ranges from 775 lbs in the SERC Tennessee Valley to 2,283 lbs in the Southwest Power Pool (SPP) North. This result does not automatically translate into the policies to discourage electricity use for home (water) heating since new electricity-based technologies, especially utilizing thermal heat pump, can be more carbon efficient than natural gas or oil heating systems (Mustafa Omer, 2008). However, the spatial variation in carbon intensities of electric power generation should certainly be considered when prioritizing energy policies. The result 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 2.1. Average annual CO_2 emission per household in the largest 125 U.S. urbanized areas, 2000.

	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.
[c] Transportation CO_2 is estimated for 2001 while residential CO_2 is estimated using the 2000 census data.

The geographic pattern of urbanized area carbon footprints shown in Figure 2.4 is consistent with previous studies (Brown, Southworth & Sarzynski, 2008; Glaeser & 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.

Figure 2.5 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, I 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.

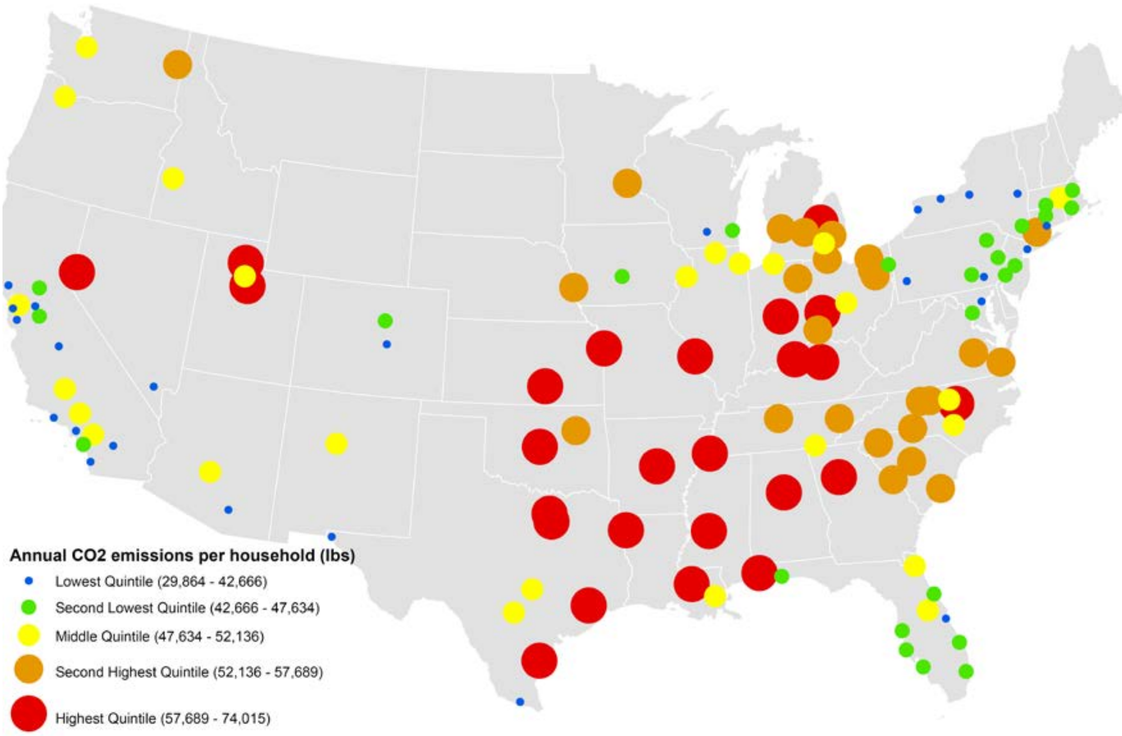


Figure 2.4. The geography of carbon footprints in U.S. urbanized areas, 2000.

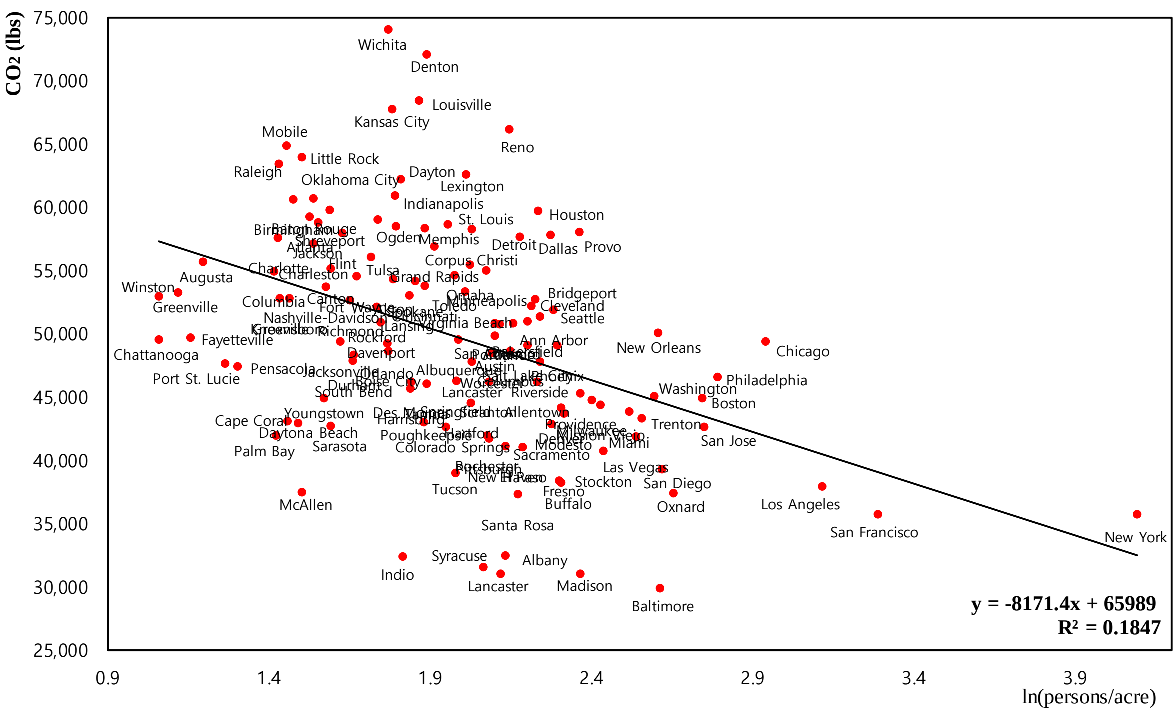


Figure 2.5. The relationship between population-weighted density and annual household CO_2 emissions.

2.4.2. Influence of urban form on household CO_2 emissions

As explained above, I model carbon dioxide emissions from travel and residential energy consumption separately, using a multilevel structural equation model (MSEM). For each sector, I estimate two alternative models, one with a conventional population density and the other with a population-weighted density. Table 2.2 summarizes several indices of overall goodness-of-fit that are recommended in the literature (Chou & Bentler, 1995; Fan, Thompson & Wang, 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 A.1 and A.2 in the Appendix A. 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. I also found that the amount of carbon emissions is more sensitive to urban form variables in transportation than in the residential sector.

Table 2.2. Goodness-of-fit measures for estimated models.

	General Criteria	Transportation CO_2		Residential CO_2	
		Model 2.1	Model 2.2	Model 2.3	Model 2.4
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 2.1 and 2.3 use a conventional population density measure, and models 2.2 and 2.4 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: $\rho = \frac{\sigma_B^2}{\sigma_B^2+\sigma_W^2}$.

2.4.2.1. Results for transportation CO_2 emissions

Table 2.3 and Figure 2.6 summarize the results of transportation CO_2 models. Since Model 2.2, with a population-weighted density, is my final model, the effects of density only are shown for Model 2.1 results in Table 2.3. 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[10]. 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

[10] The New York urbanized area can be suspected as an outlier due to its extremely high population-weighted density and mode share of public transportation. Thus, I tested the robustness of my result by running the same analysis with a sample excluding New York. All estimated coefficients were consistent with the full sample analysis result while the overall elasticity with respect to population-weighted density is slightly smaller (−0.431).

communities. These additional effects are captured by the direct impact of density in my model: −0.08.

Table 2.3. 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 1)		2)		Elasticity [a] 1) × 2)
Model 2.1:					
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 2.2:					
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

[*] Significant at 10%. [**] Significant at 5%. [***] Significant at 1%.

[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 2.1 for comparison.

[b] Full model result is reported in Table A.1 in the Appendix A.

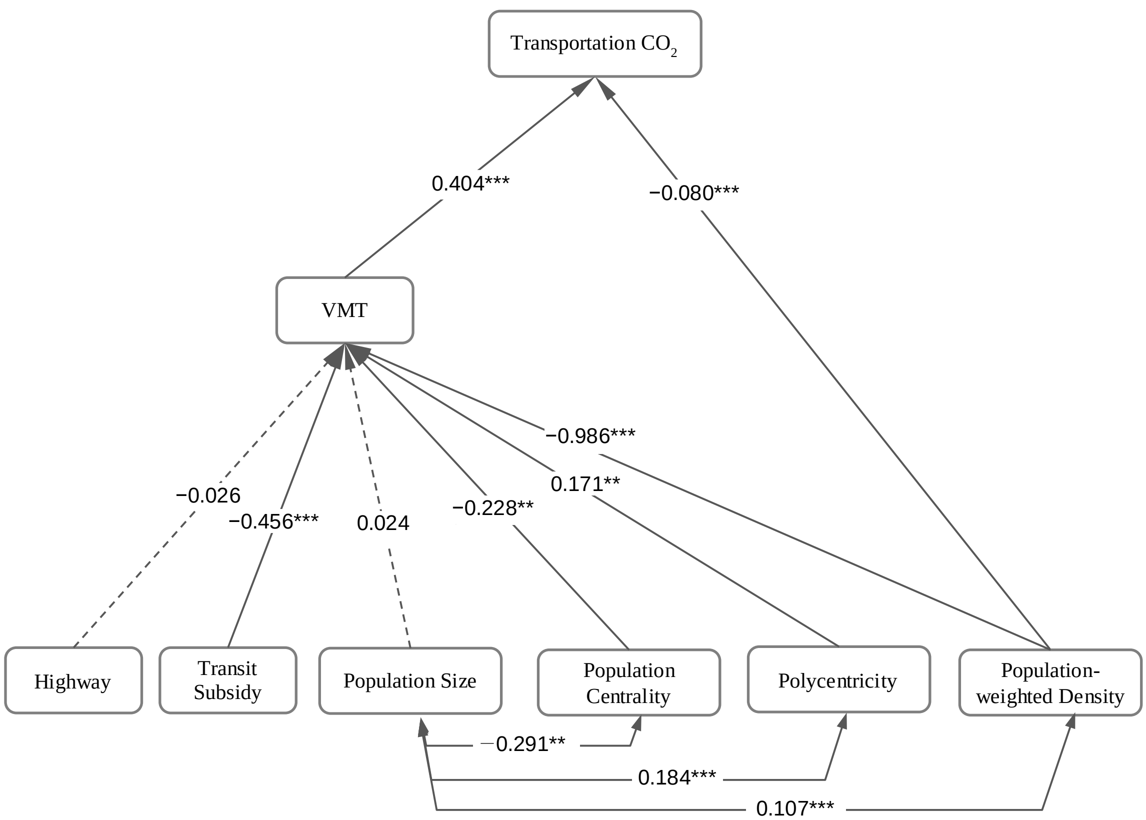
Estimated density effects are larger than most estimates in previous studies. While the average elasticity of VMT with respect to local density as one of many urban form indicators is as small as −0.04 on average (Ewing & Cervero, 2010), it is generally accepted that the density effect is as high as −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 & 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 2.1, the elasticity of VMT is much smaller (−0.371) and is almost identical to the density effect estimated by Cervero & 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.

The impacts of the other two urban form variables are estimated to be moderate. Consistent with my 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 & Ogawa, 1982; McMillen & Smith, 2003). Empirical studies have associated polycentric metropolitan structure with higher productivity (Meijers & Burger, 2010), and decentralized employment has often been connected with a shorter average commute time (Crane & Chatman, 2003; Gordon & Lee, 2014). Thus, developing public transportation networks that can efficiently serve polycentrized urban regions would be a better policy solution (Brown & Thompson, 2008) than discouraging transformation from a monocentric to polycentric urban area.



* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Notes: The results for various household level exogenous variables are suppressed for space reason. They are included in Appendix Table A.1.

Figure 2.6. Key results for the transportation carbon dioxide emissions model.

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. These elasticities are somewhat larger than expected. I suspect that the transit subsidy variable behaves as a catchall variable for many factors affecting transit ridership given my parsimonious model specification. Thus, I suggest that the coefficient should be interpreted as an association rather than a causal relationship. However, the other transportation infrastructure variable, highway lane miles per capita, was insignificant in my 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 2.1.

The results for individual household level demographic and socioeconomic variables are all consistent with my expectations, as shown in Table A.1 in the Appendix A. Higher income, larger household size, more employed workers, and being white are associated with higher CO_2 emissions from travel.

2.4.2.2. Residential CO_2 emissions

High density development also contributes to energy saving and CO_2 emission reduction in residential buildings. As shown in Table 2.4, 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 2.1 with a conventional density measure is similar, except that the estimated elasticity is slightly larger, as shown in the top panel of Table 2.4: −0.375 (−0.351)[11].

Table 2.4. 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 1)	2)	3)	Elasticity[a] 1) × 2) × 3)	
Model 2.3:					
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 2.4:					
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*	

[*] Significant at 10%. [**] Significant at 5%. [***] Significant at 1%.

[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 2.3 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 least 10%. Values in parentheses are sums of only statistically significant direct and indirect effects.

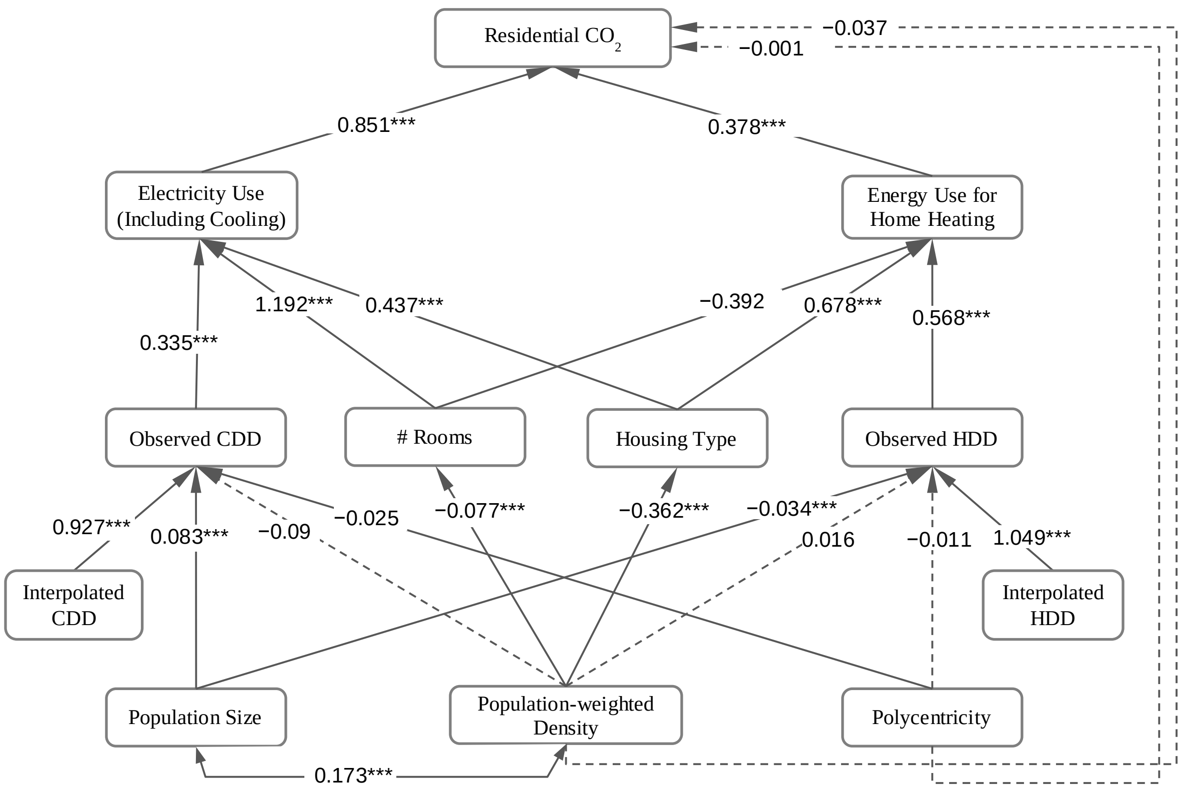
My results also show that CO_2 emissions from electricity consumption are more sensitive to population density change (−0.240) than are emissions from home heating (−0.078). This gap in sensitivity can be attributed to several factors. First, a small

[11] The result of an analysis excluding New York was almost identical to that of the full sample analysis, with estimated total effects of population–weighted density being −0.355 (−0.344).

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 ($-0.245 = -0.362 \times 0.678$) is actually larger than that of electricity consumption ($-0.158 = -0.362 \times 0.437$). 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, my 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.

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 my 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.



* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

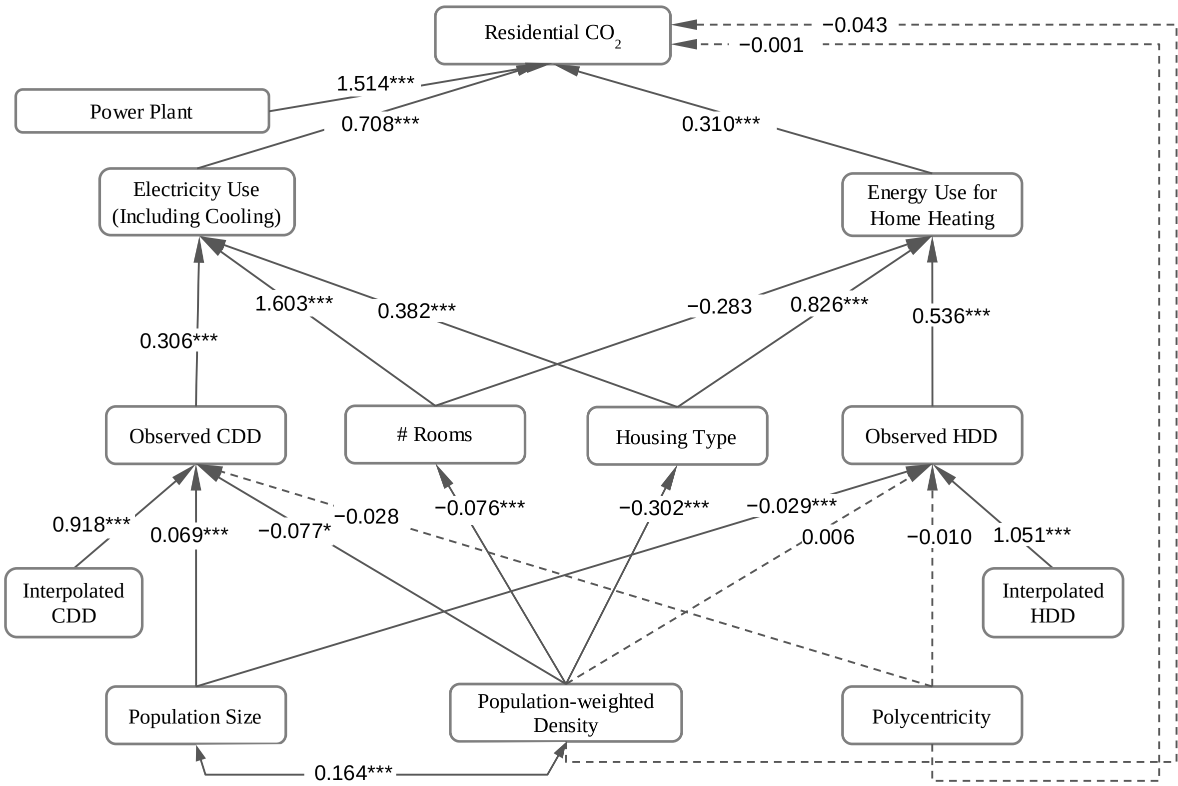
Notes: The results for various household level exogenous variables and location dummy are suppressed to conserve space. They are included in the Table A.2 in Appendix A. Housing type is an ordinal variable (0= multi-family, 1= single attached, and 2= single detached). Coefficients of exogenous variables on housing type are estimated using an ordered probit link function.

Figure 2.7. Key results for the residential carbon dioxide emissions model.

As shown in Table A.2 in the Appendix A, 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.

However, CO_2 emissions are different to generate the same energy at the production level, so their own effects should be controlled to find the marginal effects of urban structure on residential CO_2 emissions with holding production level influences. The previous results in Table 2.4 and Figure 2.7 have mixed impacts between the CO_2 intensity by different power plants at the production level and the energy usage by each household at the consumption level. Thus, the path model is slightly modified with adding one another direct path from CO_2 emissions per kilo watt hour when generating energy (production level) to the final consumption of CO_2 in each household.

The new output shows that the impacts of urban spatial structure on residential CO_2 emissions are relatively smaller than previous results (Figure 2.8, Table 2.5, and Table B.3). However, the results are not dramatically different with previous results. According to previous studies, the residential CO_2 elasticities w.r.t. population density and w.r.t. population-weighted density are −0.375 and −0.355, respectively. However, they are −0.372 and −0.300 according to new outputs, so the updated results are slightly smaller than those of previous outputs. The impact of polycentric urban structure (−0.009) is similar to previous results (−0.01), but the mediation effects of population size are slightly decreased from 0.016 to 0.01.



* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Notes: The results for various household level exogenous variables and location dummy are suppressed to conserve space. They are included in Table A.3. 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.

Figure 2.8. Key results for the residential carbon dioxide emissions model with adding one another direction from power plant to residential CO_2.

Table 2.5. Direct, indirect, and total effects of key urbanized area characteristics on residential CO_2 emissions (under controlling the production level CO_2 impacts).

Paths from UA level variables to Residential CO_2	Coefficient 1)	2)	3)	Elasticity[a] 1) × 2) × 3)	
Model 2.3:					
Total effects of conventional population density				**−0.372**	(***−0.368***)
Through electricity consumption (including home cooling)				**−0.207**	(***−0.194***)
Density $\rightarrow^{1)}$ #Rooms $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.097 ***	1.552 ***	0.705 ***	−0.106	
Density $\rightarrow^{1)}$ Housing Type[a] $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.337 ***	0.368 ***	0.705 ***	−0.087	
Density $\rightarrow^{1)}$ CDD $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.062	0.309 ***	0.705 ***	−0.014	
Through home heating				**−0.082**	(***−0.175***)
Density $\rightarrow^{1)}$ #Rooms $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.097 ***	−0.372	0.314 ***	0.011	
Density $\rightarrow^{1)}$ Housing Type[a] $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.337 ***	0.867 ***	0.314 ***	−0.092	
Density $\rightarrow^{1)}$ HDD $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.010	0.532 ***	0.314 ***	−0.002	
Density $\rightarrow^{3)}$ ResidentialCO_2			−0.083 *	−0.083	
Model 2.4:					
Total effects of population-weighted density				**−0.300**	(***−0.262***)
Through electricity consumption (including home cooling)				**−0.185**	(***−0.185***)
Density $\rightarrow^{1)}$ #Rooms $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.076 ***	1.603 ***	0.708 ***	−0.086	
Density $\rightarrow^{1)}$ Housing Type[b] $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.302 ***	0.382 ***	0.708 ***	−0.082	
Density $\rightarrow^{1)}$ CDD $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.077 *	0.306 ***	0.708 ***	−0.017	
Through home heating				**−0.072**	(***−0.077***)
Density $\rightarrow^{1)}$ #Rooms $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.076 ***	−0.283	0.310 ***	0.007	
Density $\rightarrow^{1)}$ Housing Type[b] $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.302 ***	0.826 ***	0.310 ***	−0.077	
Density $\rightarrow^{1)}$ HDD $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.010	0.536 ***	0.310 ***	−0.002	
Density $\rightarrow^{3)}$ ResidentialCO_2			−0.043	−0.043	
Total effects of polycentricity				**−0.009**	(***−0.000***)
Polycentricity $\rightarrow^{1)}$ CDD $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	−0.028	0.306 ***	0.708 ***	−0.006	
Polycentricity $\rightarrow^{1)}$ HDD $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.011	0.536 ***	0.310 ***	−0.002	
Polycentricity $\rightarrow^{3)}$ Residential CO_2			−0.001	−0.001	
Total effects of population size				**0.010**	(***0.010***)
Population $\rightarrow^{1)}$ CDD $\rightarrow^{2)}$ Electricity $\rightarrow^{3)}$ Residential CO_2	0.069 ***	0.306 ***	0.708 ***	0.015	
Population $\rightarrow^{1)}$ HDD $\rightarrow^{2)}$ Heating $\rightarrow^{3)}$ Residential CO_2	−0.029 ***	0.536 ***	0.310 ***	−0.005	

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

[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 2.3 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 least 10%. Values in parentheses are sums of only statistically significant direct and indirect effects.

2.5. Conclusions

To enhance my 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, I 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 my models. In any case, my analysis presents considerably larger elasticities than previous estimates by using population-weighted density instead of a conventional density measure. Furthermore, though not included in my 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, I 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. A caveat, though, is that the transit subsidy variable in my parsimonious model seems to capture the impacts of various factors that affect transit mode shares.

A notable limitation of the present analysis is that my urban form measures focus only on the macro spatial structure at the urbanized area level, leaving out other urban form dimensions such as land use mix and street connectivity. There is a promising research opportunity in the future in which one can examine urban form effects at both neighborhood and urban area levels in a three-level hierarchical model.

Given that household travel and residential energy use account for 42% of total U.S. carbon dioxide emissions, my 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. Changing urban settlement forms certainly require long term efforts. Researchers can only offer a wide range of scenarios regarding the percent of all new development by 2050 which is compact: between 25% and 75% (Transportation Research Board, 2009) or between 60% to 90% (Ewing et al., 2008b). However, studies show that there are latent demands for more sustainable developments in light of demographical and socio-economic changes (Nelson, 2009). My findings using population-weighted density highlight that concentrating density in central areas by strategic infill (re)development will be particularly beneficial. 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, it is suggested that electric vehicles (EVs) and electricity-based home heating should get low policy priority in regions where the carbon intensity of electric power generation is high (Kennedy, 2011). However, this kind of policy decision should also take into account that electricity-based systems can be more carbon efficient than other fuel uses depending on the efficiency of the equipment and the time of electricity use (King, 2007; Mustafa Omer, 2008). 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.

2.6. Bibliography

Anas, A., Arnott, R., & Small, K.A. (1998). Urban spatial structure. *Journal of Economic Literature, 36*, 1426-1464. Retrieved from http://www.jstor.org/stable/2564805

Arnfield, A.J. (2003). Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. *International Journal of Climatology, 23*(1), 1-26. doi:10.1002/joc.859

Baker, L.A., Brazel, A.J., Selover, N., Martin, C., McIntyre, N., Steiner, F.R., Nelson, A., & Musacchio, L. (2002). Urbanization and warming of Phoenix (Arizona, USA): Impacts, feedbacks and mitigation. *Urban Ecosystems, 6*(3), 183-203. doi:10.1023/A:1026101528700

Bento, A.M., Cropper, M.L., Mobarak, A.M., & Vinha, K. (2005). The effects of urban spatial structure on travel demand in the United States. *Review of Economics and Statistics, 87*(3), 466-478. doi:10.1162/0034653054638292

Bhat, C., Sen, S., & Eluru, N. (2009). The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. *Transportation Research Part B: Methodological, 43*(1), 1-18. doi:10.1016/j.trb.2008.06.009

Bhat, C.R., & Sen, S. (2006). Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model. *Transportation Research Part B: Methodological, 40*(1), 35-53. doi:10.1016/j.trb.2005.01.003

Boarnet, M.G., & Crane, R. (2001). *Travel by Design: The Influence of Urban form on Travel*. New York: Oxford University Press.

Boarnet, M.G., & Sarmiento, S. (1998). Can land-use policy really affect travel behavior? a study of the link between non-work travel and land-use characteristics. *Urban Studies, 35*(7), 1155-1169. doi:10.1080/0042098984538

Boies, A., Hankey, S., Kittelson, D., Marshall, J.D., Nussbaum, P., Watts, W., & Wilson, E.J. (2009). Reducing motor vehicle greenhouse gas emissions in a non-California state: A case study of Minnesota. *Environmental science & technology, 43*(23), 8721-8729. doi:10.1021/es902019z

Brown, J., & Thompson, G. (2008). Service Orientation, Bus—Rail Service Integration, and Transit Performance: Examination of 45 U.S. Metropolitan Areas. *Transportation Research Record: Journal of the Transportation Research Board, 2042*(-1), 82-89. doi:10.3141/2042-09

Brown, M.A., Southworth, F., & Sarzynski, A. (2008). *Shrinking the carbon footprint of metropolitan America*: Brookings Institution Washington, DC.

Brown, M.A., Southworth, F., & Sarzynski, A. (2009). The geography of metropolitan carbon footprints. *Policy and Society, 27*(4), 285-304. doi:10.1016/j.polsoc.2009.01.001

Brown, M.A., Southworth, F., & Stovall, T.K. (2005). *Towards a climate-friendly built environment*. Arlington, VA: Pew Center on Global Climate Change.

Brownstone, D., & Golob, T.F. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics, 65*(1), 91-98. doi:10.1016/j.jue.2008.09.002

Bryk, A.S., & Raudenbush, S.W. (1992). *Hierarchical linear models: Applications and data analysis methods*: Sage Publications, Inc.

Cao, X.Y., Mokhtarian, P.L., & Handy, S.L. (2009). Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings. *Transport Reviews, 29*(3), 359-395. doi:10.1080/01441640802539195

Cervero, R., & Duncan, M. (2006). 'Which Reduces Vehicle Travel More: Jobs-Housing Balance or Retail-Housing Mixing? *Journal of the American Planning Association, 72*(4), 475-490. doi:10.1080/01944360608976767

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: density, diversity, and design. *Transportation Research D, 2*(3), 199-219. doi:10.1016/S1361-9209(97)00009-6

Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas. *Environment and Planning A, 42*(2), 400–418. doi:10.1068/a4236

Cervero, R., Sarmiento, O.L., Jacoby, E., Gomez, L.F., & Neiman, A. (2009). Influences of built environments on walking and cycling: lessons from Bogotá. *International Journal of Sustainable Transportation, 3*(4), 203-226. doi:10.1080/15568310802178314

Chapman, L. (2007). Transport and climate change: a review. *Journal of Transport Geography, 15*(5), 354-367. doi:10.1016/j.jtrangeo.2006.11.008

Chou, C.P., & Bentler, P.M. (1995). Estimates and tests in structural equation modeling. In Hoyle, R.H. (Ed.), *Structural equation modelling: Concepts, issues, and applications* (pp. 37-55). Thousand Oaks, CA: Sage Publication.

Crane, R., & Chatman, D. (2003). Traffic and sprawl: Evidence from U.S. commuting, 1985 to 1997. *Planning and Markets, 6*(1), 14-22.

Cutsinger, J., Galster, G., Wolman, H., Hanson, R., & Towns, D. (2005). Verifying the Multi-Dimensional Nature of Metropolitan Land Use: Advancing the Understanding and Measurement of Sprawl. *Journal of Urban Affairs, 27*(3), 235-259. doi:10.1111/j.0735-2166.2005.00235.x

Downs, A. (2005). Smart Growth: Why We Discuss It More than We Do It. *Journal of the American Planning Association, 71*(4), 367-378. doi:10.1080/01944360508976707

Echenique, M.H., Hargreaves, A.J., Mitchell, G., & Namdeo, A. (2012). Growing Cities Sustainably. *Journal of the American Planning Association, 78*(2), 121-137. doi:10.1080/01944363.2012.666731

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., & Anderson, G. (2008a). Urban development and climate change. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 1*(3), 201-216. doi:10.1080/17549170802529316

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., & Chen, D. (2008b). *Growing cooler: The evidence on urban development and climate change*. Washington DC: Urban Land Institute.

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment--A Meta-Analysis. *Journal of the American Planning Association, 76*(3), 265-294. doi:10.1080/01944361003766766

Ewing, R., Pendall, R., & Chen, D. (2003). Measuring sprawl and its transportation impacts. *Transportation Research Record, 1931*, 175-183. doi:10.3141/1831-20

Ewing, R., & Rong, F. (2008). The impact of urban form on US residential energy use. *Housing Policy Debate, 19*(1), 1-30. doi:10.1080/10511482.2008.9521624

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 56-83. doi:10.1080/10705519909540119

Fang, H.A. (2008). A discrete–continuous model of households' vehicle choice and usage, with an application to the effects of residential density. *Transportation Research Part B: Methodological, 42*(9), 736-758. doi:10.1016/j.trb.2008.01.004

Fujita, M., & Ogawa, H. (1982). Multiple equilibria and structural transition of non-monocentric urban configurations. *Regional Science and Urban Economics, 12*(2), 161-196. doi:10.1016/0166-0462(82)90031-X

Gabaix, X., & Ibragimov, R. (2011). Rank − 1 / 2: A Simple Way to Improve the OLS Estimation of Tail Exponents. *Journal of Business & Economic Statistics, 29*(1), 24-39. doi:10.1198/jbes.2009.06157

Galster, G., Hanson, R., Ratcliffe, M.R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling Sprawl to the Ground: Defining and measuring an elusive concept. *Housing Policy Debate, 12*(4), 681-717. doi:10.1080/10511482.2001.9521426

Giuliano, G., & Small, K.A. (1991). Subcenters in the Los Angeles region. *Regional Science and Urban Economics, 21*(2), 163-182. doi:10.1016/0166-0462(91)90032-I

Glaeser, E.L., & Kahn, M.E. (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics, 67*(3), 404-418. doi:10.1016/j.jue.2009.11.006

Golob, T.F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological, 37*(1), 1-25. doi:10.1016/S0191-2615(01)00046-7

Gordon, P., & Lee, B. (2014). Chapter 4: Spatial structure and travel-trands in commuting and non-commuting travels in US metropolitan areas. In Hickman, R., et al. (Eds.), *International Handbook on Transport and Development*. Cheltenham, UK: Edward Elgar Publishing.

Grazi, F., van den Bergh, J.C., & van Ommeren, J.N. (2008). An empirical analysis of urban form, transport, and global warming. *The Energy Journal*, 97-122. Retrieved from http://www.jstor.org/stable/41323183

Greening, L.A., Greene, D.L., & Difiglio, C. (2000). Energy efficiency and consumption — the rebound effect — a survey. *Energy Policy, 28*(6–7), 389-401. doi:10.1016/S0301-4215(00)00021-5

Guhathakurta, S., & Gober, P. (2007). The Impact of the Phoenix Urban Heat Island on Residential Water Use. *Journal of the American Planning Association, 73*(3), 317-329. doi:10.1080/01944360708977980

Gurney, K.R., Mendoza, D.L., Zhou, Y., Fischer, M.L., Miller, C.C., Geethakumar, S., & de la Rue du Can, S. (2009). High resolution fossil fuel combustion CO2 emission fluxes for the United States. *Environmental science & technology, 43*(14), 5535-5541. doi:10.1021/es900806c

Holden, E., & Norland, I.T. (2005). Three challenges for the compact city as a sustainable urban form: household consumption of energy and transport in eight residential areas in the greater Oslo region. *Urban Studies, 42*(12), 2145. doi:10.1080/00420980500332064

Hox, J. (2010). *Multilevel analysis: Techniques and applications* (2nd Ed.): Routledge Academic.

Johansson, B. (2009). Will restrictions on CO2 emissions require reductions in transport demand? *Energy Policy, 37*(8), 3212-3220. doi:10.1016/j.enpol.2009.04.013

Kaplan, D. (1995). Statistical power in structural equation modeling. In Hoyle, R.H. (Ed.), *Structural equation modelling: Concepts, issues, and applications* (pp. 100-117). Thousand Oaks, CA: Sage Publications.

Kennedy, C. (2011). *Progress towards low carbon cities, IPCC Expert Meeting on Infrastructure and Human Settlements*. Retrieved from Kolkata, India

King, J. (2007). *The King Review of low-carbon cars: part I: the potential for CO2 reduction*.

Kockelman, K.M. (1997). Travel behavior as a function of accessibility, land-use mixing, and land-use balance: Evidence from the San Francisco bay area. *Transportation Research Record, 1607*, 116-125. doi:10.3141/1607-16

Kromer, J. (2010). *Fixing broken cities: The implementation of urban development strategies*: Routledge New York, NY.

Lee, B. (2007). "Edge" or "Edgeless" Cities? Urban Spatial Structure in US Metropolitan Areas, 1980 to 2000. *Journal of Regional Science, 47*(3), 479-515. doi:10.1111/j.1467-9787.2007.00517.x

Lee, B. (2014). Determinants of spatial structure in U.S. urbanized areas. under review. *Environment and Planning A*.

Liu, C., & Shen, Q. (2011). An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment and Urban Systems, 35*(5), 347-357. doi:10.1016/j.compenvurbsys.2011.05.006

Marshall, J. (2008). Energy-efficient urban form. *Environmental science & technology, 42*(9), 3133-3137. doi:10.1021/es087047l

Massey, D.S., & Denton, N. (1988). The dimensions of residential segregation. *Social Forces, 67*, 281-313. doi:10.1093/sf/67.2.281

McMillen, D.P. (2001). Nonparametric employment subcenter identification. *Journal of Urban Economics, 50*(3), 448-473. doi:10.1006/juec.2001.2228

McMillen, D.P., & Smith, S.C. (2003). The number of subcenters in large urban areas. *Journal of Urban Economics, 53*(3), 321-338. doi:10.1016/s0094-1190(03)00026-3

Meijers, E. (2008). Measuring polycentricity and its promises. *European Planning Studies, 16*(9), 1313-1323. doi:10.1080/09654310802401805

Meijers, E.J., & Burger, M.J. (2010). Spatial structure and productivity in US metropolitan areas. *Environment and Planning A*, *42*(6), 1383-1402. doi:10.1068/a42151

Mokhtarian, P.L., & Cao, X. (2008). Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. *Transportation Research Part B: Methodological*, *42*(3), 204-228. doi:10.1016/j.trb.2007.07.006

Morrow, R.W., Gallagher, K.S., Collantes, G., & Lee, H. (2010). Analysis of policies to reduce oil consumption and greenhouse-gas emissions from the US transportation sector. *Energy Policy, 38*(3), 1305-1320. doi:10.1016/j.enpol.2009.11.006

Mui, S., Alson, J., Ellies, B., & Ganss, D. (2007). *A Wedge Analysis of the US Transportation Sector*. Retrieved from http://www3.epa.gov/otaq/climate/420r07007.pdf

Mustafa Omer, A. (2008). Ground-source heat pumps systems and applications. *Renewable and Sustainable Energy Reviews*, *12*(2), 344-371. doi:10.1016/j.rser.2006.10.003

Muthén, B.O. (1994). Multilevel covariance structure analysis. *Sociological Methods & Research, 22*(3), 376-398. doi:10.1177/0049124194022003006

Myors, P., O'Leary, R., Helstroom, R., Wales, N.S., & Australia, E. (2005). *Multi Unit Residential Buildings Energy & Peak Demand Study* (0734754930). Retrieved from Melbourne, VIC

Næss, P. (2005). Residential location affects travel behavior—but how and why? The case of Copenhagen metropolitan area. *Progress in Planning, 63*(2), 167-257. doi:10.1016/j.progress.2004.07.004

Navigant Consulting. (2009). *Assessment of International Urban Heat Island Research: review and critical analysis of international UHI studies*. Retrieved from Vienna, VA: http://www.eereblogs.energy.gov/buildingenvelope/file.axd?file=2011/10/uhi_report.pdf

Nelson, A.C. (2009). The new urbanity: The rise of a new America. *The ANNALS of the American Academy of Political and Social Science, 626*(1), 192-208. doi:10.1177/0002716209344172

Nordregio. (2005). *ESPON 1.1.1: potentials for polycentric development in Europe.* . Retrieved from Stockholm/Luxembourg.: http://www.espon.eu/export/sites/default/Documents/Projects/ESPON2006Projects/ThematicProjects/Polycentricity/fr-1.1.1_revised-full.pdf

Oke, T.R. (1973). City size and the urban heat island. *Atmospheric Environment (1967), 7*(8), 769-779. doi:10.1016/0004-6981(73)90140-6

Oke, T.R., Johnson, G.T., Steyn, D.G., & Watson, I.D. (1991). Simulation of surface urban heat islands under 'ideal' conditions at night part 2: Diagnosis of causation. *Boundary-Layer Meteorology, 56*(4), 339-358. doi:10.1007/BF00119211

Pacala, S., & Socolow, R. (2004). Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies. *Science, 305*(5686), 968-972. doi:10.1126/science.1100103

Parshall, L., Gurney, K., Hammer, S.A., Mendoza, D., Zhou, Y., & Geethakumar, S. (2010). Modeling energy consumption and CO2 emissions at the urban scale: Methodological challenges and insights from the United States. *Energy Policy, 38*(9), 4765-4782. doi:10.1016/j.enpol.2009.07.006

Perkins, A., Hamnett, S., Pullen, S., Zito, R., & Trebilcock, D. (2009). Transport, Housing and Urban Form: The Life Cycle Energy Consumption and Emissions of City Centre Apartments Compared with Suburban Dwellings. *Urban policy and research, 27*(4), 377-396. doi:10.1080/08111140903308859

Preacher, K.J., Zhang, Z., & Zyphur, M.J. (2011). Alternative Methods for Assessing Mediation in Multilevel Data: The Advantages of Multilevel SEM. *Structural Equation Modeling: A Multidisciplinary Journal, 18*(2), 161-182. doi:10.1080/10705511.2011.557329

Preacher, K.J., Zyphur, M.J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological methods, 15*(3), 209-233. doi:10.1037/a0020141

Richardson, K., Steffen, W., Schellnhuber, H.J., Alcamo, J., Barker, T., Kammen, D.M., Leemans, R., Liverman, D., Munasinghe, M., & Osman-Elasha, B. (2009). *Synthesis Report, Climate Change: Global Risks, Challenges and Decisions*. Retrieved from Copenhagen, Denmark: http://curis.ku.dk/ws/files/14774466/http___climatecongress.ku.pdf

Rosenfeld, A.H., Akbari, H., Bretz, S., Fishman, B.L., Kurn, D.M., Sailor, D., & Taha, H. (1995). Mitigation of urban heat islands: materials, utility programs, updates. *Energy and buildings, 22*(3), 255-265. doi:10.1016/0378-7788(95)00927-P

Smith, J.B., Schneider, S.H., Oppenheimer, M., Yohe, G.W., Hare, W., Mastrandrea, M.D., Patwardhan, A., Burton, I., Corfee-Morlot, J., Magadza, C.H.D., Füssel, H.-M., Pittock, A.B., Rahman, A., Suarez, A., & van Ypersele, J.-P. (2009). Assessing dangerous climate change through an update of the Intergovernmental Panel on Climate Change (IPCC) "reasons for concern". *Proceedings of the National Academy of Sciences, 106*(11), 4133-4137. doi:10.1073/pnas.0812355106

Sorrell, S., Dimitropoulos, J., & Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy, 37*(4), 1356-1371. doi:10.1016/j.enpol.2008.11.026

Stone, B. (2007). Urban and rural temperature trends in proximity to large US cities: 1951–2000. *International Journal of Climatology, 27*(13), 1801-1807. doi:10.1002/joc.1555

Stone, B., & Rodgers, M.O. (2001). Urban Form and Thermal Efficiency:How the Design of Cities Influences the Urban Heat Island Effect. *Journal of the American Planning Association, 67*(2), 186-198. doi:10.1080/01944360108976228

Sun, X., Wilmot, C.G., & Kasturi, T. (1998). Household travel, household characteristics, and land use: an empirical study from the 1994 Portland activity-based travel survey. *Transportation Research Record: Journal of the Transportation Research Board, 1617*(1), 10-17. doi:10.3141/1617-02

Transportation Research Board. (2009). *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions* (298). Retrieved from Washington, D.C.

U.S. Department of State. (2010). *US Inscription to the UNFCCC on the Copenhagen Accord*. Washington, D.C. Retrieved from https://unfccc.int/files/meetings/cop_15/copenhagen_accord/application/pdf/unitedstatescphaccord_app.1.pdf.

U.S. Environmental Protection Agency. (2012). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2010*. Washington, D.C.: U.S. Environmental Protection Agency.

UNFCCC, E. (2009). *Copenhagen Accord*. Copenhagen: COP 15.

Veneri, P. (2010). Urban polycentricity and the costs of commuting: evidence from Italian metropolitan areas. *Growth and Change, 41*(3), 403-429. doi:10.1111/j.1468-2257.2010.00531.x

Zhou, Y., & Gurney, K.R. (2011). Spatial relationships of sector-specific fossil fuel CO2 emissions in the United States. *Global Biogeochemical Cycles, 25*(3), GB3002. doi:10.1029/2010GB003822

CHAPTER 3
SUSTAINABLE URBAN FORM AT LOCAL AND REGIONAL SCALES

3.1. Introduction

In the past twenty years or so, a great number of studies have examined the associations between urban form and travel behavior. These studies show that sustainable urban development can lead to a significant reduction of greenhouse gas emissions, thus providing the basis for smart growth policies. The five elements (the “5Ds”) of the built environment are regarded as the fundamental principles for land use policies to promote more sustainable transportation. These elements include high density, highly mixed land use (diversity), highly interconnected street networks (street design), and good accessibility to main facilities and transit (distance to transit & destination access) (Cervero & Kockelman, 1997; Cervero et al., 2009; Ewing et al., 2008; Ewing & Cervero, 2001, 2010; Handy et al., 2002; Krizek, 2003a).

While the 5Ds principles are very important factors in designing sustainable and livable communities, one of their critical limitations lies in their focus on neighborhood level characteristics. Many existing studies largely fail to take into account regional level urban form factors. Although one of the 5Ds—Destination access typically measured by job accessibility by auto and distance to downtown variables—does indirectly relate to regional level urban structures, it still remains to be a local measure but fails to capture various features of regional level distribution of population and workplaces. Aside from accessibility, all other elements are generally defined at the neighborhood level, typically represented by census block group, census tract, and Traffic Analysis Zone (TAZ).

Few studies have investigated how both local and regional level urban form influence travel behavior. Some earlier studies that examined the relationship between urban spatial structure and travel behavior took a regional approach only by using aggregate data (Eager, 1993; Giuliano, 1989, 1991; Gomez-Ibanez, 1991; Newman & Kenworthy, 1989; Pucher, 1988). These studies analyzed the linkages between aggregated geographic elements—population density in most cases—and aggregated travel patterns such as per capita VMT or gasoline consumption at the metropolitan area level. Such an approach cannot properly capture the marginal impacts of urban structure underlying individual travel decisions while controlling for individual household characteristics. Indeed, some of the studies may be subject to the *ecological fallacy* (Piantadosi, Byar & Green, 1988). While many recent studies use individual level data and more sophisticated econometric models to reveal how urban form influences individuals' travel decisions, again, they tend to focus on neighborhood level urban form characteristics, often ignoring the effects of metropolitan level spatial structure.

Given the limitations of the existing studies, I focus on the influences of urban structure on travel behavior at two different geographic scales. In other words, this study aims to consider both regional level (urbanized area) spatial characteristics and neighborhood level urban form elements in explaining individual level travel and hence greenhouse gas (GHG) emission behaviors. In addition, this study will also investigate the interaction effects of urbanized area level spatial structure and sustainable neighborhood built form. I assume that well-designed transit-oriented neighborhoods will promote sustainable travel behavior more in high-density urbanized areas than in auto-oriented urbanized areas. Therefore, the aim of this study is twofold: to find the different geographic scale impacts of urban spatial structure and to investigate the interaction effects between different spatial level land use variables on both travel behavior and carbon dioxide emissions. A multi-level regression method is employed to overcome the statistical issues arising from the nested data structure.

3.2. The influence of urban form at two spatial levels

Since the linkage between land use and travel behavior is very important in designing successful public policies that promote sustainable development and smart growth, a number of recent studies have investigated the relationship, targeting various regions and neighborhoods in the US (For recent surveys of the literature, see Boarnet & Crane, 2001b; Cao, Mokhtarian & Handy, 2006; Ewing & Cervero, 2001, 2010; and Handy, 2005). Because the transportation sector is responsible for about 30% of GHG emissions in the US (U.S. Energy Information Administration, 2011), research has recently begun to examine the impacts of spatial structure on climate change (Brown, Southworth & Sarzynski, 2008; Glaeser & Kahn, 2010; Jones & Kammen, 2014; Lee & Lee, 2014). Although technological development and market solutions may significantly contribute to mitigating the environmental impact, many scholars argue that without moderating the energy demand, these policies alone cannot achieve the “2°C guardrail” goal (Boies et al., 2009; Grazi & van den Bergh, 2008; Johansson, 2009; Kromer, Bandivadekar & Evans, 2010; Morrow et al., 2010). Therefore, as one of many methods to moderate the energy demand, many urban planners believe that transit-friendly neighborhoods discourage private vehicle use and hence reduce GHG emissions in the transportation sector.

As a result, many recent studies have focused on examining whether, and to what extent, well-designed neighborhoods trigger the shift in individual travel behavior away from private vehicle use. The literature shows substantial progress in many related topical areas, including how to measure and classify both the built environment (Cervero & Kockelman, 1997; Cervero et al., 2009; Handy, 1996b) and travel behavior (Cao, Mokhtarian & Handy, 2006; Ewing & Cervero, 2001; Frank, 2000; Handy, 1996a), and how to handle the self-selection bias (Cao, Mokhtarian & Handy, 2009; Ewing & Cervero, 2010; Mokhtarian & Cao, 2008). However, the geographical scale of the built environment has received less attention. Specifically, most empirical studies investigate how neighborhood level urban form and land use influence travel behavior, even though regional level spatial structure can have larger impacts.

According to the National Household Travel Survey (NHTS, 2009), in the U.S., the average one-way trip distance by auto is about 10 miles; while it is approximately 3 miles and 1 mile for bike and walking trips, respectively. (Table 3.1). Moreover, most Americans (over 85%) still use their private vehicle when they travel and only about 10% of all travel is related to walking. In sum, these statistics imply that the spatial boundary within which land uses matter for private vehicle use is significantly larger than that for non-motorized travel. Since intra-urban daily trips in U.S. cities are overwhelmingly dominated by vehicle travel, both research and policy considerations for sustainable urban form should be pursued at a larger scale beyond the neighborhood level.

Many empirical studies have examined the links between neighborhood level land use characters and vehicle miles traveled (VMT). VMT can be considered to be a composite index of many other travel-related variables such as auto ownership, trip frequency, mode choice, and trip length (Ewing & Cervero, 2001). Small scale land use elements indeed affect the mode shift from private vehicles to public transit or non-motorized travel that is the outcome of neighborhood level attraction. However, the lengths of commuting trips or shopping trips to main shopping districts are largely determined by regional level urban structure.

Table 3.1. The average one-trip travel miles and travel frequency by different modes in the 121 UAs (NHTS, 2009 [a)]).

	Travel Miles (One-trip) [b)]				**Travel Frequency Ratio** [c)]			
	Total (121 UAs)	High Density UAs[1)]	Medium Density UAs[2)]	Low Density UAs[3)]	**Total** (121 UAs)	High Density UAs[1)]	Medium Density UAs[2)]	Low Density UAs[3)]
Auto	**8.79**	8.55	8.89	9.25	**85.58%**	84.12%	88.15%	89.21%
Transit	**7.69**	7.84	7.32	8.12	**2.90%**	3.33%	2.90%	2.75%
Bike	**2.76**	2.96	2.65	2.25	**0.95%**	1.12%	0.85%	1.09%
Walk	**0.70**	0.69	0.71	0.70	**10.57%**	13.92%	10.23%	9.09%

a) Sample size: 452,748.
b) One-trip travel miles exclude the samples of long distance travel such as city to city travel, the trip using airplane or inter-city trains.
c) 'Travel Frequency Ratio' is the ratio among different modes.
1) The high density urbanized areas (UAs) are defined as the UAs of which population-weighted density (PWD) is higher than 5,000, and there are 28 in 121 UAs.
2) The medium density UAs are defined as the UAs of which PWD is higher than 2,500 UAs except the 28 high density UAs, and there are 63 in 121 UAs.
3) The low density UAs are designated as the UAs of which PWD is lower than 2,500, and there are 30 among 121 UAs.

Table 3.2. The average one-trip travel miles and travel frequency by different trip purposes with different modes in the 121 UAs (NHTS, 2009 [a)]).

	Travel Miles (One-trip) [b)]					**Travel Frequency Ratio** [c)]				
	HBW[1)]	HBSs[2)]	$HBSs_R$[3)]	HBO[4)]	NHB[5)]	HBW[1)]	HBSs[2)]	$HBSs_R$[3)]	HBO[4)]	NHB[5)]
Total	**11.65**	**5.24**	**8.85**	**6.68**	**9.06**	**9.48%**	**23.78%**	**15.05%**	**21.83%**	**29.85%**
Auto	11.94	5.54	12.19	7.64	9.88	93.35%	92.65%	68.97%	82.11%	88.39%
Transit	11.47	5.54	9.53	5.54	10.29	3.83%	1.28%	1.24%	5.97%	2.49%
Bike	4.19	1.45	2.70	1.53	4.71	0.82%	0.53%	3.28%	0.59%	0.42%
Walk	1.12	0.57	0.85	0.56	0.63	2.01%	5.54%	26.52%	11.33%	8.70%

a) Sample size: 452,748.
b) One-trip travel miles exclude the samples of long distance travel such as city to city travel, the trip using airplane or inter-city trains.
c) 'Total Travel Frequency Ratio (1st row)' is the ratio among different travel purposes such as HBW, HBSs, $HBSs_R$, HBO, and NHB, while the other 'Travel Frequency Ratios' from 'Auto' to 'Walk' (2nd to 5th rows) are the ratio among 4 different travel modes from 'Auto' to 'Walk.'
1) ~ 5) 'Home-based Work (HBW)', 'Home-based Shopping (HBSs)', 'Home-based Social/Recreational ($HBSs_R$)', 'Other home-based (HBO)', and 'Not home-based (NHB)'.

In the 1990s, empirical studies primarily investigated the relatively easily-measured impacts of regional level urban structure on aggregated travel patterns (Eager, 1993; Giuliano, 1989, 1991; Gomez-Ibanez, 1991; Newman & Kenworthy, 1992). For example, Newman & Kenworthy (1989) examined the association between urbanized area level population density and per capita energy use in 10 U.S. cities and 22 global cities. They concluded that U.S. cities used twice, 4 times, and 10 times the amount of gasoline on average as those in Australia, Europe, and Asia as of the 1980s, respectively. However, this research has been heavily criticized for several reasons, including that: 1) it oversimplifies and disregards the complex realities for different cultures, political backgrounds, and economic contexts; 2) it has statistical problems for limited variances, for both independent and dependent variables; 3) it doesn't consider the trip purpose; 4) the single "average density" variable represents the land use pattern; and 5) it over-interprets statistical results (Gomez-Ibanez, 1991; Gordon & Richardson, 1989).

Newman & Kenworthy (2006) went on to update their research, but that study too was criticized for its statistical problems (Ewing & Cervero, 2010). The 'average density' at the urbanized area level cannot explain the land use pattern sufficiently. Handy (1996a) points out that the 'average density' at the regional level can mask the diverse densities within the region, the different land use patterns, and the various neighborhood designs in the region.

Criticism of the regional level analysis presented a turning point toward neighborhood level research. Crane (2000) adds that the many limitations of previous simulation studies also necessitated neighborhood level empirical studies with disaggregate data to better understand the subtle built environmental impacts on travel behavior. In addition, the needs for specific land use policies to promote non-motorized travel may be another reason. Since the scale of non-motorized travel is far smaller than motorized trips, the subtle built environmental impacts on travel behavior.

Early neighborhood level studies focused on narrative descriptions with relatively coarse categories based on the 'pattern language' in the field of urban design. However, the research trend gradually moved to more statistical analyses (Handy et al., 2002). Cervero & Seskin (1995) and Handy (1992) empirically verified that compact neighborhoods led to a decrease in vehicle trips by boosting non-motorized travel. They suggested a variety of examples: people typically do not use cars for short trip distances, and high-density neighborhoods are connected to good transit services, relatively mixed land-use, and low-income levels. After this data appeared, the number of neighborhood level studies increased dramatically, involving different trip purposes and targeting diverse regions (Boarnet & Crane, 2001b; Cao, Handy & Mokhtarian, 2006; Cao, Mokhtarian & Handy, 2007; Cervero & Gorham, 1995; Cervero & Seskin, 1995; Krizek, 2003a, b).

Cervero & Kockelman (1997) identified three important built-environment elements—density, diversity, and design—and called them the 3Ds. Ewing & Cervero (2001) compare the influences of the 3Ds with regional accessibility on travel behavior, such as trip frequency, length, mode choice, and VMT based on more than 50 empirical studies. In 2009, Cervero et al. (2009) added ‘destination accessibility’ and ‘distance to transit’ to the 3Ds, forming the “5Ds”. Ewing & Cervero (2010) then adopted the 5Ds from Cervero et al. (2009), updating their meta-analysis. Their results show that residents in more compact and transit-friendly neighborhoods drive less and hence emit significantly less carbon dioxide than those living in sprawled neighborhoods. Moreover, the travel impacts of neighborhood characteristics were found to be significant even after normalizing for the effects of residential self-sorting by preferences and environmental attitudes (Cao, Mokhtarian & Handy, 2009; Mokhtarian & Cao, 2008).

To this day, the neighborhood level studies have been useful in supporting the ideal of New Urbanism. However, the importance of the regional level spatial structure should not be overlooked. Despite the trend toward New Urbanism in the past two decades, driving alone is still the predominant travel mode in most U.S. cities. According to the U.S. National Household Travel Survey (2009), more than 90% of workers use their own vehicles to commute, with an average commute of almost 15 miles. Without altering the automobile-oriented regional level spatial arrangement, neighborhood level efforts to promote density and land use mix are not likely to see expected outcomes.

Indeed, studies show that variables such as job accessibility and distance to downtown have larger impacts on VMT reduction (with a typical elasticity of −0.2) than do neighborhood level attributes, whose elasticities range between −0.04 and −0.12 (Cervero & Duncan, 2006; Ewing & Cervero, 2001, 2010; Kockelman, 1997; Næss, 2005; Sun, Wilmot & Kasturi, 1998). Handy et al. (2002) suggest that 'commuting trips', perhaps the longest daily trip segment for most people, are affected by travel patterns at the metropolitan scale, while 'non-work trips' are more associated with neighborhood scale attributes.

These findings imply that location and the distribution of developments in the metropolitan context may be more important than neighborhood level characteristics in moderating travel demand. Nonetheless, the impacts of the urbanized or metropolitan area level urban form have been examined in only a handful of recent studies (Bento et al., 2005; Cervero & Murakami, 2010; Ewing, Pendall & Chen, 2003), mainly due to the difficulty in quantifying spatial structure at the metropolitan and urbanized area levels. This is also one of the reasons why existing studies at the urbanized or metropolitan area levels only considered population density (Cervero & Murakami, 2010; Ewing, Pendall & Chen, 2003) and job centrality (Bento et al., 2005).

Furthermore, metropolitan level spatial structure seems to moderate neighborhood effects. Cervero & Gorham (1995) show that in the San Francisco region transit ridership is significantly higher in transit-oriented neighborhoods than in auto-oriented communities, but the difference is not nearly as strong in the Los Angeles metropolitan area. They conclude that 'islands of neo-traditional development in a sea of freeway-oriented suburbs will do little to change fundamental commuting habits'.

Lin & Long (2008) examine the journey to work vehicle trip rate between urban and suburban neighborhoods. They find that various neighborhood characteristics significantly affect travel behavior for urban groups, but not for suburban groups. In fact, the results of all these studies imply that regional scale urban structure can overwhelm neighborhood scale effects.

The purpose of this research is to examine the impact of built environments on travel behavior at two different geographic levels—neighborhood and urbanized area. I assume that regional level urban form has large impacts on both VMT and CO_2 emissions, since, in the U.S., a typical trip distance by auto passes over the small neighborhood boundary. Thus, regional level spatial structure has more direct impacts on auto-oriented travel behavior and should receive more attentions in both research and policy implementation.

3.3. Urban form and individual characteristics that affect travel behaviors

Various factors influence individual travel behavior both directly and indirectly, but all of them can be summarized under three level elements: individual household, neighborhood (census tract), and regional (urbanized area) levels.

Individual/household level (level1)

Many studies have investigated individual or individual household characteristics as main determinants of travel behavior. Although this research focuses on urban form variables, individual or household level elements should be controlled for in order to capture the marginal impacts on urban structure. Previous studies have shown that socio-economic status is an important element; the wealthy and the upper classes tend to spend more money on, and time toward, gasoline consumption. In addition, a households' life-cycle status, the number of household members or workers, and the gender and age of the household head can affect the total use of household vehicle.

Neighborhood level (level 2: census tract)

Many researchers have developed methods to construct variables to represent neighborhood level urban form and design characteristics in an effort to analyze neighborhood effects on travel behavior. Crane & Crepeau (1998) focus on street patterns with street design, the distance to downtown at the census tract level, and land use characteristics, such as residential, commercial and vacant. Snellen, Borgers & Timmermans (2002) consider transportation network type, and distance from the central business district (CBD), subcenter, and intercity station. Krizek (2003a) identifies four elements describing neighborhood design: 1) densities for population, housing units, and employment; 2) land use mix with several quantified variables such as presence of a food/drug store, entropy, or a dissimilarity index; 3) street design for 'X' type intersections (4-way intersections), total street miles, or traffic volumes; and 4) composite indices such as pedestrian-friendliness. Zhang (2004) compares travel behavior in Boston and Hong Kong, for three land use dimensions: density, diversity, and street design at the TAZ level. The study covers population and job density, cul-de-sac density, and the entropy index of land use with public parking spaces per number of jobs for both travel origin and destination. Although there are numerous categories used by different studies, Ewing & Cervero (2010) summarize all of them under the 5Ds (density, diversity, street design, destination accessibility, and distance to transit) in their meta-analysis.

Residential neighborhood variables include gross population density, an entropy index for land use among residential, commercial, industrial and office sectors, street densities for beta index and 4-way intersection density, and the distance from the closest regional CBD and subcenter. Workplace neighborhood variables include all residential neighborhood variables except gross residential density. Instead, gross employment density is considered for workplace neighborhood studies. The specific measurements of the neighborhood variables are explained in Appendix Table C.1 and C.2.

The neighborhood geographic scope is represented by the census tract in this study.[12] Several scholars point out that the census tract is a relatively wide boundary for

[12] In general, the size of the neighborhood has been defined as 'census tract', 'block group', 'block', 'Traffic Analysis Zone (TAZ)' or 'zip code' level, while a region is often defined as an 'urbanized area' or 'Metropolitan Statistical Area'. Boarnet and Crane (2001a) apply two different geographic scales to define different density variables; population density is measured at the 'census block group' but retail and service density is accounted at the 'census tract' level. Guo and Bhat (2007) try to find the optimal neighborhood boundary by testing three alternative methods including census based, circular-unit, and network band representation. However, their results show that there is no superior definition that satisfies all criteria.

neighborhood level studies since non-motorized activities are generally at the mercy of walkability and, in the U.S., the census tract is too large to cover by foot. However, the portion of bike users has steadily increased, and the bike mode should be covered at the neighborhood level as well. In addition, the small areas are generally homogenous.

Some scholars suggest using the traffic analysis zone (TAZ) for neighborhood studies. However, the unit of the TAZ is different for different metropolitan areas; while the TAZ is equivalent to a 'census block group' or 'census block' in some regions, 'census tract' is used to define the TAZ in others. Since the boundary of the TAZ is delineated by Metropolitan Planning Organizations (MPO), the TAZ can be a good alternative if the study area is limited to one metropolitan region. However, as this study covers 121 urbanized areas, having the same standard among different urbanized areas is critical.

Regional level (level 3: urbanized area)

The major UA level spatial structure variables can be classified into four distinctive dimensions: population density, centrality, polycentricity, and job accessibility. Population density is the most important element in checking the intensity of land use at the UA level. The conventional population density is too sensitive to the designated boundary and does not cover the distribution of population in each urbanized area. For example, according to 1990, 2000, and 2010 census statistics, Los Angeles is ranked as the densest urbanized area, surpassing New York, even as most people believe New York to be far denser than Los Angeles. The disconnect can be overcome by using population-

---

After testing a quarter mile buffer, Frank et al. (2007) apply a 1-km buffer for general built environment variables. Hong et al. (2014) tested two different geographic scales, the 1 km buffer and the TAZ.

weighted density (PWD), the weighted mean of census block group level density with each block group's population being used as the weight. Thus, the PWD of New York is considerably higher than that of the Los Angeles urbanized area. As such, several studies indicate that the new population density captures more vividly the urban experiences of daily lives (Lee & Lee, 2014; Transportation Research Board, 2009).

Another example of the importance of population-weighted density concerns Houston and Philadelphia. Conventional population density in Houston is higher than that of Philadelphia, although a larger population is gathered near the central business district (CBD) in the latter than that in the former (Figure 3.1). Reflecting this, the PWD of Philadelphia is far higher than that of Houston—nearly double. This is because the new index (PWD) covers the intra-urban distribution of population in the designated boundary (UA)—a population distribution that conventional density measurements cannot capture. Therefore, this study focuses on PWD as one of the main regional level land use characteristics, though I consistently compare the variable with traditional population density.

Centrality measures the degree of the concentrated population near the major job center (Anas, Arnott & Small, 1998; Galster et al., 2001; Lee & Lee, 2014). There are numerous indicators to capture this centrality, such as CBD population share, the area-based centrality index (ACI), the ratio of weighted to unweighted average distance (WUAD), and the population density gradient. The CBD population share is estimated as the share of the UA population in the CBD (Lee, 2007; Lee & Lee, 2014). The ACI estimates how fast population cumulates relative to distance from the CBD compared to land area accumulation (Lee & Lee, 2014; Massey & Denton, 1988). The WUAD indicates the concentration of the whole population in the CBD (weighted) and a perfectly even distribution of population throughout the UA (unweighted) (Cutsinger et al., 2005; Lee & Lee, 2014). The population density gradient is the rate of decrease in population density as dependent on distance from the CBD (Lee & Lee, 2014). Each index has its own advantages and disadvantages; thus, all centrality indicators are summarized as one variable applying a standard principal component analysis.

Polycentricity represents the extent of the shared function from the traditional CBD to subcenters such as economic, commercial and recreational activities (Lee & Lee, 2014). As polycentricity increases, the new job centers are newly clustered; however, overall regional employment is de-centralized from the CBD, morphologically. The benefit of increasing polycentricity leads to a reduction in the average commuting distance. Various indices have been suggested to measure the polycentricity, such as the subcenters' share of center employment (SUB), the number of extra subcenters (EXS), the slope of the rank-size distribution (RS), the primacy index, and the commuter shed ratio. The SUB is the employment in the subcenter divided by both employment between the CBD and subcenter (Lee, 2007; Lee & Lee, 2014). The EXS is the difference between the number of identified subcenters and the predicted number from the UA population Poisson regression (Lee & Lee, 2014; Veneri, 2010). The RS is the estimated coefficient of the rank-size distribution of employment centers in each UA (Lee & Lee, 2014; Meijers & Burger, 2010). The primacy index is the extent of the deviation from the estimated rank-size distribution among the subcenters (Lee & Lee, 2014; Meijers, 2008). Both the RS and the primacy index are based on rank-size theory, meaning the more flat the distribution, the more polycentric the urban area. Applying it to job centers in the intra-UA, the primacy index is more beneficial when analyzing UAs with small subcenters since the index excludes the largest employment center. The commuter shed ratio measures the subcenter commuter shed portion of all employment center commuter shed (Lee & Lee, 2014). The diverse indices are also encapsulated into one polycentricity index.

Besides the four dimensions describing population and employment distributions in UAs, I also consider a jobs-to-housing ratio to measure regional level land use mix. The jobs-to-housing ratio is estimated in two steps: 1) to estimate census tract level index by simply dividing the number of employment by the number of households within ten-mile buffers, and 2) to estimate a UA level index by getting the population weighted average. I chose the 10 mile buffer since it is about the average one-way trip distance by auto, according to the National Household Travel Survey (NHTS, 2009).

The density of total lane mile and public transit service supply are not urban spatial variables, but both are important variables affecting the VMT. This study uses the total lane mile density for both freeways and major arterial roads at the regional level. With any increase to these thoroughfares, I can expect an increase in commuting distance, since the high-speed roads lead to a decrease in the travel time. In comparison to road construction, I can assume that increasing public transit would attract people to change the mode choice from private car to public transit, and thereby the number of VMT would decrease. This research covers both vehicle revenue miles and public transit subsidy.

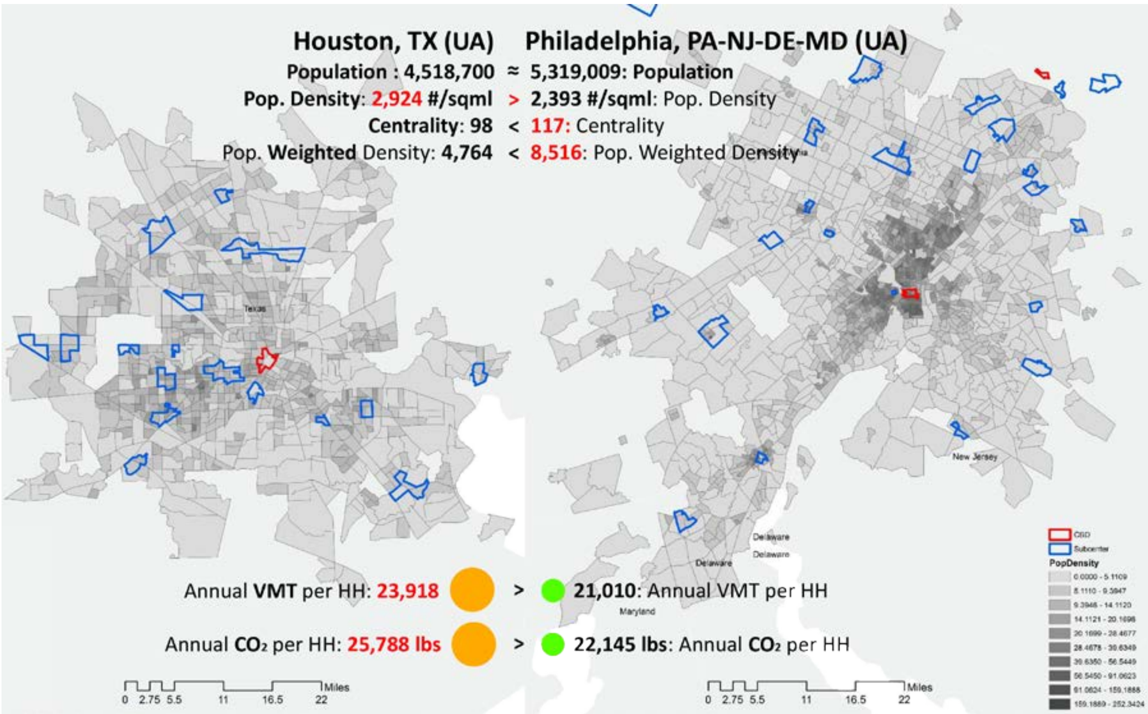


Figure 3.1. Conventional population density and population-weighted density in Houston (left) and in Philadelphia (right) based on CENSUS population (2010).

3.4. Land use effects at neighborhood and urbanized area levels

This section compares the marginal impacts of several urban form variables on VMT at both neighborhood and regional levels. Multilevel regression modeling is an appropriate approach to addressing the research question, as it accounts for the hierarchical structure of the data (Hox, 2010). When a data set is structured hierarchically, ordinary least square regression (OLS) models may lead to false inferences because they tend to violate the assumption of independency among observations. More discussion on model specification is provided in Appendix B and the descriptions and data sources for all variables used are presented in Appendix C.

Table 3.3 presents a summary result of the analysis, and full model results are provided in Appendix D. All variables are transformed into logarithm forms, so each coefficient can be directly interpreted as VMT elasticities with respect to each variable. There clearly are density effects to mitigate VMT and CO_2 at both spatial levels. Under different model specifications, the influences of population density at the urbanized area level are consistently larger than those at the neighborhood level. A 100% increase of urbanized area population density leads to a decrease in VMT by about 6 to 9%, but the density impacts at the census tract level are only about 5%.

More importantly, the spatial distributions of population and employment at the regional level rather than a simple density are the keys to reducing private vehicle use and CO_2 emissions. There are six variables related to the intra-regional population and employment distributions: PWD, centrality index, polycentricity index, job accessibility, distance to downtown, and distance to the closest subcenter. Four of the variables, excluding polycentricity and distance to the closest subcenter, are significantly associated with VMT (Table 3.3).

The coefficient of population-weighted density (PWD) is far larger than those of both conventional regional population density and neighborhood density. Beyond the overall intensity of land use in the region, a high PWD means that the UA has several focal spots including the typical CBD and subcenters where population is highly concentrated. The results of this study imply that increasing population and employment densities in these centers would reduce VMT much more effectively than the policies that increase the overall UA density.

Population centrality is also a significant factor in reducing private vehicle use, but polycentricity is not significantly. Given the same level of overall UA density, increasing the density near the downtown will additionally decrease VMT and GHG emissions, perhaps expanding the proportion of urban residents who are covered by better public transit systems. Polycentric structure may lead to either direction. While decentralized concentration of employment in multiple subcenters is expected to reduce average travel distances for notably commuting trips and other trips for center-oriented activities; travels to subcenters are more likely to be done by private cars because these areas are not well served by transit and have less traffic congestion than in downtown. These two effects seem to cancel out in our analysis.

Jobs-housing ratio within a 10 mile buffer has the largest coefficient to decrease VMT with statistical significance. A 10% increase in this meso scale land use mix variable reduces VMT by about 1.5 to 2.6%, and leads to CO_2 reduction of about 3.6 to 3.7%. This is a very interesting and important finding: combining the results of centrality and polycentricity, it suggests that how to balance housing and workplaces development or land use mix at a larger-than-neighborhood scale matters more than whether the region is monocentric or polycentric.

The results of neighborhood level variables are all consistent with an expectation and previous studies except for street design variables. VMT elasticity with respect to neighborhood population density is around −6% which is smaller the UA level elasticity. The influence of land-use diversity (land-use mix) is only −3% which is relatively smaller than the estimates in previous studies. In our model, street design measured by beta index turns out to be not statistically significant.

The distance to the downtown (i.e., CBD) is as an important factor as the density in affecting travel behavior, as indicated by the similar size of coefficients. However, it should be noted that the distance to the CBD represents a contextual location within an urbanized area although this variable is measured at the census tract level. Again, this result highlights the importance of population distribution at the urbanized area level. It is also notable that the strong impacts of the CBD together with the insignificance of proximity to the closest subcenter are in accordance with the results of regional level spatial variables, centrality and polycentricity.

Table 3.3. VMT elasticities with respect to each variable.

	Model 3.1			Model 3.2			Model 3.2'		
	Beta	t-value		**Beta**	t-value		**Beta**	t-value	
Urbanized Area Level (Level 3)									
Population weighted Density (PWD)	**−0.108**	−4.0	***						
Population Density				**−0.066**	−2.5	**	**−0.065**	−2.5	**
Centrality Index				**−0.031**	−1.8	*	**−0.028**	−1.8	*
Polycentricity Index							**0.022**	0.7	
Jobs-to-housing ratio	**−0.264**	−1.8	*	**−0.171**	−1.9	*	**−0.147**	−1.8	*
Transit Service Supply	**−0.104**	−2.6	***	**−0.043**	−3.1	***	**−0.042**	−2.9	***
Total Lane Miles	**−0.016**	−1.1		**−0.053**	−1.0		**−0.049**	−0.9	
Census Tract Level (Level 2)									
Population Density	**−0.058**	−10.7	***	**−0.058**	−10.5	***	**−0.060**	−10.7	***
Land-use Mix (Entropy Index)	**−0.031**	−4.3	***	**−0.031**	−4.3	***	**−0.031**	−4.4	***
Street Design (Beta Index)	**−0.057**	−1.1		**−0.074**	−1.4		**−0.071**	−1.3	
Distance to the Closest Transit Stop	**0.033**	5.8	***	**0.034**	6.0	***	**0.034**	5.9	***
Distance to the Downtown (CBD)	**0.051**	9.7	***	**0.050**	9.3	***	**0.049**	9.2	***
Proximity to the Closest Subcenter	**−0.002**	−1.0		**−0.002**	−0.9		**−0.002**	−1.0	

***: significant at 1%, **: significant at 5%, and *: significant at 10%

Note:
1) Full model result is reported in Table D.1 in Appendix D.
2) Dependent and all continuous independent variables except proximity to the closest subcenter are in natural logarithm, so estimated coefficients can be interpreted as elasticities.
3) The elasticity is defined as the ratio of the percent change in dependent variable to the percent change in each independent variable.

3.5. Interaction effects of neighborhood and urbanized area level urban forms

The analysis of interaction effects of urban forms at two spatial scales further highlights the importance of regional level spatial structure. I hypothesized that VMT and CO_2 emission reduction effects of compact neighborhoods are greater in urban areas that have higher density, better jobs-housing balance, and more centralized structure. Random coefficient models enable us to investigate how urbanized area level spatial structure moderates neighborhood level effects on travel behavior, by producing different coefficients of neighborhood urban form variables under the different regional characteristics.

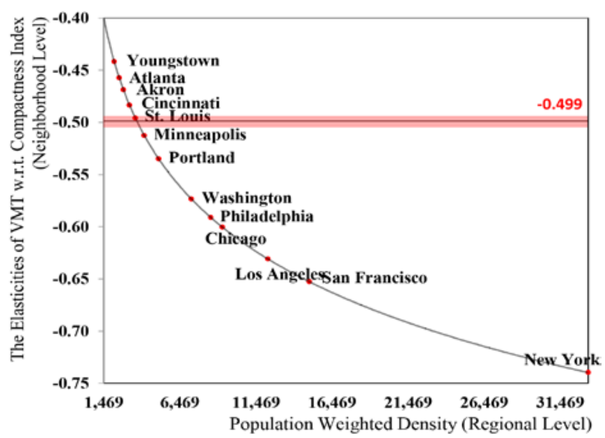
The results indeed show that more sustainable regional level structures serve to increase the effects of compact neighborhood level land use and design. Table 3.4 presents the summary result of a model which includes a cross-level interaction term between UA level population-weighted density and the census tract level compactness index developed by Hamidi & Ewing (2014). The interaction term was highly significant with an expected negative sign, indicating a larger VMT reduction effect of compact urban form in a high density urbanized area. As simulated in the graph, an increase in the neighborhood compactness level by 100 lowers VMT by about 50% in an average population-weighted density urban area, such as St. Louis; however, the neighborhood impacts increase to 75% when the UA PWD is as high as New York level.

Further, I found similar interaction effects when used alternative regional level spatial variables such as conventional density and population centrality and neighborhood level urban form variables such as the compactness index, population density, and the proximity to transit terminal (Table D.2). As summarized in Figure 3.2, VMT reducing effects of compact neighborhood forms are intensified when overall UA level spatial characteristics support more sustainable transportation by increasing density or centralized population distribution. Particularly interesting to observe is that the interaction term between regional level density and the proximity to subcenter is negatively connected with VMT, with statistical significance. The connection was not significant absent the interaction model. The results indicate that the distance to subcenter can also be an important element under higher regional population density.

The significance of the interaction term between PWD and the distance to transit stop supports the idea that transit oriented development (TOD) rather than increasing overall UA density should be given a higher policy priority. Similar to VMT results, the interaction term was highly significant with an expected negative sign, indicating a larger CO_2 reduction effect of compact urban form in a high density UA (Table E.1 in Appendix E). For example, double increase in the neighborhood compactness level lowers CO_2 by about 78% in an average PWD UA; however, the neighborhood impacts increase to 153% when the UA PWD is as high as New York level.

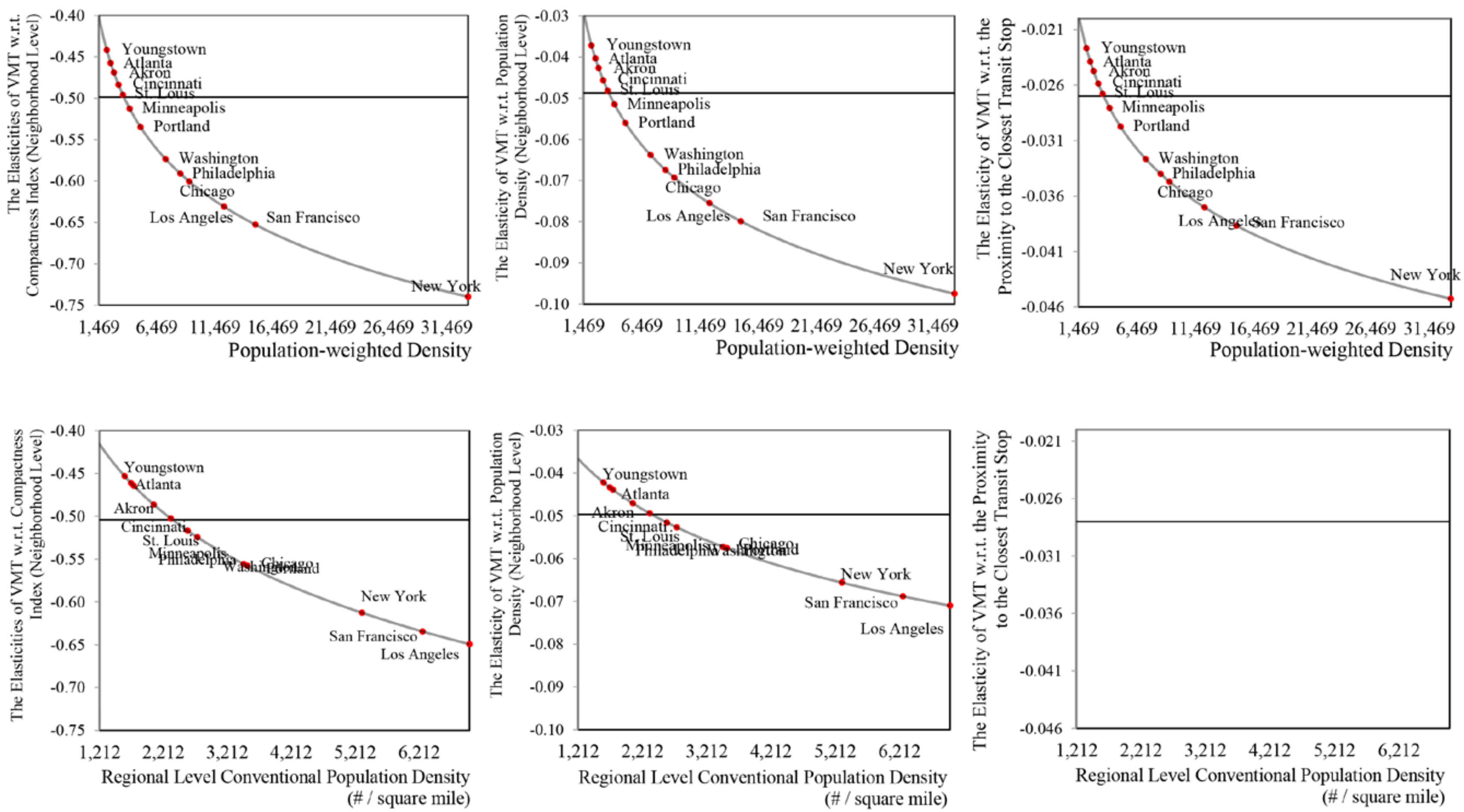
Table 3.4. The interpretation of interaction terms with census tract level coefficients.

	Model 3.5	
	Beta	t-value
Urbanized Area Level (Level 3)		
Population Weighted Density (PWD)	**−0.099**	−3.50 ***
Jobs-to-housing ratio (10 mile Buffer)	−0.242	−2.03 **
Transit Service Supply (VRM / pop)	−0.088	−2.10 **
Total Lane Miles (TLM / pop)	−0.008	−0.60
Census Tract Level (Level 2)		
Neighborhood Compactness Index	**−0.499**	−22.20 ***
Interaction Effect(Level 3 × Level 2)		
[UA] Pop. Weighted Density × [CT] Compactness Index	**−0.251**	−10.30 ***
Household Level (Level 1)		
< Skip >		



***: significant at 1%, **: significant at 5%, and *: significant at 10%

Note:
1) Full model result is reported in Table D.2 (Model 3.5).
2) The elasticity is defined as the ratio of the percent change in dependent variable to the percent change in each independent variable.



Note: The interaction term between the proximity to the closest transit stop and regional level conventional population density is not statistically significant (final graph).

Figure 3.2. The variations of VMT elasticities w.r.t. neighborhood level urban form elements (compactness index, population density, and the proximity to the closest transit stop) under the different regional level urban form elements (population-weighted density, and conventional population density).

3.6. Conclusions

This study is significant in that I empirically uncover how multi-scale urban spatial structures interact to mitigate auto-oriented travel behavior. I found that regional level spatial structure variables such as population density, centrality, and jobs-housing balance have significant impacts on reducing VMT, perhaps more so than compact neighborhood design. Further, urbanized area level spatial characteristics moderate the impacts of compact neighborhoods in a way to intensify the neighborhood impacts. For example, while doubling neighborhood compactness level is associated with a VMT reduction by about 50% in an average population-weighted density urban area, such as St. Louis; however, this neighborhood impact increases to 75% when the UA's population weighted density is as high as New York level. I found similar results when used other urbanized area level spatial variables such as conventional density and population centrality.

What are the policy implications of the synergic impacts between different geographic scales of urban forms? First, the findings of this chapter reveal the specific ways that regional development can be effectively pursued with limited resources to minimize auto dependency. Many planners and policy makers agree that regional policy is important, but are hesitant to support it, as the time scale of regional improvement is long. This research, however, shows that concentrating population density in several focal spots is a more effective policy than increasing overall urban density to curb the excessive auto dependency in U.S. cities. The policies to increase the population near downtown areas and along transit corridors are indeed beneficial. Polices for balancing jobs and population at a sub-regional scale beyond neighborhood boundaries, also, are helpful to decrease VMT. In sum, “where” to locate new residential development is far more important than “how” to develop them.

Second, the role of metropolitan planning organizations (MPO) is important in order to plan and guide regional developments in a sustainable way. Every census urbanized area (UZA) is currently represented by an MPO (23 USC 134(b) and 49 USC 5303(c)), but their roles are extremely limited. The delegation of greater authorities and responsibilities to MPOs is necessary to guide and coordinate the locations of new developments at the regional scale. This will inevitably involve state level legislation.

3.7. Bibliography

Anas, A., Arnott, R., & Small, K.A. (1998). Urban spatial structure. *Journal of Economic Literature, 36*, 1426-1464. Retrieved from http://www.jstor.org/stable/2564805

Bento, A.M., Cropper, M.L., Mobarak, A.M., & Vinha, K. (2005). The effects of urban spatial structure on travel demand in the United States. *Review of Economics and Statistics, 87*(3), 466-478. doi:10.1162/0034653054638292

Boarnet, M.G., & Crane, R. (2001a). The influence of land use on travel behavior: specification and estimation strategies. *Transportation Research A, 35*, 823-845. doi:10.1016/S0965-8564(00)00019-7

Boarnet, M.G., & Crane, R. (2001b). *Travel by Design: The Influence of Urban form on Travel*. New York: Oxford University Press.

Boies, A., Hankey, S., Kittelson, D., Marshall, J.D., Nussbaum, P., Watts, W., & Wilson, E.J. (2009). Reducing motor vehicle greenhouse gas emissions in a non-California state: A case study of Minnesota. *Environmental science & technology, 43*(23), 8721-8729. doi:10.1021/es902019z

Brown, M.A., Southworth, F., & Sarzynski, A. (2008). *Shrinking the carbon footprint of metropolitan America*: Brookings Institution Washington, DC.

Cao, X., Mokhtarian, P.L., & Handy, S.L. (2006). Neighborhood design and vehicle type choice: Evidence from Northern California. *Transportation Research Part D: Transport and Environment, 11*(2), 133-145.

Cao, X.Y., Handy, S.L., & Mokhtarian, P.L. (2006). The influences of the built environment and residential self-selection on pedestrian behavior: Evidence from Austin, TX. *Transportation, 33*(1), 1-20. Retrieved from http://www.springerlink.com/content/7356r13j41266x67/fulltext.pdf

Cao, X.Y., Mokhtarian, P.L., & Handy, S.L. (2007). Cross-sectional and quasi-panel explorations of the connection between the built environment and auto ownership. *Environment and Planning A, 39*(4), 830-847. Retrieved from http://escholarship.org/uc/item/5nw2t7cc.pdf

Cao, X.Y., Mokhtarian, P.L., & Handy, S.L. (2009). Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings. *Transport Reviews, 29*(3), 359-395. doi:10.1080/01441640802539195

Cervero, R., & Duncan, M. (2006). 'Which Reduces Vehicle Travel More: Jobs-Housing Balance or Retail-Housing Mixing? *Journal of the American Planning Association, 72*(4), 475-490. doi:10.1080/01944360608976767

Cervero, R., & Gorham, R. (1995). Commuting in transit versus automobile neighborhoods. *Journal of American Planning Association, 61*(2), 210-225. doi:10.1080/01944369508975634

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: density, diversity, and design. *Transportation Research D, 2*(3), 199-219. doi:10.1016/S1361-9209(97)00009-6

Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas. *Environment and Planning A, 42*(2), 400–418. doi:10.1068/a4236

Cervero, R., Sarmiento, O.L., Jacoby, E., Gomez, L.F., & Neiman, A. (2009). Influences of built environments on walking and cycling: lessons from Bogotá. *International Journal of Sustainable Transportation, 3*(4), 203-226. doi:10.1080/15568310802178314

Cervero, R., & Seskin, S. (1995). An evaluation of the relationships between transit and urban form. *TCRP Research Results Digest*(7). Retrieved from http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rrd_07.pdf

Crane, R. (2000). The influence of urban form on travel: an interpretive review. *Journal of Planning Literature, 15*(1), 3. doi:10.1177/08854120022092890

Crane, R., & Crepeau, R. (1998). Does neighborhood design influence travel?: A behaviorl analysis of travel diary and GIS data. *Transportation Research D, 3,* 225-238. doi:10.1016/S1361-9209(98)00001-7

Cutsinger, J., Galster, G., Wolman, H., Hanson, R., & Towns, D. (2005). Verifying the Multi-Dimensional Nature of Metropolitan Land Use: Advancing the Understanding and Measurement of Sprawl. *Journal of Urban Affairs, 27*(3), 235-259. doi:10.1111/j.0735-2166.2005.00235.x

Eager, W.R. (1993). Accommodating land use and transportation planning. *Land Use in Transition*, 32-37.

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., & Chen, D. (2008). *Growing cooler: The evidence on urban development and climate change*. Washington DC: Urban Land Institute.

Ewing, R., & Cervero, R. (2001). Travel and the built environment: a synthesis. *Transportation Research Record: Journal of the Transportation Research Board, 1780*, 87-114. doi:10.3141/1780-10

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment--A Meta-Analysis. *Journal of the American Planning Association, 76*(3), 265-294. doi:10.1080/01944361003766766

Ewing, R., Pendall, R., & Chen, D. (2003). Measuring sprawl and its transportation impacts. *Transportation Research Record, 1931*, 175-183. doi:10.3141/1831-20

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T.K. (2007). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation, 35*(1), 37-54. doi:10.1007/s11116-007-9136-6

Frank, L.D. (2000). Land Use and Transportation Interaction: Implications on Public Health and Quality of Life. *Journal of Planning Education and Research, 20*(1), 6-22. doi:10.1177/073945600128992564

Galster, G., Hanson, R., Ratcliffe, M.R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling Sprawl to the Ground: Defining and measuring an elusive concept. *Housing Policy Debate, 12*(4), 681-717. doi:10.1080/10511482.2001.9521426

Giuliano, G. (1989). Incident characteristics, frequency, and duration on a high volume urban freeway. *Transportation Research Part A: General, 23*(5), 387-396. doi:10.1016/0191-2607(89)90086-1

Giuliano, G. (1991). Is jobs-housing balance a transportation issue? *University of California Transportation Center*. Retrieved from https://escholarship.org/uc/item/4874r4hg.pdf

Giuliano, G., & Small, K.A. (1991). Subcenters in the Los Angeles region. *Regional Science and Urban Economics, 21*(2), 163-182. doi:10.1016/0166-0462(91)90032-I

Glaeser, E.L., & Kahn, M.E. (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics, 67*(3), 404-418. doi:10.1016/j.jue.2009.11.006

Gomez-Ibanez, J.A. (1991). Big-city transit rider snip, deficits, and politics: avoiding reality in Boston. *Journal of the American Planning Association, 61*(1), 30-50. doi:10.1080/01944369608975669

Gordon, P., & Richardson, H.W. (1989). Gasoline consumption and cities; a reply. *Journal of the American Planning Association, 55*, 342-346. doi:10.1080/01944368908975421

Gordon, W.J., & Wixom, J.A. (1978). Shepard's method of "metric interpolation" to bivariate and multivariate interpolation. *Mathematics of Computation, 32*(141), 253-264. doi:10.1090/S0025-5718-1978-0458027-6

Grazi, F., & van den Bergh, J.C.J.M. (2008). Spatial organization, transport, and climate change: Comparing instruments of spatial planning and policy. *Ecological economics, 67*(4), 630-639. doi:10.1016/j.ecolecon.2008.01.014

Guo, J.Y., & Bhat, C.R. (2007). Operationalizing the concept of neighborhood: Application to residential location choice analysis. *Journal of Transport Geography, 15*(1), 31-45. doi:10.1016/j.jtrangeo.2005.11.001

Hamidi, S., & Ewing, R. (2014). A longitudinal study of changes in urban sprawl between 2000 and 2010 in the United States. *Landscape and Urban Planning, 128*(0), 72-82. doi:10.1016/j.landurbplan.2014.04.021

Handy, S. (1992). *How land use patterns affect travel patterns: A bibliography*.

Handy, S. (1996a). Methodologies for exploring the link between urban form and travel behavior. *Transportation Research D, 1*(2), 151-165. doi:10.1016/S1361-9209(96)00010-7

Handy, S. (1996b). Understanding the Link Between Urban Form and Nonwork Travel Behavior. *Journal of Planning Education and Research, 15*(3), 183-198. doi:10.1177/0739456x9601500303

Handy, S. (2005). Smart Growth and the Transportation-Land Use Connection: What Does the Research Tell Us? *International regional science review, 28*(2), 146-167. doi:10.1177/0160017604273626

Handy, S.L., Boarnet, M.G., Ewing, R., & Killingsworth, R.E. (2002). How the built environment affects physical activity: Views from urban planning. *American journal of preventive medicine, 23*(2, Supplement 1), 64-73. doi:10.1016/S0749-3797(02)00475-0

Hong, J., Shen, Q., & Zhang, L. (2014). How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. *Transportation, 41*(3), 419-440. doi:10.1007/s11116-013-9462-9

Hox, J. (2010). *Multilevel analysis: Techniques and applications* (2nd Ed.): Routledge Academic.

Johansson, B. (2009). Will restrictions on CO2 emissions require reductions in transport demand? *Energy Policy, 37*(8), 3212-3220. doi:10.1016/j.enpol.2009.04.013

Jones, C., & Kammen, D.M. (2014). Spatial distribution of U.S. household carbon footprints reveals suburbanization undermines greenhouse gas benefits of urban population density. *Environmental science & technology, 48*(2), 895-902. doi:10.1021/es4034364

Kockelman, K.M. (1997). Travel behavior as a function of accessibility, land-use mixing, and land-use balance: Evidence from the San Francisco bay area. *Transportation Research Record*, *1607*, 116-125. doi:10.3141/1607-16

Krizek, K.J. (2003a). Operationalizing neighborhood accessibility for land use-travel behavior research and regional modeling. *Journal of Planning Education and Research, 22*, 270-287. doi:10.1177/0739456X02250315

Krizek, K.J. (2003b). Residential relocation and changes in urban travel: Does neighborhood-scale urban form matter? *Journal of the American Planning Association, 69*(3), 265-281. doi:10.1080/01944360308978019

Kromer, M.A., Bandivadekar, A., & Evans, C. (2010). Long-term greenhouse gas emission and petroleum reduction goals: Evolutionary pathways for the light-duty vehicle sector. *Energy, 35*(1), 387-397. doi:10.1016/j.energy.2009.10.006

Lee, B. (2007). "Edge" or "Edgeless" Cities? Urban Spatial Structure in US Metropolitan Areas, 1980 to 2000. *Journal of Regional Science, 47*(3), 479-515. doi:10.1111/j.1467-9787.2007.00517.x

Lee, S., & Lee, B. (2014). The influence of urban form on GHG emissions in the U.S. household sector. *Energy Policy, 68*(0), 534-549. doi:10.1016/j.enpol.2014.01.024

Lin, J., & Long, L. (2008). Model-based approach to synthesize household travel characteristics across neighborhood types and geographic areas. *Journal of Transportation Engineering, 134*(12), 493-503. doi:10.1061/(ASCE)0733-947X(2008)134:12(493)

Massey, D.S., & Denton, N. (1988). The dimensions of residential segregation. *Social Forces, 67*, 281-313. doi:10.1093/sf/67.2.281

McMillen, D.P. (2001). Nonparametric employment subcenter identification. *Journal of Urban Economics, 50*(3), 448-473. doi:10.1006/juec.2001.2228

Meijers, E. (2008). Measuring polycentricity and its promises. *European Planning Studies, 16*(9), 1313-1323. doi:10.1080/09654310802401805

Meijers, E.J., & Burger, M.J. (2010). Spatial structure and productivity in US metropolitan areas. *Environment and Planning A, 42*(6), 1383-1402. doi:10.1068/a42151

Mokhtarian, P.L., & Cao, X. (2008). Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. *Transportation Research Part B: Methodological, 42*(3), 204-228. doi:10.1016/j.trb.2007.07.006

Morrow, R.W., Gallagher, K.S., Collantes, G., & Lee, H. (2010). Analysis of policies to reduce oil consumption and greenhouse-gas emissions from the US transportation sector. *Energy Policy, 38*(3), 1305-1320. doi:10.1016/j.enpol.2009.11.006

Mui, S., Alson, J., Ellies, B., & Ganss, D. (2007). *A Wedge Analysis of the US Transportation Sector*. Retrieved from http://www3.epa.gov/otaq/climate/420r07007.pdf

Næss, P. (2005). Residential location affects travel behavior—but how and why? The case of Copenhagen metropolitan area. *Progress in Planning, 63*(2), 167-257. doi:10.1016/j.progress.2004.07.004

Newman, P., & Kenworthy, J. (1989). Gasoline consumption and cities: A Comparison of U.S. Cities with a Global Survey. *Journal of the American Planning Association, 55*(1), 24-37. doi:10.1080/01944368908975398

Newman, P., & Kenworthy, J. (2006). Urban design to reduce automobile dependence. *Opolis, 2*(1), 35-52. Retrieved from http://escholarship.org/uc/item/2b76f089.pdf

Newman, P.W.G., & Kenworthy, J.R. (1992). Is there a role for physical planners? *American Planning Association. Journal of the American Planning Association, 58*, 353-362. doi:10.1080/01944369208975814

Piantadosi, S., Byar, D.P., & Green, S.B. (1988). The ecological fallacy. *American Journal of Epidemiology, 127*(5), 893-904. Retrieved from http://www.scientificintegrityinstitute.org/aje050188.pdf

Pucher, J. (1988). Urban travel behavior as the outcome of public policy: the example of modal-split in Western Europe and North America. *Journal of American Planning Association*(3), 509-520. doi:10.1080/01944368808976677

Snellen, D., Borgers, A., & Timmermans, H. (2002). Urban form, road network type, and mode choice for frequently conducted activities: A multilevel analysis using quasi-experimental design data. *Environment and Planning A, 34*(7), 1207-1220. doi:10.1068/a349

Sun, X., Wilmot, C.G., & Kasturi, T. (1998). Household travel, household characteristics, and land use: an empirical study from the 1994 Portland activity-based travel survey. *Transportation Research Record: Journal of the Transportation Research Board*, *1617*(1), 10-17. doi:10.3141/1617-02

Transportation Research Board. (2009). *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions* (298). Retrieved from Washington, D.C.

U.S. Energy Information Administration. (2011). *Monthly Energy Review: November 2011*. (DOE/EIA-0035). Washington, DC Retrieved from www.eia.gov/mer.

Veneri, P. (2010). Urban polycentricity and the costs of commuting: evidence from Italian metropolitan areas. *Growth and Change*, *41*(3), 403-429. doi:10.1111/j.1468-2257.2010.00531.x

Zhang, M. (2004). The role of land use in travel mode choice: Evidence from Boston and Hong Kong. *Journal of the American Planning Association*, *70*(3), 344-360. doi:10.1080/01944360408976383

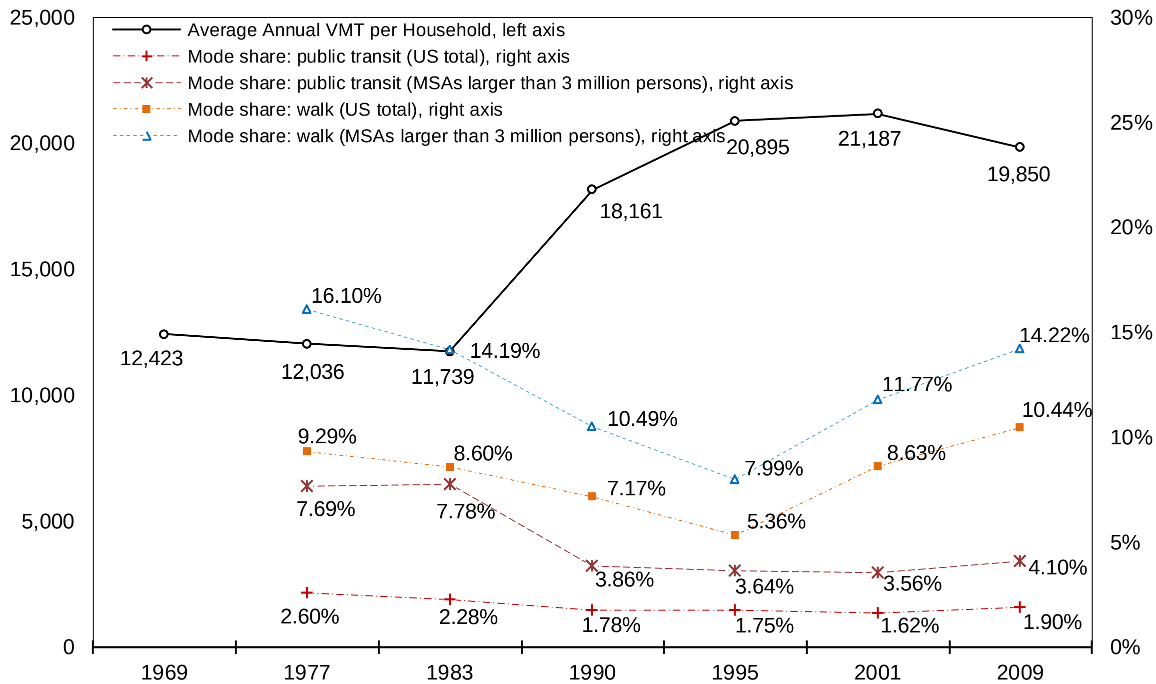
CHAPTER 4
COMPLEMENTARITY BETWEEN LAND USE PLANNING AND PRICING IN VMT REDUCTION

4.1. Background

Transportation policy in the U.S. has been recently shifting away from a focus on increasing mobility with expanded physical infrastructures and toward sophisticated transportation demand control.

Since the Interstate Highway Act of 1956, the federal government had poured vast resources to build one of the most extensive national highway networks in the world. However, this massive expansion of the highway system has led to a marked increase in automobile travel throughout the country. From 1969 to 2001, the average annual vehicle miles traveled (VMT) per household nearly doubled, from 12,423 to 21,187, according to data from the Nationwide Personal Transportation Survey (NPTS, 1969) and the subsequent National Household Travel Survey (NHTS, 2001). This occurred even while the number of people per household actually decreased from 3.16 in 1969 to 2.58 in 2001.

Over the same period, the use of public transit and non-motorized travel plummeted, as automobile dependency increased (Figure 4.1). Such an auto-oriented lifestyle resulted in many environmental and health issues including greenhouse gas (GHG) emissions, air pollution, and obesity. As a result, the Department of Transportation (DOT) recently changed their funding priorities away from roads and highways and toward transit, biking and walking. As a corollary, sustainable development, smart growth, and growth management have also become important strategic goals in transportation planning.



Notes: the original sources from 1977 to 1995 come from Nationwide Personal Transportation Survey (NPTS), while the sources of 2001 and 2009 stem from National Household Travel Survey (NHTS). This table is re-calculated from the table 7 in the summary report for NPTS and NHTS by Santos et al. (2011).

Figure 4.1. Average annual VMT per household and travel mode split, 1969-2009.

Owing in part to these efforts, the average VMT per household slightly deceased by 6 percent from 2001 to 2009. However, this reduction is far short of the one that is required to meet GHG reduction goals in transportation and to mitigate climate change. According to the Organization for Economic Co-operation and Development (OECD, 2006), the annual VMT per capita in the U.S. is nearly twice that in Western European countries such as Sweden, Belgium, and the United Kingdom; three times higher than that in Eastern Europe and North Eastern Asia; and ten times higher than the VMT in Turkey (VTPI, 2007).

Various policy recommendations have been proposed to reduce VMT, including the extension and improvement of public transit, an increase in urban density, land use mix, the construction of grid road networks, fuel price increases by taxation, and parking price increases. These proposals can be largely classified into two groups: land use change policies and pricing policies. Behind land use policies is an assumption that personal travel attitudes can be changed if we build urban structures in a different way. Following this line of thought, building new subway or light rail lines would encourage people to change travel modes from private vehicles to mass transit. Furthermore, land use mix and grid-based street designs are expected to reduce VMT by shortening travel distances.

In general, increased urban density provides many environmental benefits, as denser urban areas (UA) are likely to employ, out of necessity, a high land use mix, and have a high neighborhood population density, good network connectivity, a high jobs-to-housing rate, and relatively good transit accessibility. Statistically, UA level population density is strongly correlated with other land use variables.

Price policies employ an economic theory to internalize external side effects in to the market. Retail gasoline prices or road prices do not cover the external environmental costs of gasoline consumption and road usage, so people tend to overconsume gasoline and roads—drive too much. Pricing policies are to reduce personal vehicle use to a socially desirable level by getting the price right.

However, both land use and pricing policies have their limitations. Critics argue that land use policies are long-term and relatively expensive, while fuel taxation is a hot-button issue politically and thus difficult to enact. Thus, it is important to demonstrate how and to what extent these land use and pricing policies can contribute to reducing VMT. The majority of empirical studies, however, show that both VMT elasticities with regard to (w. r. t.) land use and fuel prices are quite small, even though the impacts are statistically significant in most studies. As several studies reveal, VMT reduction associated with doubling neighborhood density ranges from 4% (Ewing & Cervero, 2010) to 12% (Brownstone & Golob, 2009), and to 19% (Heres-Del-Valle & Niemeier, 2011). These estimated effects of compact development in the literature are far smaller than what planners had expected. One recent study by Lee & Lee (2014) shows that the VMT elasticity with respect to (w.r.t.) urban area level density can be as high as 37%.

VMT is also inelastic with regard to fuel prices: long-run elasticity is about 30% (Small & Van Dender, 2007), but short-run elasticity only ranges from about 3% to 16% (Hughes, Knittel & Sperling, 2008). Moreover, price elasticities have declined over time. Current fuel price fluctuation indicates that doubling fuel prices is not an unlikely scenario (Figure 4.2), but several studies show that the price policy alone is insufficient for fundamental travel behavior modifications (Cervero & Landis, 1995; Winkelman, Bishins & Kooshian, 2010).

Several researchers have recently argued that quantity regulation, such as land use planning, and price regulations, such as congestion pricing and gasoline prices, are complementary and potentially synergistic, rather than competing and conflicting (Boarnet, 2010; Guo, Agrawal & Dill, 2011; Lee & Lee, 2013; May, Kelly & Shepherd, 2006; Zhang, 2004). If the two types of policy instruments are not in conflict with each other, they argue, both policies should be fully employed and coordinated to achieve climate-stabilizing GHG reduction targets. Thus, policy analysts and decision makers should understand the complex interactions between diverse policy instruments to mitigate policy conflicts and maximize synergetic effects. Nonetheless, empirical research on the synergy effects of complementary policy approaches in transportation planning is extremely rare.

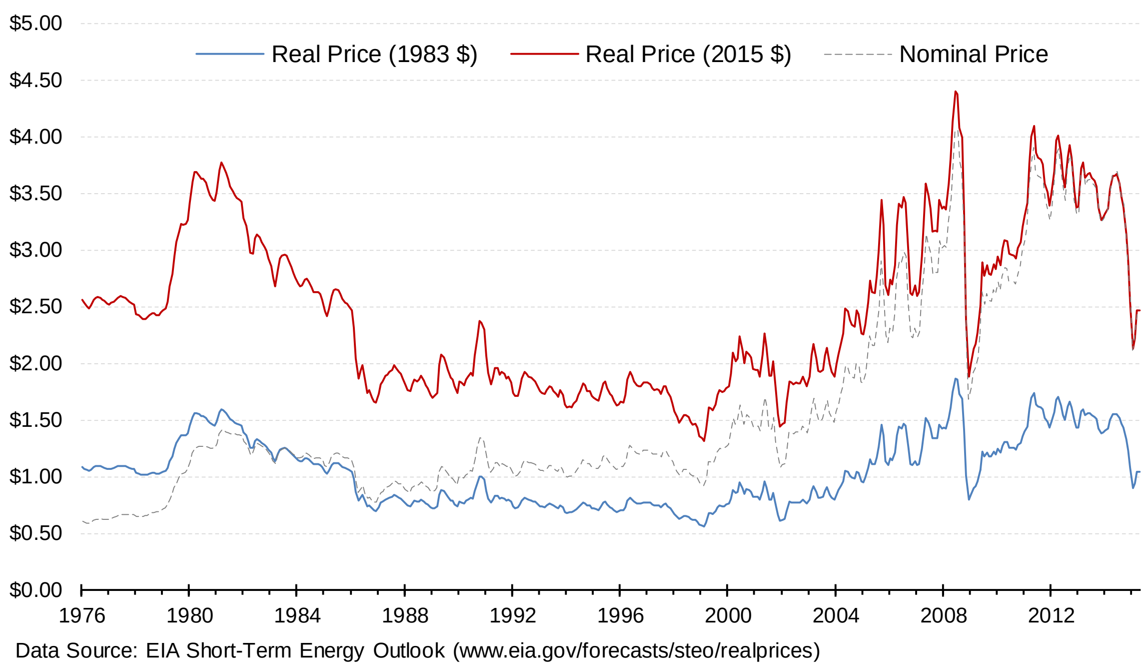


Figure 4.2. Monthly motor gasoline regular grade retail price (dollars per gallon, source: EIA).

To enhance our understanding of the policy synergy between pricing and land use planning approaches, this paper will examine the interaction effects between fuel prices and land use (urban form) variables in reducing the VMT in U.S. urbanized areas. More specifically, this study focuses on whether the elasticity of the VMT with respect to fuel prices is augmented in more compact and transit friendly urban areas. It will also investigate how the elasticity of the VMT with respect to urban form variables such as population density varies with fuel price changes. To obtain more robust analysis results, this study employs various regression models from ordinary least-squares regression (OLS), panel regression with both fixed- and random-effect models, and a non-parametric approach— panel type locally weighted smoothing (P-LOESS).

4.2. Land use planning and fuel price impacts on travel behavior

As mentioned above, urban policies employed to reduce VMT and GHG emissions can be categorized into two groups: 1) land use control and 2) market solution. Market oriented approaches are primarily developed by urban and environmental economists, and aim to achieve climate mitigation by price policy without market distortion. Planners mostly support land use planning approaches to smart growth, and suggest diverse ways of curbing urban sprawl (Brueckner, 2000; Ewing, 1997; Gordon & Richardson, 1997; Knaap, 2008).

The price solution emphasizes "getting-the-right-price" (Brueckner, 2005; Parry & Small, 2005; Small, 1997), and suggests that the price of travel should cover the cost of negative externalities such as congestion, air pollution, and GHGs, as well as the private expenses of vehicle use. The proponents of pricing approaches believe that correct pricing that includes social costs will immediately and efficiently moderate the travel demand for private vehicles through the market system (Anas & Rhee, 2006, 2007; Brueckner, 2007; Moore, Staley & Poole Jr., 2010; Staley, 2006). Congestion pricing, congestion fee for parking, VMT tax for trucks, gasoline tax, and carbon tax are good examples of pricing approaches.

However, pricing approach has been criticized for several reasons. The first argument is that pricing is not a realistic strategy for controlling travel demand in the U.S. because most politicians oppose the raising of fuel taxes or the imposing of any new fees. Further, since the fuel tax portion of the total gasoline price in the U.S. is very small, any attempts through taxing gasoline consumption would work only at the margins in practice (Bento et al., 2009; Parry & Small, 2005). As of April 2014, both state and federal gasoline taxes constitute only about 50 cents per gallon on average, ranging between 30.8 cents (Alaska) and 71.3 cents (California).

A second argument is that the pricing approach alone is insufficient to induce travel behavior change from a car-oriented to a transit-friendly lifestyle (Cervero & Landis, 1995; Winkelman, Bishins & Kooshian, 2010). A number of estimated elasticities of the VMT w.r.t. the gasoline price support such arguments. Regardless of the short run and long run standards, travel behavior has been estimated to be inelastic with respect to fuel prices. For the period from 1997 to 2001, Small and Van Dender found −0.07 short run and −0.34 long run elasticities (Small & Van Dender, 2007). Komanoff reported −0.04 for 2004, −0.08 for 2005, −0.12 for 2006, −0.16 for 2007, and −0.29 for 2011 (Komanoff, 2008-2011). For the period of 2001 to 2006, Hughes and his colleague published short run elasticities ranging from −0.077 to −0.034 (Hughes, Knittel & Sperling, 2008). The inelastic demand for gasoline or VMT is mainly a result of insufficient substitutes for private vehicle travel in many U.S. cities (Cervero & Landis, 1995; Winkelman, Bishins & Kooshian, 2009). Even when the substantial increase in gasoline prices incentivizes a mode shift away from private vehicles, people cannot easily change their travel mode since urban areas have become dispersed over the last several decades and public transit does not reach most of the residential areas.

Through the land use planning approaches, various policies in line with smart growth principles can reverse the sprawling trend and more sustainable built environments are expected to positively drive changes in travel behavior (Handy et al., 2008). Planners have identified five elements of the built environment that significantly affect people's travel behavior: high density, diverse land use (mixed-use), walkable street design, close destination to transit service, and short distance from job centers. Various policy tools including smart codes, transit-oriented development, job-housing balance programs, and urban growth boundaries have been increasingly proposed and adopted to promote the “5 Ds” (Cao, Mokhtarian & Handy, 2009; Ewing & Cervero, 2001, 2010; Kuzmyak et al., 2003).

Many studies report a wide range of estimated elasticities of the VMT w.r.t. the characteristics of neighborhood built environments. A typical elasticity of VMT w.r.t. population density ranges from −0.07 to −0.19 (−0.07 (Bento et al., 2005); −0.09 (Fang, 2008); −0.12 (Brownstone & Golob, 2009); −0.19 (Heres-Del-Valle & Niemeier, 2011)). However, all these studies were done at the neighborhood level density. A more recent study by Lee & Lee (2014) shows that the elasticity of the VMT w.r.t urban area (UA) level population density is −0.37, and an elasticity w.r.t population-weighted density can be as high as −0.99. Many planners believe a sustainable urban form also creates livable, healthy, and diverse communities (Aytur et al., 2008; Boarnet, 2011; Heath et al., 2006; Levine, Inam & Torng, 2005).

Nevertheless, some studies still cast doubt on the impacts of sustainable urban form on travel behavior (Brueckner, 2007; Echenique et al., 2012; Mitchell et al., 2011; Staley, 2008), arguing that land use regulations distort housing prices (Dawkins & Nelson, 2002; Phillips & Goodstein, 2000), cause congestion (Sorensen et al., 2008), and ultimately impose negative impacts on economies (Small, 1992). These researchers are concerned that the losses outweigh the gains. Furthermore, recent work has revealed that urban form impacts from many old studies were overestimated, due to self-selection bias (Cao, Mokhtarian & Handy, 2007; Handy, Cao & Mokhtarian, 2006). Although sustainable urban structures seem to be significantly associated with non-motorized travel and less driving, the ultimate cause may be the residents' preferences or lifestyles, rather than the physical environment. That is, the effect may be attributed to the fact that people who prefer to walk self-select more walkable neighborhoods. If this is the case, many people who enjoy a car-oriented lifestyle would not change their behavior simply because the built form changes. Recent studies show, however, that there are clear causal relationships between the land use character and travel behavior, even after self-selection is controlled for, although the size of urban form variables' coefficients usually shrinks (Cao, Mokhtarian & Handy, 2009; Ewing & Cervero, 2010).

Few studies focus on the interaction between land use policies and pricing approaches. To estimate travel mode choice and trip frequency, Crane & Crepeau (1998) take into account both price and land use variables, but the study does not directly measure the complementary effect between them. Zhang (2004) points out that the coordination between the market approach and spatial regulation is important in reducing private vehicle use. Stepp et al. (2009) describe the complex relationships between factors affecting travel behavior, noting that fuel price, built environment, and individual characteristics are both directly and indirectly related, such that some are reciprocally supportive while others substitute for or conflict with each other.

There are only a handful of empirical studies that directly estimate the complementary effects of urban form and pricing policies. Rufolo & Kimpel (2009) find that the impacts of road pricing on reducing the VMT substantially increase in areas with high bus stop frequency, such as Portland, OR. Guo, Agrawal & Dill (2011) directly focuses on the interaction effects between land use planning and congestion pricing and empirically tests them with a pilot mileage fee program in Portland, OR. A synergistic effect was found; congestion pricing was shown to have a greater impact on VMT reduction in traditional neighborhoods than in low density suburban neighborhoods. The impact of density and land use mix was also higher in areas imposing congestion pricing than in areas without the pilot program.

The findings from Rufolo & Kimpel (2009) and Guo, Agrawal & Dill (2011) are useful, but it is hard to generalize with results based on several small neighborhood cases in the Portland MSA. Lee & Lee (2013) focus on the interaction effects on increasing transit ridership in 67 UAs from 2002 to 2010. They find that the ridership elasticity w.r.t. fuel price increases as population density increases, and the elasticity is higher in UAs having a containment policy comapred with other UAs without one. However, the mode share of public transit is under 2% in the U.S., and, as of 2009, major MSAs's transit share is only about 4% (Figure 4.1). For this reason, this study will use VMT, rather than the transit ridership, which is the ultimate indicator of the reduction of GHGs. I will also employ a more advanced method. The Lee and Lee study finds a constant value for the complementary effect between transit ridership and the fuel price due to panel analysis limitations. However, the effect can vary based on the level of the fuel price or the UA density. Thus, my research will relax the constant complementary effect assumption by using the P-LOESS model as well as panel analysis.

The main hypothesis of this study is that compact development and high fuel prices are complementary in reducing VMT. Put another way, the impacts of the compact urban form on travel behavior would be reinforced under high fuel prices. Conversely, the influence of high gasoline price on moderating private vehicle use would be stronger in denser urbanized areas than in sprawling areas. As the gasoline price increases, people who live in transit accessible or walkable areas would easily shift from private vehicle use to public transit services, though it would be difficult for someone who resides in a non-transit friendly city to do the same. Inconvenient physical environments would lead to long commute times, just as long shopping distances combined with insufficient alternative travel modes would inhibit behavioral change.

To test the hypothesis discussed above, this study investigates the changes in the elasticity of monthly VMT w. r. t. both fluctuating gasoline prices over time and varied spatial forms in the cross section of large urban areas. The VMT elasticities are defined as the percentage change in monthly VMT per capita from a one-percent change in either fuel price or urban form variables, *ceteris paribus*. The influence of both urban form and gasoline prices on per capita VMT is analyzed over 10 years, from 2002 to 2011, in the largest 115 urbanized areas (UAs) in the U.S. The modeling strategy employs various regression models to analyze the panel data (115 UAs and 120 time-series from Jan. 2002 to Dec. 2011), including ordinary least-squares regression (OLS) analysis for every month, a fixed and random effect panel analysis with multiplicative interaction terms, and fixed panel type locally weighted smoothing (P-LOESS). The specific methods and data sources are described in the appendices.

4.3. Descriptive comparative analysis results

This study covers 115 largest urban areas in the U.S. over 120 months, so as to allow abundant variations in terms of land use, fuel price, and VMT. Before a series of regression analyses for the full sample, this section presents a descriptive analysis that explores how differently compact and sprawled UAs responded to the fluctuation of gasoline prices in the last decade. To do this, I compared per capita VMT changes between high density and low density UAs that are otherwise comparable, over three distinctive periods (Figure 4.3).

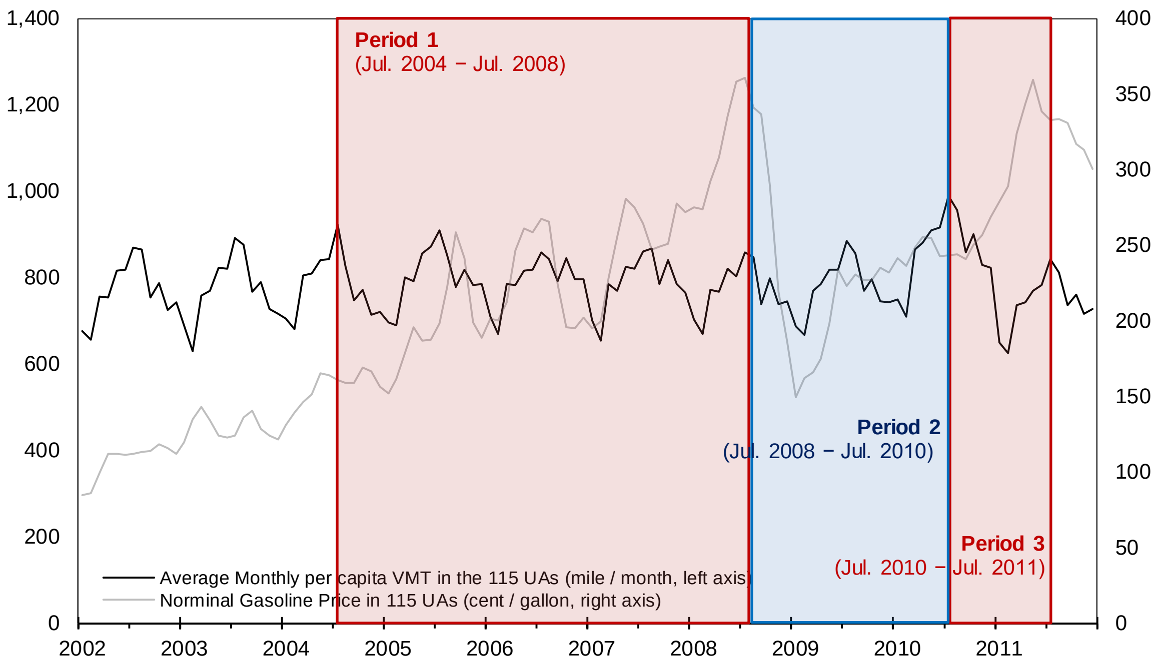


Figure 4.3. Three distinctive periods of fuel price fluctuation.

The first term is a 5 year range from July 2004 to July 2008. During this period, fuel price steadily increased, with seasonal fluctuations, so we can examine the effects of continuous fuel price increase on VMT. Although the increasing trend of fuel prices had already began prior to 2004, the shortage of crude oil supplies in May of 2004 gave the consumer market a strong signal of rising fuel prices, and as a result most economic sectors began to react sensitively to the fuel price change. Per capita VMT trend also shows that July 2004 was a turning point.

The second study period is a two year period, from July 2008 to July 2010. Although the gasoline price plummeted from almost $4 to $1.5 per gallon in the third and fourth quarters of 2008, the period was too short to observe a significant change in VMT. Rather, I include the months until July 2000 since relatively low fuel price was sustained under the 2.5 dollar level for another year after the price collapse and its rapid recovery. The third term represents a second “rebounding” period of gasoline price from July 2010 to July 2011.

To identify comparable UAs with different urban form characteristics, I classified 115 UAs into 5 different urban groups using a cluster analysis. For the specific cluster analysis, I applied the flexible-beta method—one of the most common approaches developed by Lance & Williams (1967). Demographic factors (population) and economic variables (household income, housing price, cost of living, employment and unemployment rate, among others) were used in the cluster analysis. But, three key variables of this study—VMT, urban density (population-weighted density), and fuel price—were not included.

Table 4.1 provides summary statistics of the five cluster groups and the detailed information about individual urban areas is reported in Appendix H. Overall, population size appears to be a dominating factor in clustering urban groups and, in general, socio-economic variables such as average median household income, housing price, transit subsidy, and living cost decrease with population size, with a notable exception of groups 1 and 2.

Table 4.1. Summary statistics of five urban clusters.

Group†	# of UAs	Average Population	Housing Price Index (HPI)*	Median household annual income**	Cost of living Index	Employment rate	Transit subsidy per 100 persons
0	3	12,903,713	267	59,259	1.617	62.653	93,454
1	9	2,653,351	255	59,360	1.313	64.973	67,439
2	8	4,563,275	222	60,081	1.227	64.531	59,089
3	36	1,173,463	195	53,207	1.127	63.142	32,210
4	59	412,960	185	47,451	1.083	61.587	19,194
Total	115	1,440,929	204	51,372	1.139	62.571	31,757

Note:

† Group 0: New York, Los Angeles, and Chicago (see Figure I.1).
Group 1: San Francisco, San Diego, Baltimore, Denver, Seattle, Phoenix, Minneapolis, Tampa, and St. Louis.
Group 2: Philadelphia, Boston, Miami, Washington, D.C., Houston, Dallas, Detroit, and Atlanta.
Group 3: San Jose, Las Vegas, Milwaukee, Bridgeport, Providence, Jacksonville, Nashville, Raleigh, Charlotte, Birmingham, and the other 26 UAs.
Group 4: Fresno, Madison, Allentown, Lansing, Lexington, Greenville, Knoxville, Augusta, Winston, Chattanooga, and the other 49 UAs.
Full UA lists in each group are reported in Figure H.1 in Appendix H.

* Original data sources comes from monthly HPI (Federal Housing Finance Agency) at the MSA level, and the table values are average of all 120 month HPIs by each UA matched to MSA.

** Data Source: US. Bureau of the Census.

In the next step, I compared the changes in per capita VMT between the four to five highest and lowest density UAs in each cluster. Group 0 composed of only three largest UAs in the 115 UAs was excluded from the analysis. Analysis results are presented in Table 4.2 and Figures 4.4-4.7. Overall, monthly per capita VMT is apparently lower in high density UAs than in low density UAs in all groups and the hypothesized trend that VMT change would be more responsive to gasoline price fluctuation in high density UAs is partially observed. The pattern of larger VMT reductions in high density UAs than in low density UAs is more pronounced in period 1 during which gasoline prices constantly increased to the unprecedented level. The gaps between high and low density UAs are larger in small urban areas in groups 3 and 4. Group 2 is an exception in which high density UAs experienced an increase in VMT despite the fast fuel price appreciation. I believe this is due to some measurement errors or city specific issues in Boston and Washington, D.C. that have unusual drops in VMT in 2004.

In period 3 when gasoline prices resurged after a quick drop, groups 3 and 4 again show an expected change, steeper VMT reductions in high density UAs. But, the opposite pattern is observed in UAs of groups 1 and 2. The two year period when gasoline price fell after the peak of 2008 (period 2) shows a more mixed pattern: VMT bounced back more quickly in low density UAs in groups 1 and 3, but in high density UAs in group 3. All in all, the results of descriptive comparative analysis are not conclusive although an expected trend is found in small urbanized areas. Since the changes in VMT can be caused by many other factors such as economic conditions and transportation policies specific to certain urban areas, these variables should be controlled for to isolate the effects of gasoline price changes. A more rigorous multivariate analysis in the next section does this.

Table 4.2. The percent change of VMT in the 5 highest and 5 lowest population-weighted density UAs in each group by three different fuel price periods.

	Period 1 [fuel price ↑] Smr.* 2004−Smr.* 2008		**Period 2 [fuel price ↓]** Smr.* 2008−Smr.* 2010		**Period 3 [fuel price ↑]** Smr.* 2010−Smr.* 2011	
	High PWD	Low PWD	High PWD	Low PWD	High PWD	Low PWD
Group 1[2)]	**−7.2%**	**−5.2%**	**11.2%**	**14.3%**	**−11.8%**	**−14.3%**
	(−12.0%)	(−6.5%)	(12.1%)	(15.5%)	(−11.6%)	(−14.9%)
Group 2[3)]	**5.0%**	**−8.2%**	**10.3%**	**9.3%**	**−14.1%**	**−17.3%**
	(−3.3%)	(−11.3%)	(10.8%)	(10.8%)	(−13.5%)	(−17.2%)
Group 3[4)]	**−4.5%**	**1.9%**	**5.5%**	**10.5%**	**−18.0%**	**−15.3%**
	(−7.5%)	(−1.2%)	(6.4%)	(12.4%)	(−17.8%)	(−16.7%)
Group 4[5)]	**−10.6%**	**−1.5%**	**16.7%**	**2.9%**	**−16.0%**	**−8.3%**
	(−14.4%)	(−4.8%)	(18.4%)	(5.3%)	(−18.0%)	(−9.9%)

Notes:

[*] The summer (Smr.) is defined two ways; 1) June, July, and August (bold figures), 2) July (parenthesis figures).

[1)] In the group 1, there are only 9 UAs, so average VMT change is measured by each 4 UAs of high and low PWD rather than by each 5 UAs. The 4 highest PWD UAs are San Francisco, San Diego, Baltimore, and Denver, while the 4 lowest PWD UAs are Phoenix, Minneapolis, Tampa, and St. Louis.

[2)] The group 2 also has only 8 UAs, so 4 highest and lowest PWD UAs are selected. The 4 highest PWD UAs are Philadelphia, Boston, Miami, and Washington, while the 4 lowest PWD UAs are Houston, Dallas, Detroit, and Atlanta in the group 2 as of 2010 Census.

[3)] The 5 highest PWD UAs are San Jose, Las Vegas, Milwaukee, Bridgeport, and Providence, while the 5 lowest PWD UAs are Jacksonville, Nashville-Davidson, Raleigh, Charlotte, and Birmingham in the group 3 as of 2010 Census.

[4)] The 5 highest PWD UAs are Fresno, Madison, Allentown, Lansing, and Lexington, while the 5 lowest PWD UAs are Greenville, Knoxville, Augusta, Winston, and Chattanooga in the group 4 as of 2010 Census.

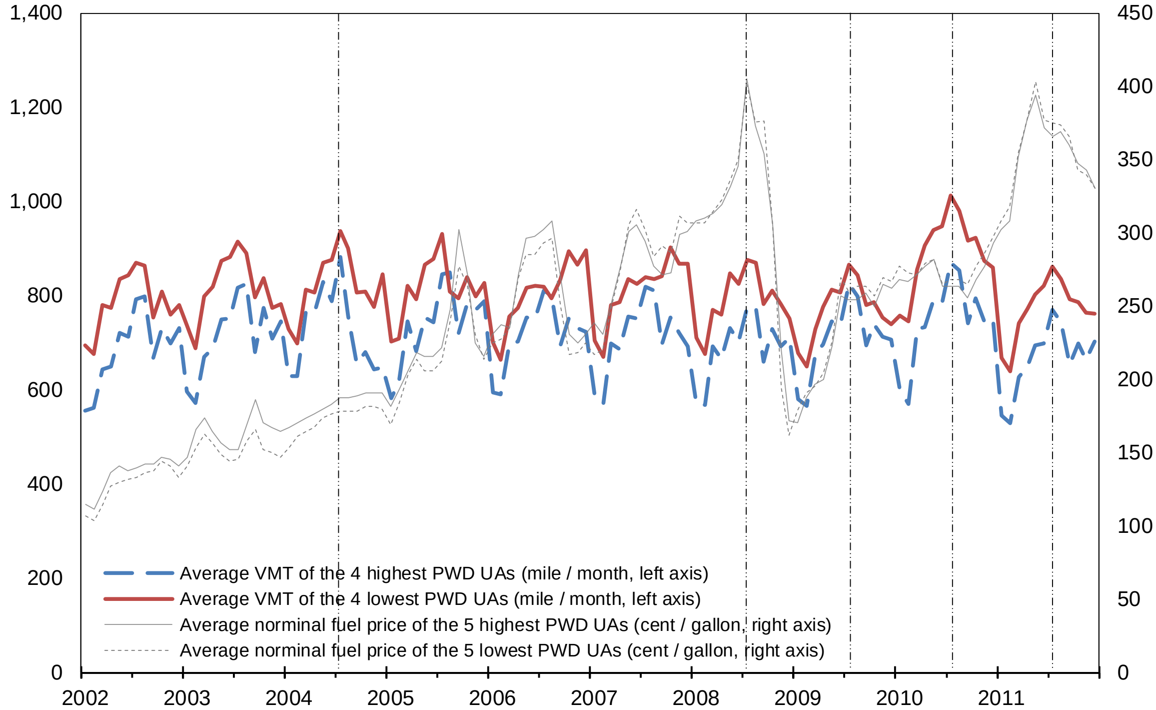


Figure 4.4. The monthly per capita VMTs in the 4 highest population-weighted density UAs (blue line, left axis) and 4 lowest population-weighted density UAs (red line, left axis) of group 1, and their monthly fuel prices (right axis, cent per gallon).

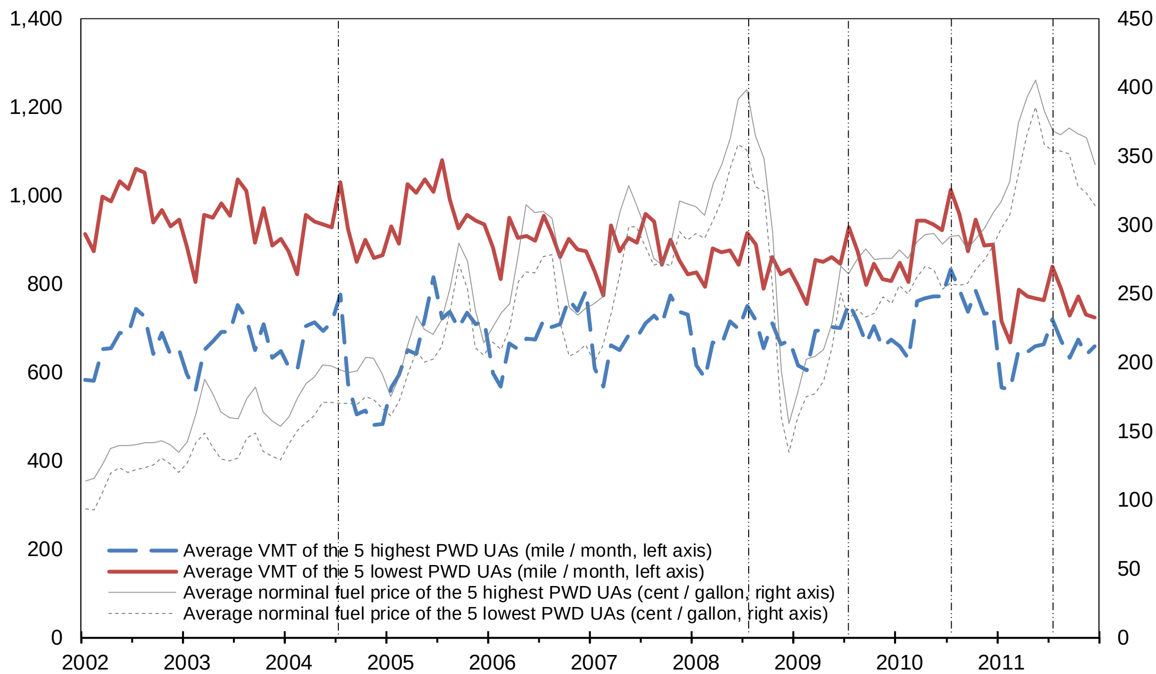


Figure 4.5. The monthly per capita VMTs in the 5 highest population-weighted density UAs (blue line, left axis) and 5 lowest population-weighted density UAs (red line, left axis) of group 2, and their monthly fuel prices (right axis, cent per gallon).

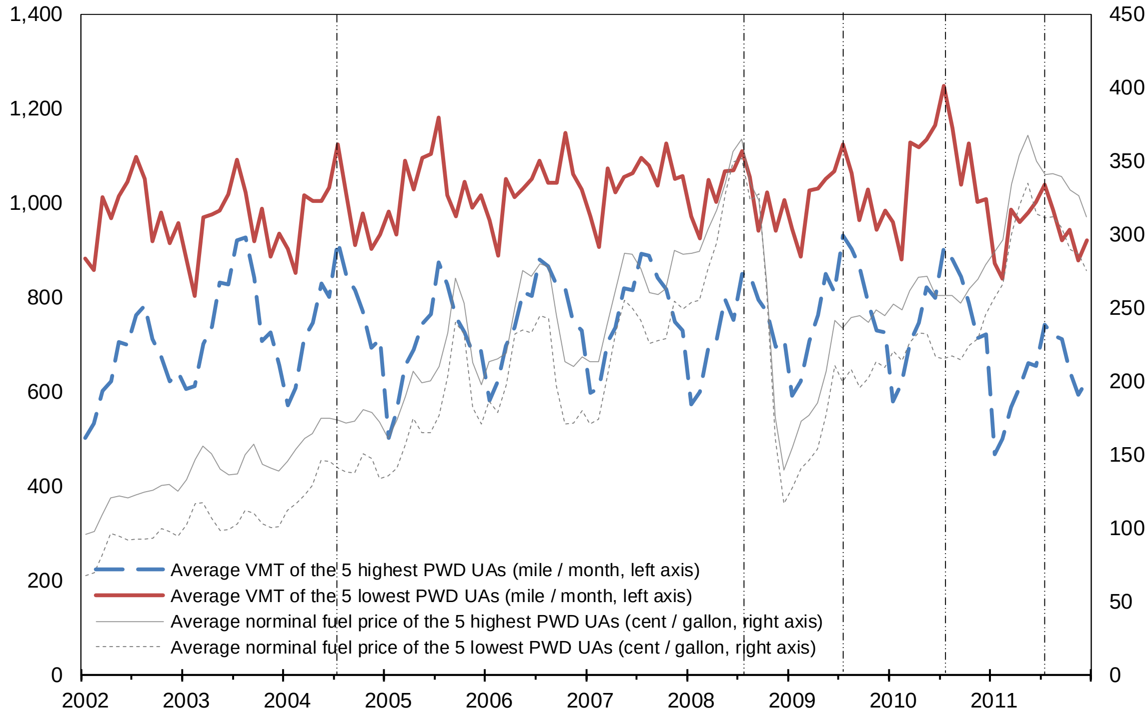


Figure 4.6. The monthly per capita VMTs in the 5 highest population-weighted density UAs (blue line, left axis) and 5 lowest population-weighted density UAs (red line, left axis) of group 3, and their monthly fuel prices (right axis, cent per gallon).

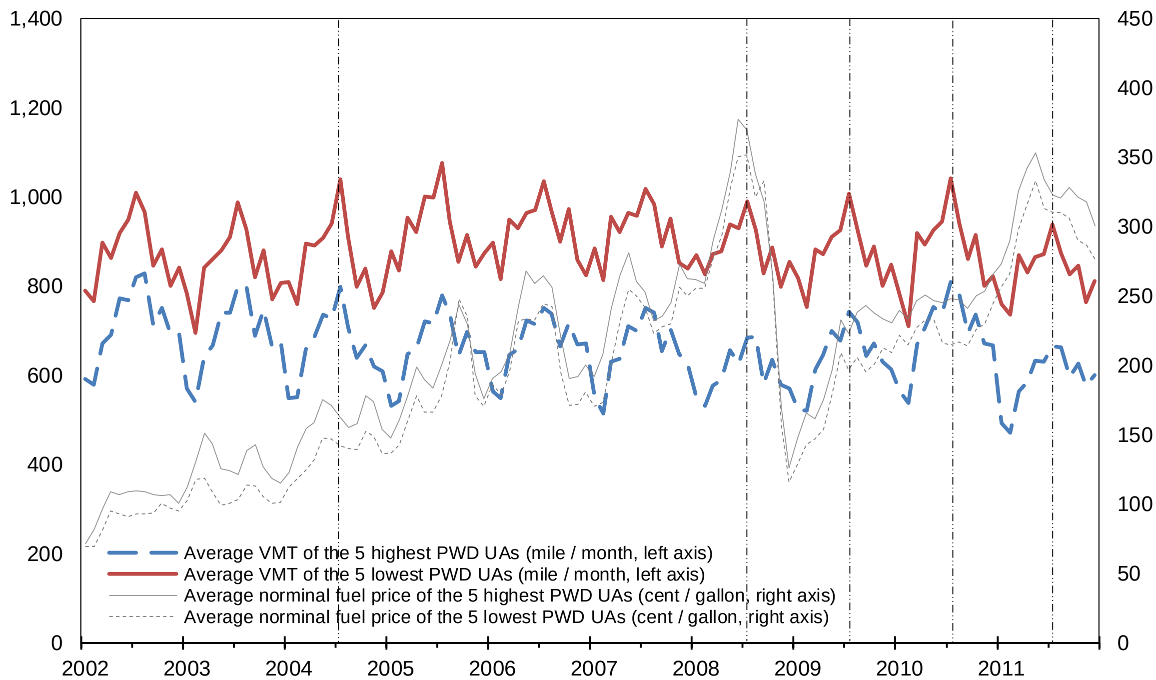


Figure 4.7. The monthly per capita VMTs in the 5 highest population-weighted density UAs (blue line, left axis) and 5 lowest population-weighted density UAs (red line, left axis) of group 4, and their monthly fuel prices (right axis, cent per gallon).

4.4. Multivariate analysis results

4.4.1. Panel model analysis

The first approach to testing the complementarity between fuel price and urban form in VMT reduction is a panel analysis with multiplicative interaction terms of gasoline price and various urban form variables. I tried both random and fixed effects models. To control for other socio-economic and physical infrastructure conditions in each urban area, various control variables were included in panel models. Table 4.3 presents a summary result of the panel analysis, showing only land use, gasoline price, and their interaction variables.

Full models are reported in Appendix F and the descriptions and data sources for all variables used are presented in Appendix G. The results of both fixed and random effects models are similar. But the results of the Hausman tests suggest that a random effects model better fits models 1R (population-weighted density) and 2R (population density), while a fixed effects model shows a better fit for model 3F (compactness index). Both dependent and all independent variables are in natural logarithm, so all estimated coefficients (Coef.) can be interpreted as the elasticities of VMT w.r.t. corresponding independent variables. To compare the relative size of the impacts of independent variables on VMT, standardized coefficients (Std. Coef.) are additionally conducted.

All key independent variables are significant with expected signs. Gasoline price is negatively associated with per capita VMT with statistical significance. VMT elasticities w.r.t. gasoline price are comparable with previous estimates of short term elasticities (Hughes, Knittel & Sperling, 2008; Small & Van Dender, 2007), which are in the range of −0.05 to −0.07. All alternative urban form variables such as population density, population-weighted density (PWD), and compactness index also have significant and negative impacts, and the estimated elasticities range from −0.37 to −0.29. These elasticities are also within the range of previous estimates at the urbanized area level (the VMT elasticity w.r.t. density: −0.381 (Cervero & Murakami, 2010), −0.371 (Lee & Lee, 2014); the VMT elasticity w.r.t. PWD: −0.986 (Lee & Lee, 2014)). Population centrality given urban density also works to reduce VMT and the estimated elasticity is −0.24. But, the impact of polycentric structure is not statistically significant.

Interaction terms with gasoline price were significant for population-weighted density and sprawl index, indicating synergistic effects between high gasoline price and compact urban form, but not for conventional density variable. First, population-weighted density and fuel price interactions were negative with statistical significance. This means that the marginal impact of high population-weighted density on VMT is higher under the condition of high gasoline price; alternatively, the influence of gasoline price on VMT will be intensified in cities with high population-weighted density. The main hypothesis of the complementary impacts of land use and gasoline price was also confirmed when the sprawl index variable was used instead. However, the interaction term was not significant when the conventional density variable was used.

Table 4.3. The results of panel model analysis.

Dep. Variable Monthly per capita VMT	Model 4.1R				Model 4.2R				Model 4.3F			
	Std. Coef.	Coef.	t-value		Std. Coef.	Coef.	t-value		Std. Coef.	Coef.	t-value	
Indep. Variables												
Real gasoline price	−0.069	**−0.048**	−2.79	***	−0.094	**−0.066**	−3.64	***	−0.096	**−0.067**	−3.75	***
Population-weighted density	−0.580	**−0.292**	−10.95	***								
× gasoline price	−0.044	**−0.003**	−1.69	*								
Population density					−0.470	**−0.310**	−9.90	***				
× gasoline price					−0.087	**−0.007**	−1.04					
Pop. centrality					−0.221	**−0.242**	−8.87	***				
× gasoline price					0.274	**0.036**	4.14	***				
Polycentricity					0.016	**0.014**	1.03					
× gasoline price					−0.189	**−0.025**	−2.68	***				
Sprawl index									−0.300	**−0.288**	−6.09	***
× gasoline price									−0.049	**−0.006**	−1.86	*
Pseudo R-square	0.385				0.388				0.776			
F-test									141.23***			
Hausman Test	16.94				23.38							
Breush-Pagan Test	203,029***				190,675***				201,103***			

Note: ***: significant at 1%, **: significant at 5%, *: significant at 10%

1) Full model result is reported in Table J.2 (Model 4.1R & 4.2R) and Table J.1 (Model 4.3F) in Appendix J.
2) As the control variables, population size, freeway lane miles, transit service supply, employment rate, trend, post-peak dummy, monthly dummies are considered.
3) 'Std. Coef.' indicates the coefficient of standardized regression for each independent variable, so we can compare the relative impacts of different independent variables on monthly per capita VMT.
4) Dependent and all continuous independent variables are in natural logarithm, so estimated coefficients (Coef.) can be interpreted as elasticities. The elasticity is defined as the ratio of the percent change in dependent variable to the percent change in each independent variable.

From the results of panel analysis, it is hard to clearly confirm that there are complementary relations between land use elements and fuel price. The interaction term between population-weighted density and gasoline price shows a significant and negative coefficient as hypothesized, but the interaction between fuel price and population density is not statistically significant. In following next sections, I further relax the assumption of linear interaction effects. The marginal impacts of land use on VMT can be seen to sensitively react to increasing retail gasoline price, while the influence of fuel price on VMT can be relatively stable if urban population density increases. Therefore, I re-analyze the interactions between land use and fuel price on VMT using P-LOESS analysis.

4.4.2. Varying Land Use Effects Depending on Fuel Prices

The built environment changes slowly, but personal attitudes toward land use change and land use policies can evolve relatively easily. In this study, I assume that the fluctuation of gasoline price significantly alters people's perception of land use, leading to a change in travel behavior. This attitude change can be captured by the change of VMT elasticities w.r.t. land use variables. Figure 4.8 depicts monthly VMT elasticities w.r.t. PWD that look to move in the opposite direction of the gasoline price trend, with the range of the elasticity changes being almost 25%. Over the ten years (2002-2012), average PWD in 115 urban areas decreased by only 3.56 percent, from 4,508 to 4,263, with no violent fluctuation of density. Thus, it is likely that the observed changes in the elasticities came from the variations in gasoline price. The elasticities of VMT w. r. t. population density seem to follow a similar pattern (Figure 4.9) in a wider range of change, nearly 40%.

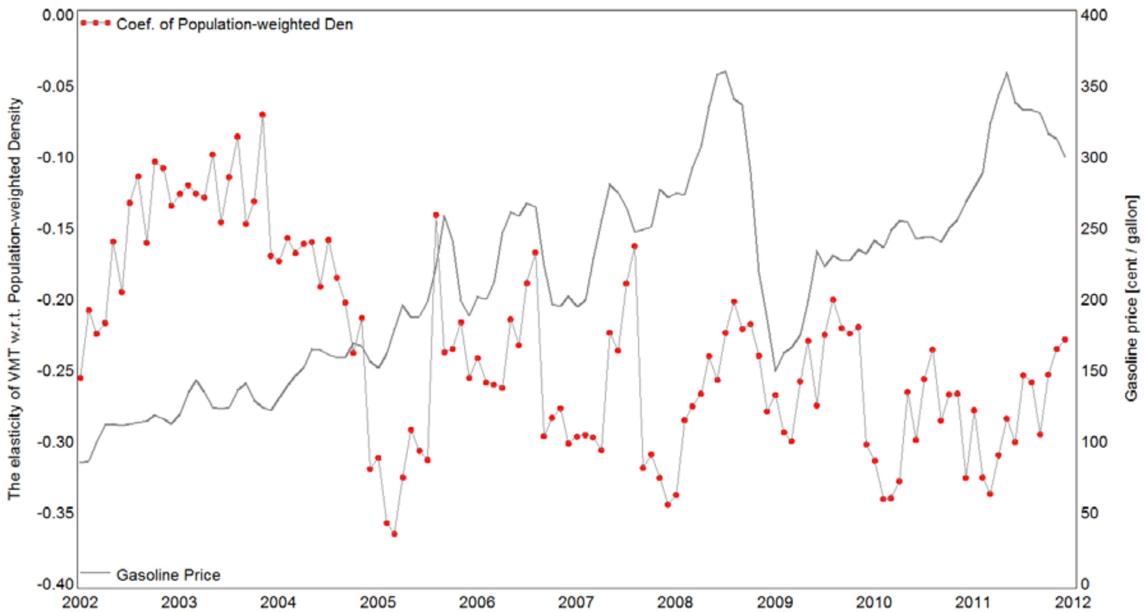


Figure 4.8. The elasticity of per capita VMT w.r.t. population-weighted density (red point, left axis) compared to average nominal gasoline price (gray line, right axis), Jan. 2002 - Dec. 2011.

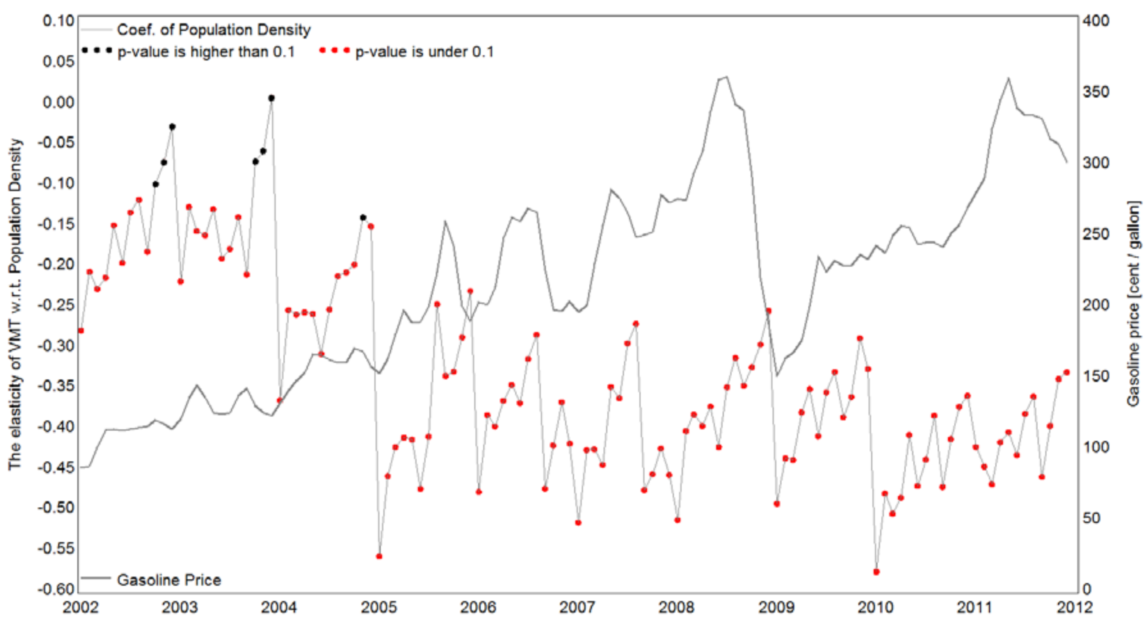


Figure 4.9. The elasticity of per capita VMT w.r.t. conventional population density (red point, left axis) compared to average nominal gasoline price (gray line, right axis), Jan. 2002 - Dec. 2011.

These simple comparisons, however, cannot control for the impacts of other time variant characteristics of each urban area. Thus, in the next step, I conducted P-LOESS analysis with a window size of 2,930 (20% of all 14,652 observations in the sample). Figure 4.10 shows the results, with each point indicating the local VMT elasticity w.r.t. PWD under different fuel price levels. There is a clear pattern that the elasticity grows bigger with the fuel price to a certain price level, \$2.5 per gallon in 2015 real dollars (\$1 in 1983 real dollars)). When the gasoline price is about \$1 (all in 2015 real dollars hereafter), the VMT elasticities w.r.t. PWD is about −0.19, but it increases to around −0.27 when the gasoline price is about \$2.50. But, the impacts of higher density remain the constant when gasoline price further moves beyond \$2.50.

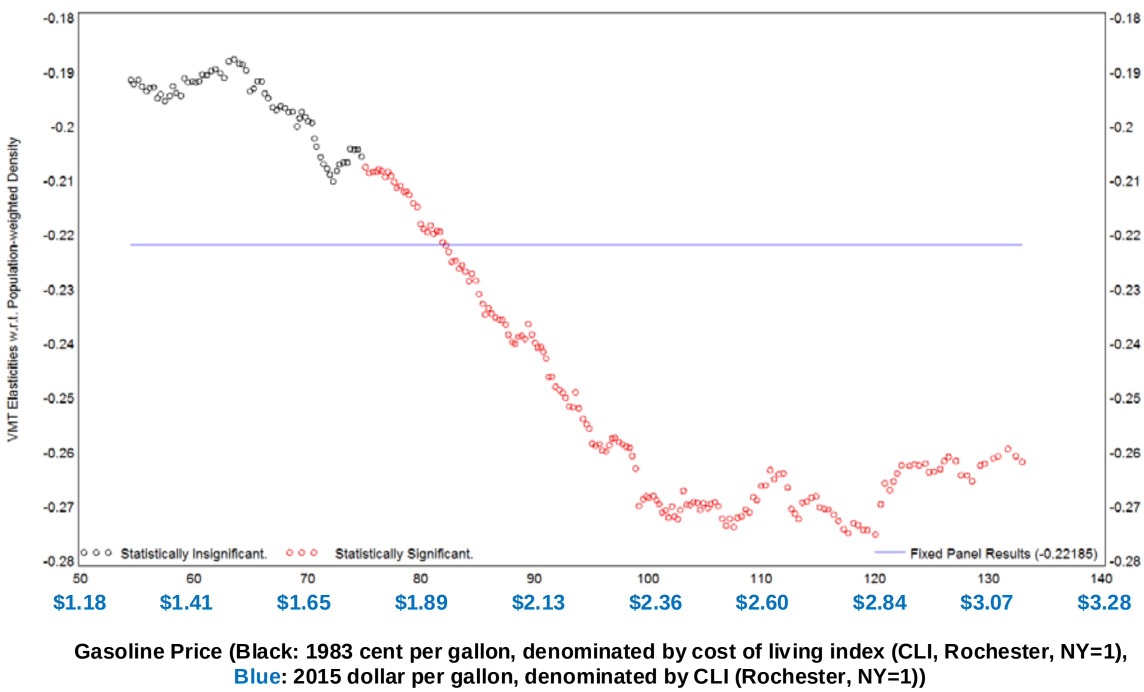


Figure 4.10. VMT elasticity w.r.t. population-weighted density under the different fuel price from the results of P-LOESS analysis (band size: 2,930 (20%), total sample size: 14,652).

As shown in Figure 4.11, an analysis with conventional population density variable also shows a similar pattern. The elasticities of VMT move from about −0.21 to −0.29 as gasoline price increases from $1 to $2.5 and they stay at the range between −0.27 and −0.29 under higher gasoline prices than $2.5.

However, the impacts of compactness index on VMT show quite a different pattern (Figure 4.12). The synergistic effects of compact development and higher gasoline prices exist only up to a certain price level, $1.8 per gallon. Beyond that gasoline price level, the elasticity of VMT w. r. t. the compactness index seems to rather shrink. This is a puzzling result, which needs to be further explicated in future research.

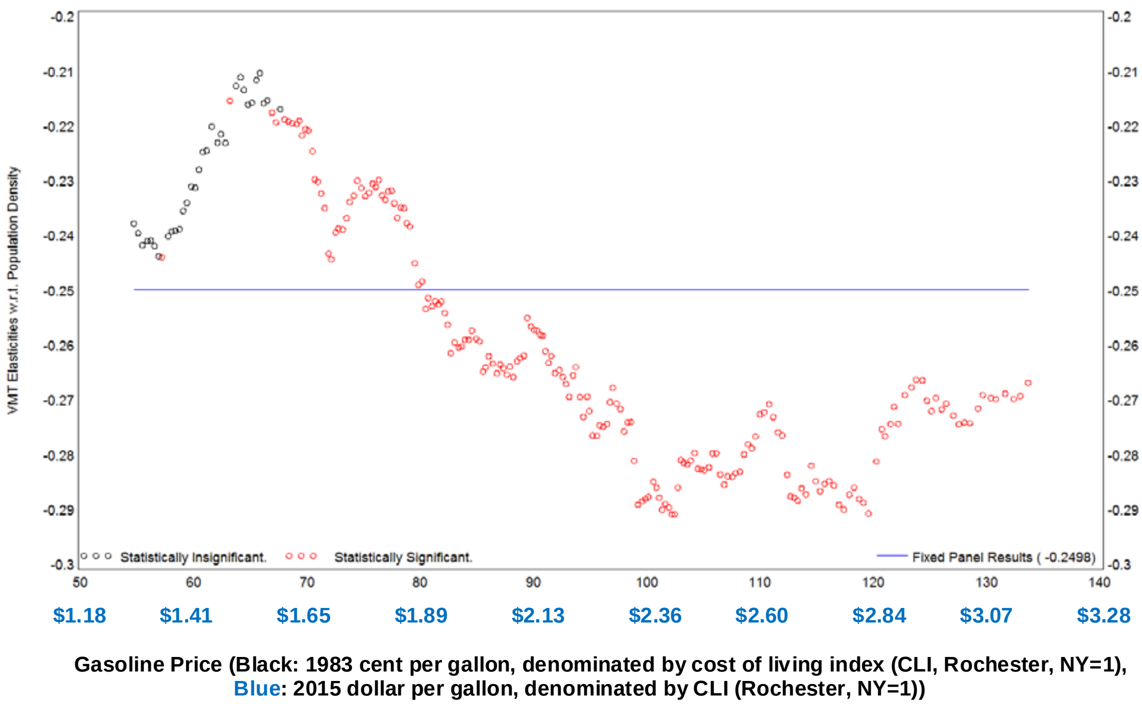
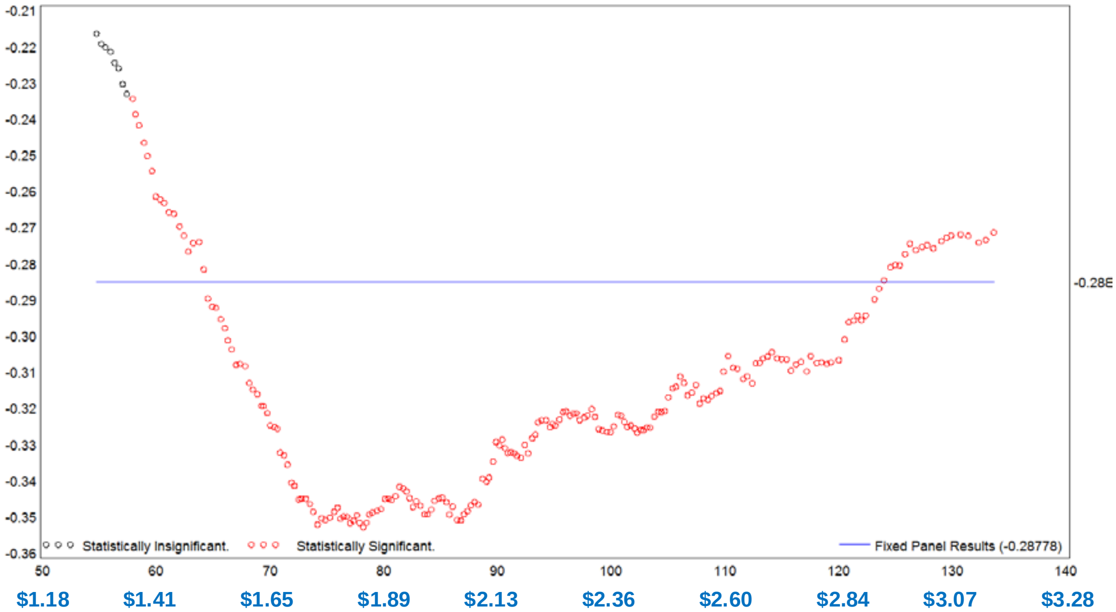


Figure 4.11. VMT elasticity w.r.t. conventional population density under the different fuel price from the results of P-LOESS analysis (band size: 2,930 (20%), total sample size: 14,652).



Gasoline Price (Black: 1983 cent per gallon, denominated by cost of living index (CLI, Rochester, NY=1), Blue: 2015 dollar per gallon, denominated by CLI (Rochester, NY=1))

* Note: Compactness Index estimated by Ewing & Hamidi (2014) does not cover 7 urban areas (Colorado Spring, CO; Bridgeport-Stamford, CT-NY; Virginia Beach, VA; San Diego, CA; Santa Rosa, CA; Providence, RI-MA) among 115 UAs, so the total sample and band size are smaller than those of the other analysis.

Figure 4.12. VMT elasticity w.r.t. compactness index under the different fuel price from the results of P-LOESS analysis (band size: 2,738 (20%), total sample size: 13,692).

4.5. Conclusions

This chapter examined how land use policies and fuel price policies can jointly affect the travel behavior, using diverse statistical methods. When sustainable land use keeps pace with adequate fuel price, they generate synergistic effects in reducing VMT. When population-weighted density doubles, VMT is reduced by about 19% when gasoline price is about $1/gallon in 2015 dollars, but the impact of higher density increases to about 27% under $2.5. Under higher fuel prices, VMT reducing impacts of most compact urban form variables including urban density, compactness index, and population centrality index were estimated to be stronger. This confirms the hypothesis of this chapter that sustainable land use policy can have much stronger impacts under higher gasoline prices.

However, their complementary relations do not seem constant. The elasticities of VMT remain at around 27%, even when the fuel price increases beyond $2.5 to $4 per gallon (in 2015 dollars). The elasticities of urban compactness and centrality also show a similar pattern, in which they stabilize at a certain level or even shrink as gasoline prices continue to rise over 2 dollars (in 2015 dollars).

Even though the study focuses on the two elements between land use regulation and fuel price and their complementary effects, the two elements represent diverse policies in the implementation stage. Fuel price stands for gasoline tax, carbon tax, VMT fee, and parking fee, congestion charge and other policies for increasing costs of driving. UA level land use policies encompass transit oriented development (TOD), compact development, land-use mix exceeding neighborhood boundary, and so on. Even for the same goal of discouraging driving and attaining sustainable travel behavior, it is true that most planners and policy makers have exclusively focused on either land use regulation or fuel pricing policy. However, the results of this study draw an important implication that land use regulation and fuel price increase can be mutually supportive to reduce auto-oriented travel patterns. They are not in a competitive relationship, but a complementary one with synergic effects. This means that both policy areas should recognize the significance of the other part and make a collaborative effort to enhance the policy effectiveness.

4.6. Bibliography

Anas, A., & Rhee, H.-J. (2006). Curbing excess sprawl with congestion tolls and urban boundaries. *Regional Science and Urban Economics, 36*(4), 510-541. doi:10.1016/j.regsciurbeco.2006.03.003

Anas, A., & Rhee, H.-J. (2007). When are urban growth boundaries not second-best policies to congestion tolls? *Journal of Urban Economics, 61*(2), 263-286. doi:10.1016/j.jue.2006.09.004

Aytur, S.A., Rodriguez, D.A., Evenson, K.R., & Catellier, D.J. (2008). Urban Containment Policies and Physical Activity: A Time–Series Analysis of Metropolitan Areas, 1990–2002. *American journal of preventive medicine, 34*(4), 320-332. doi:10.1016/j.amepre.2008.01.018

Bento, A.M., Cropper, M.L., Mobarak, A.M., & Vinha, K. (2005). The effects of urban spatial structure on travel demand in the United States. *Review of Economics and Statistics, 87*(3), 466-478. doi:10.1162/0034653054638292

Bento, A.M., Goulder, L.H., Jacobsen, M.R., & Roger, H.v.H. (2009). Distributional and Efficiency Impacts of Increased US Gasoline Taxes. *The American Economic Review, 99*(3), 667-699. doi:10.2307/25592478

Boarnet, M.G. (2010). Planning, climate change, and transportation: Thoughts on policy analysis. *Transportation research. Part A, Policy and practice, 44*(8), 587. doi:10.1016/j.tra.2010.03.001

Boarnet, M.G. (2011). A Broader Context for Land Use and Travel Behavior, and a Research Agenda. *Journal of the American Planning Association, 77*(3), 197-213. doi:10.1080/01944363.2011.593483

Brambor, T., Clark, W.R., & Golder, M. (2006). Understanding Interaction Models: Improving Empirical Analyses. *Political Analysis, 14*(1), 63-82. doi:10.1093/pan/mpi014

Breusch, T.S., & Pagan, A.R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies, 47*(1), 239-253. doi:10.2307/2297111

Brownstone, D., & Golob, T.F. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics, 65*(1), 91-98. doi:10.1016/j.jue.2008.09.002

Brueckner, J.K. (2000). Urban sprawl: diagnosis and remedies. *International regional science review, 23*(2), 160-171. doi:10.1177/016001700761012710

Brueckner, J.K. (2005). Transport subsidies, system choice, and urban sprawl. *Regional Science and Urban Economics, 35*(6), 715-733. doi:10.1016/j.regsciurbeco.2005.01.001

Brueckner, J.K. (2007). Urban growth boundaries: An effective second-best remedy for unpriced traffic congestion? *Journal of Housing Economics, 16*(3-4), 263-273. doi:10.1016/jjhe.2007.05.001

Cao, X., Mokhtarian, P.L., & Handy, S.L. (2007). Do changes in neighborhood characteristics lead to changes in travel behavior ? A structural equations modeling approach. *Transportation, 34*(5), 535-556. doi:10.1007/s11116-007-9132-x

Cao, X.Y., Mokhtarian, P.L., & Handy, S.L. (2009). Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings. *Transport Reviews, 29*(3), 359-395. doi:10.1080/01441640802539195

Cervero, R., & Landis, J. (1995). The Transportation-Land Use Connection Still Matters. *ACCESS Magazine, 1*(7), 2-10. Retrieved from http://escholarship.org/uc/item/7x87v1zk.pdf

Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas. *Environment and Planning A, 42*(2), 400–418. doi:10.1068/a4236

Cleveland, W.S. (1979). Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association, 74*, 829-836. doi:10.2307/2286407

Cleveland, W.S., & Devlin, S.J. (1988). Locally weighted regression: an approach to regression analysis by local fitting. *Journal of the American Statistical Association, 83*(403), 596-610. doi:10.1080/01621459.1988.10478639

Crane, R., & Crepeau, R. (1998). Does neighborhood design influence travel?: A behaviorl analysis of travel diary and GIS data. *Transportation Research D, 3*, 225-238. doi:10.1016/S1361-9209(98)00001-7

Dawkins, C.J., & Nelson, A.C. (2002). Urban containment policies and housing prices: an international comparison with implications for future research. *Land Use Policy, 19*(1), 1-12. doi:10.1016/S0264-8377(01)00038-2

Echenique, M.H., Hargreaves, A.J., Mitchell, G., & Namdeo, A. (2012). Growing Cities Sustainably. *Journal of the American Planning Association, 78*(2), 121-137. doi:10.1080/01944363.2012.666731

Ewing, R. (1997). Is Los Angeles-style sprawl desirable? *Journal of the American Planning Association, 63*(1), 107-126. doi:10.1080/01944369708975728

Ewing, R., & Cervero, R. (2001). Travel and the built environment: a synthesis. *Transportation Research Record: Journal of the Transportation Research Board, 1780*, 87-114. doi:10.3141/1780-10

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment--A Meta-Analysis. *Journal of the American Planning Association, 76*(3), 265-294. doi:10.1080/01944361003766766

Ewing, R., & Hamidi, S. (2014). *Measuring Urban Sprawl and Validating Sprawl Measures*. Washington, DC: National Institutes of Health and Smart Growth America.

Fang, H.A. (2008). A discrete–continuous model of households' vehicle choice and usage, with an application to the effects of residential density. *Transportation Research Part B: Methodological, 42*(9), 736-758. doi:10.1016/j.trb.2008.01.004

Friedrich, R.J. (1982). In Defense of Multiplicative Terms in Multiple Regression Equations. *american Journal of political Science, 26*(4), 797-833. doi:10.2307/2110973

Gordon, P., & Richardson, H.W. (1997). Are compact cities a desirable planning goal? *Journal of the American Planning Association, 63*(1), 95-106. doi:10.1080/01944369708975727

Guo, Z., Agrawal, A.W., & Dill, J. (2011). Are Land Use Planning and Congestion Pricing Mutually Supportive? *Journal of the American Planning Association, 77*(3), 232-250. doi:10.1080/01944363.2011.592129

Hamidi, S., & Ewing, R. (2014). A longitudinal study of changes in urban sprawl between 2000 and 2010 in the United States. *Landscape and Urban Planning, 128*(0), 72-82. doi:10.1016/j.landurbplan.2014.04.021

Handy, S., Cao, X., & Mokhtarian, P.L. (2006). Self-Selection in the Relationship between the Built Environment and Walking: Empirical Evidence from Northern California. *Journal of the American Planning Association, 72*(1), 55-74. doi:10.1080/01944360608976724

Handy, S., Sallis, J.F., Weber, D., Maibach, E., & Hollander, M. (2008). Is Support for Traditionally Designed Communities Growing? Evidence From Two National Surveys. *Journal of the American Planning Association, 74*(2), 209-221. doi:10.1080/01944360802010418

Hausman, J.A. (1978). Specification Tests in Econometrics. *Econometrica, 46*(6), 1251-1271. doi:10.2307/1913827

Heath, G.W., Brownson, R.C., Kruger, J., Miles, R., Powell, K.E., & Ramsey, L.T. (2006). The Effectiveness of Urban Design and Land Use and Transport Policies and Practices to Increase Physical Activity: A Systematic Review. *Journal of Physical Activity & Health, 3*, S55-S76. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=rss&AN=20971308&site=ehost-live

Heres-Del-Valle, D., & Niemeier, D. (2011). CO2 emissions: Are land-use changes enough for California to reduce VMT? Specification of a two-part model with instrumental variables. *Transportation Research Part B: Methodological, 45*(1), 150-161. doi:10.1016/j.trb.2010.04.001

Hughes, J.E., Knittel, C.R., & Sperling, D. (2008). Evidence of a shift in the short-run price elasticity of gasoline demand. *The Energy Journal*, 113-134. Retrieved from http://www.jstor.org/stable/41323146

Knaap, G.-J. (2008). The sprawl of economics: A response to Jan Brueckner. In Cornia, G.C., & Riddell, J. (Eds.), *Toward a Vision of Land in 2015: International Perspectives*. Cambridge, MA: Lincoln Institute of Land Policy.

Komanoff, C. (2008-2011). Gasoline Price-Elasticity Spreadsheet. In Consulting, K.E. (Ed.).

Kuzmyak, J.R., Pratt, R.H., Douglas, G.B., & Spielberg, F. (2003). *Land Use and Site Design: Traveler Response to Transportation System Changes* (0-309-08763-5). Retrieved from Washington, D.C.: www.TRB.org

Lance, G.N., & Williams, W.T. (1967). A General Theory of Classificatory Sorting Strategies: 1. Hierarchical Systems. *The computer journal, 9*(4), 373-380. doi:10.1093/comjnl/9.4.373

Lee, B., & Lee, Y. (2013). Complementary Pricing and Land Use Policies: Does It Lead to Higher Transit Use? *Journal of the American Planning Association*, *79*(4), 314-328. doi:10.1080/01944363.2014.915629

Lee, S., & Lee, B. (2014). The influence of urban form on GHG emissions in the U.S. household sector. *Energy Policy, 68*(0), 534-549. doi:10.1016/j.enpol.2014.01.024

Levine, J., Inam, A., & Torng, G.-W. (2005). A Choice-Based Rationale for Land Use and Transportation Alternatives Evidence from Boston and Atlanta. *Journal of Planning Education and Research, 24*(3), 317-330. doi:10.1177/0739456X04267714

May, A.D., Kelly, C., & Shepherd, S. (2006). The principles of integration in urban transport strategies. *Transport Policy, 13*(4), 319-327. doi:10.1016/j.tranpol.2005.12.005

Mitchell, G., Hargreaves, A., Namdeo, A., & Echenique, M. (2011). Land use, transport, and carbon futures: the impact of spatial form strategies in three UK urban regions. *Environment and Planning A, 43*(9), 2143-2163. doi:10.1068/a43570

Moore, A.T., Staley, S.R., & Poole Jr., R.W. (2010). The role of VMT reduction in meeting climate change policy goals. *Transportation Research Part A: Policy and Practice*, *44*(8), 565-574. doi:10.1016/j.tra.2010.03.012

OGJ. (2009). Oil and Gas Journal Gasoline Pump Prices – By City (weekly) – data 1/1/1986 thru 3/1/2009.

Parry, I.W.H., & Small, K. (2005). Does Britain or the United States have the right gasoline tax? *The American Economic Review, 95*(4), 1276-1289. doi:10.1257/0002828054825510

Phillips, J., & Goodstein, E. (2000). Growth management and housing prices: the case of Portland, Oregon. *Contemporary Economic Policy, 18*(3), 334-344. doi:10.1111/j.1465-7287.2000.tb00030.x

Rufolo, A.M., & Kimpel, T.J. (2009). Transit's effect on mileage responses to Oregon's experiment in road pricing. *Transportation Research Record: Journal of the Transportation Research Board*, *2115*(1), 60-65. doi:10.3141/2115-08

Santos, A., McGuckin, N., Nakamoto, H.Y., Gray, D., & Liss, S. (2011). *Summary of travel trends: 2009 national household travel survey*. Retrieved from http://nhts.ornl.gov/2009/pub/stt.pdf

Small, K. (1992). Using the revenues from congestion pricing. *Transportation, 19*(4), 359-381. doi:10.1007/BF01098639

Small, K.A. (1997). Economics and urban transportation policy in the United States. *Regional Science and Urban Economics, 27*(6), 671-691. doi:10.1016/S0166-0462(96)02166-7

Small, K.A., & Van Dender, K. (2007). Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. *The Energy Journal, 28*(1), 25-51. doi:10.2307/41323081

Sorensen, P., Wachs, M., Min, E.Y., Kofner, A., & Ecola, L. (2008). *Moving Los Angeles: Short-term policy options for improving transportation*. Santa Monica, CA: Rand Corporation.

Staley, S.R. (2006). Sustainable development in American planning: A critical appraisal. *Town Planning Review, 77*(1), 99-126. doi:10.3828/tpr.77.1.6

Staley, S.R. (2008). Missing the forest through the trees? Comment on Reid Ewing and Fang Rong's "the impact of urban form on U.S. residential energy use". *Housing Policy Debate, 19*(1), 31-43. doi:10.1080/10511482.2008.9521625

Stepp, M.D., Winebrake, J.J., Hawker, J.S., & Skerlos, S.J. (2009). Greenhouse gas mitigation policies and the transportation sector: The role of feedback effects on policy effectiveness. *Energy Policy, 37*(7), 2774-2787. doi:10.1016/j.enpol.2009.03.013

VTPI. (2007). OECD Country Data Summary Spreadsheet. Retrieved from www.vtpi.org/OECD2006.xls. from Victoria Transport Policy Institute.

Wallace, T.D., & Hussain, A. (1969). The Use of Error Components Models in Combining Cross Section with Time Series Data. *Econometrica, 37*(1), 55-72. doi:10.2307/1909205

Winkelman, S., Bishins, A., & Kooshian, C. (2009). *Cost-effective GHG reductions through smart growth and improved transportation choices: An economic ase for investment of cap-and-trade revenues*. Retrieved from Washington, DC

Winkelman, S., Bishins, A., & Kooshian, C. (2010). Planning for economic and environmental resilience. *Transportation Research Part A: Policy and Practice, 44*(8), 575-586. doi:10.1016/j.tra.2010.03.011

Wright, G.C., Jr. (1976). Linear Models for Evaluating Conditional Relationships. *american Journal of political Science, 20*(2), 349-373. doi:10.2307/2110649

Zhang, M. (2004). The role of land use in travel mode choice: Evidence from Boston and Hong Kong. *Journal of the American Planning Association, 70*(3), 344-360. doi:10.1080/01944360408976383

CHAPTER 5
CONCLUSIONS

The aim of this dissertation is to elucidate the role of urban spatial structure in mitigating GHG emissions to stabilize climate change. A large and increasing volume of empirical studies have been investigating the connections between specific land-use elements and sustainable travel behaviors in U.S. cities, but most of these studies have mainly focused on examining neighborhood scale links between urban form and transportation. However, the average one-way trip distance of automobile trips in U.S. cities is about ten miles. In other words, the changes in small scale built environments may not have significant impacts on most urban trips. As such, geographical scale of land use-transportation links is a critical dimension to come up with effective policies. But it did not get much attention in previous studies mainly due to the difficulty of measuring urban spatial structure at the urban area or MSA level. In this dissertation, I advanced the way to measure spatial structure at the urban area level by developing several spatial indicators such as population-weighted density, centrality index, and polycentricity index. Using these spatial measures, I investigated how urban spatial structure influences travel behavior and residential energy consumption from various angles.

The dissertation presented three pieces of semi-independent but related empirical studies. Chapter 2 examined the comprehensive impacts of urban spatial structure on household GHG emissions by tracing various paths between them through housing type choices, vehicle type choices, travel mode choices, and so on. Chapter 3 compared the impacts of built environment characteristics on VMT at neighborhood and urban area levels, and examined the complementary nature of the two scale land use characteristics. Chapter 4 compared and contrasted land use and pricing policies, and explored how the two different policies interact with each other to reduce car-oriented travel behavior. All three papers aim to discover and highlight the role of urban spatial structure in mitigating household GHGs.

5.1. Summary

Chapter 2 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. The result of the multilevel SEM analyses shows that doubling population-weighted density is associated with a reduction in CO_2 emissions from household travel and residential energy consumption by 48% and 30%, respectively. The impacts of centralized population and polycentric structure are only moderate. The result also shows that doubling per capita transit subsidy is associated with a nearly 46% lower VMT and 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 research findings corroborate the notion that urban land use and transportation policies to build more compact and transit friendly cities should be a crucial part of any strategic efforts to mitigate GHG emissions and stabilize climate at all levels of government.

Chapter 3 focuses on urban form at two different geographic scales and their influences on travel behaviors. Travel behaviors are affected by regional scale development patterns as well as by physical characteristics of a resident's neighborhood. The analysis results show that regional scale urban form elements are far more important than neighborhood land use design in mitigating the environmental impacts of auto-oriented travel. Specifically, population-weighted density, centrality, job accessibility, and the proximity to downtown significantly decrease VMT and GHG emissions. Moreover, the results show that there are positive interaction effects between compact urban forms at the two scales: the influences of neighborhood level land use design on both VMT and GHGs are amplified in cities with higher population-weighted density.

The VMT elasticities with respect to neighborhood compactness is approximately 50% in the average population-weighted density, but these increase to 75% when population-weighted density increases from average levels to the New York urbanized area level.

Chapter 4 assesses how land use policies and gasoline prices jointly affect travel behavior. When the fuel price is at a moderate level, there are significant complementary effects between sustainable land use policy and rising gasoline price. Under $1/gallon in 2015 constant dollars, doubling population-weighted density is associated with a 19% lower VMT per capita, but the VMT elasticity rises to about −27% when gasoline price is about $2.5. Population centrality and compactness index developed by Ewing and Hamidi (2014) also show stronger VMT reduction effects under higher gasoline prices. These complementary effects peter out when fuel prices increase to the upper range above 2 dollars.

5.2. Policy implications

All three papers included in this dissertation bear profound policy implications in sustainable land use and transportation planning. Chapter 2 makes a strong case for land use planning as an important GHG mitigation strategy while current federal- and state-level climate change policies predominantly rely on technology solutions. Although a growing body of literature has explored the mechanisms by which urban form influences household sector GHG emissions especially in transportation, there remains a lack of agreement among researchers on the magnitude of urban form effects. Current metropolitan area- or urban area-level studies have critical limitations in providing a generalizable assessment of the role of sustainable urban form and the national scale studies are in their infancy. Chapter 2 advances our knowledge of the connections between urban form and household sector carbon emissions. By studying multiple scales and dimensions of urban form and addressing both transportation and residential carbon emissions, this research yields rich insights into the spatial changes that are needed to significantly reduce total household carbon emissions.

Chapter 3 poses a serious question of the state of the regional governance to develop a strategic land use plan to effectively reduce GHG emissions. It shows empirical evidence that sustainable regional spatial structure not only matters more but also augments the positive impacts of neighborhood level compact design. In other words, scattered and fragmented development of compact neighborhoods is not enough to modify automobile dependent travel behavior. Regional scale coordination of smart growth strategies such as urban growth boundaries, balanced jobs-housing development, and transit oriented development would foster sustainable transportation in a much more effective way. Chapter 3 raises important implementation issues regarding regional level smart growth policies. Who should plan for regional smart growth strategies and who should be empowered to execute them? Which system would work more effectively, state government-led initiatives or voluntary regional governance based on communicative and collaborative planning? How can we cultivate voluntary governance or build the consensus with institutional arrangements to overwhelm local resistance under the 'bottom-up' framework? While more research is needed to address these issues in the future, my study highlights that regional level coordination of smart growth policies is imperative. Increasing number of metropolitan planning organizations (MPOs) have been exercising regional scenario planning to develop a regional blueprint–e.g. Denver's Metro Vision, Chicago's 2040, and so on. However, resulting plans of these efforts are largely conceptual, but lack in specific measures and tools to assure implementation at the local level. In this regard, state level legislation empowering regional level governments or MPOs such as a series of growth management codes in the State of Oregon and, more recently, California's AB 32 in 2006 and SB 375 in 2008 seems to be a necessary condition for more effective smart growth policies and the regional level.

Chapter 4 highlights the importance of how urban form structure influence is changed under the fluctuation of gasoline price, which has been largely ignored by planners. The important implication is that both land use and gasoline price are closely connected to reduce private vehicle use, so we need to take both elements into account for transportation policy. When sustainable land use policy keeps pace with adequate fuel price, they create complementary effects with corresponding reductions in the demand for gasoline, but the policies need to be applied in sophisticated ways in the implementation stage. Urban density increase gives rise to diverse benefits, but it also causes land value increase around the denser areas. High population density can negatively affect residents' ability to find affordable housing near job centers, so it can lead to average commuting distances increase. Given the density increases, enough alternative public transits seem to be supported as urban density increases.

APPENDIX A
FULL MODEL RESULTS (CHAPTER 2)

Table A.1. Full result of transportation CO_2 model (Model 2.2).

	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					

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:
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).

Table A.2. Full result of residential CO_2 model (Model 2.4).

	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	0.414	0.00***												
Electricity Use	0.448	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							

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:

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).

Table A.3. Full result of residential CO_2 model (modified version of Model 2.4).

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	0.310	0.00***												
Electricity Use	0.708	0.00***												
Power Plant	1.514	0.00***												
Observed HDD			0.536	0.00***										
Predicted HDD											1.051	0.00***		
Observed CDD					0.306	0.00***								
Predicted CDD													0.918	0.00***
Population Size											−0.029	0.00***	0.069	0.00***
Weighted Density	−0.037	0.27					−0.076	0.00***	−0.302	0.00***	0.006	0.70	−0.077	0.06
Polycentricity	−0.001	0.95									−0.010	0.29	−0.028	0.12*
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	−0.064	0.19

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	0.418	0.00***								
Number of Rooms			0.303	0.00***	0.469	0.00***				
Housing Type			0.424	0.00***	0.405	0.00***				
Sex			−0.079	0.00***	0.017	0.52	0.000	0.97	0.187	0.00***
Age1 (younger than 21)			0.378	0.00***	0.375	0.00***	−0.205	0.00***	−0.728	0.00***
Age2 (21−30)			0.184	0.00***	0.106	0.01***	−0.133	0.00***	−0.512	0.00***
Age4 (41− 50)			−0.035	0.20*	−0.035	0.19	0.065	0.00***	0.199	0.00***
Age5 (51− 65)			−0.097	0.01***	−0.136	0.00***	0.116	0.00***	0.407	0.00***
Age6 (older than 65)			−0.112	0.02***	−0.190	0.00***	0.149	0.00***	0.483	0.00***
Race1 (White)			−0.185	0.00***	−0.093	0.01***	0.163	0.00***	0.361	0.00***
Race2 (African American)			0.030	0.38	0.017	0.64	0.104	0.00***	0.039	0.49
Employment Status1			−0.013	0.60	0.041	0.13	0.030	0.01***	−0.014	0.76
Education1 (less than high chool)			0.163	0.15	0.018	0.86	−0.241	0.00***	−0.386	0.01**
Education2 (high school)			0.020	0.69	−0.006	0.90	−0.093	0.00***	−0.240	0.00***
Education4 (some college)			−0.012	0.61	0.006	0.79	0.051	0.00***	0.014	0.72
Education5 (4 year university)			−0.047	0.09*	−0.035	0.18	0.080	0.00***	0.075	0.07*
Education6 (Graduate)			0.002	0.95	0.021	0.57	0.124	0.00***	0.002	0.97
Income1 (less than \$17,500)			0.140	0.00***	0.113	0.01***	−0.135	0.00***	−0.439	0.00***
Income2 (\$17,500–\$32,300)			0.089	0.02***	0.071	0.04**	−0.094	0.00***	−0.301	0.00***
Income4 (\$56,000–\$90,000)			−0.096	0.01***	−0.057	0.12	0.104	0.00***	0.363	0.00***
Income5 (\$90,000–\$139,700)			−0.159	0.00***	−0.103	0.05**	0.197	0.00***	0.586	0.00***
Income6 (higher than \$139,700)			0.024	0.65	0.025	0.68	0.297	0.00***	0.588	0.00***
Household Size			−0.034	0.02***	−0.023	0.09**	0.048	0.00***	0.198	0.00***
Built Year1 (less than 10 years)			−0.012	0.63	−0.026	0.36				
Built Year3 (21–40 years ago)			0.063	0.01***	0.031	0.24				
Built Year4 (older than 40 years)			0.124	0.00***	0.018	0.53				

Goodness of fit	
Comparative fit index (CFI)	0.985
Tucker-Lewis index (TLI)	0.961
Root mean square error of approximation (RMSEA)	0.030
Standard root mean square residual (SRMR), Within	0.215
Standard root mean square residual (SRMR), Between	0.137
Interclass correlation (ρ)	0.201

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:
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).

APPENDIX B
MODEL SPECIFICATION (CHAPTER 3)

Level 1 (individual household): $Y_{ijk} = \pi_{0jk} + \sum_{p=1}^{P} \pi_{pjk} a_{pjk} + e_{pjk}$, $e_{ijk} \sim N(0, \sigma^2)$,

Level 2 (neighborhood): $\pi_{pjk} = \beta_{p0k} + \sum_{q=1}^{Q_p} \beta_{pqk} X_{qjk} + r_{pjk}$,

Level 3 (urbanized area): $\beta_{pqk} = \beta_{pq0} + \sum_{s=1}^{S_{pq}} \gamma_{pqs} W_{sk} + u_{pqk}$,

where Y_{ijk} is the per capita VMT or CO_2 emission for the *i*-th household in the *j*-th neighborhood within the *k*-th urbanized area; a_{pjk} are the household characteristics such as age, education, household income, race, household size and the number of workers; π_{pjk} are the coefficients of the household behaviors with other covariates; π_{0jk} is the intercept of the household level; e_{pjk} is the error term of the household level; X_{ijk} are the neighborhood characteristics (5Ds) such as neighborhood level population density, land use mix, beta index, distance from the CBD, and distance from the subcenter; β_{pqk} are the coefficients of the neighborhood within the *k*-th urbanized area,; β_{p0k} is the intercept of the neighborhood level; r_{pjk} is the error term of the neighborhood level; W_{sk} are the urbanized area (UA) characteristics such as UA population density, UA population-weighted density, centrality, polycentricity, UA level sprawl index, freeway lane mile, vehicle revenue miles, and the subsidies for public transit; γ_{pqs} are the coefficients of the urbanized area variables; β_{pq0} is the intercept of the urbanized area level; u_{pqk} is the error term of the urbanized area level. All dependent and independent variables are the natural logarithm form, thus all coefficients can be interpreted as elasticity.

APPENDIX C
MEASURES OF DEPENDENT AND INDEPENDENT VARIABLES (CHAPTER 3)

Dependent variables
Both the annual VMT per household and CO_2 emissions generated from the transportation sector are considered. The VMT variable covers all other travel behavior indices such as trip frequency, trip length, trip time, and mode choice (Ewing & Cervero, 2001). The amount of GHGs per household comes from the output of the multiplication of the VMT and pounds of CO_2 per 1 gallon of gasoline divided by miles per gallon (see Mui et al. (2007) and Cervero & Murakami (2010)).

Independent variables
As mentioned above, there are three levels of independent variables representing household, neighborhood and urbanized characteristics. Household characteristics are largely divided into demographic and socioeconomic factors. More specifically, demographic factors include the number of households, age of the household head, race, and family life cycle. Socioeconomic factors include household income, employment status, and education attainment. All of the data for household variables comes from the NHTS (2009). The sample size of the total number of households is 48,831 in the largest 121 urbanized areas.

Next, neighborhood characteristics are based on diverse sources. Census tract level population and employment densities come from the NHTS (2009). Land use mix index is accounted for based on Longitudinal Employment-Household Dynamics (LODES, 2009). Street design variables such as the beta index and 4-way intersection density are measured with CENSUS TIGER files (2009) covering all arterial, collector and local roads except freeways. Distances from the CBD and the closest subcenter are based on the Gaussian distance from the centroid of each census tract to the CBD and the closest subcenter. The physical boundary files come from the CENSUS TIGER file (2010) and the employment information from LODES (2009) and population information taken from the CENSUS (2010) are used to identify urban employment centers such as the CBD and subcenters.

To build the job centers, a geographically weighted regression (GWR) procedure derived from Giuliano & Small (1991) and McMillen (2001) is applied under the assumption that urban centers should have higher employment density than the surrounding areas. The differentials between two estimated employment density surfaces are estimated, one with a small window size (10 neighboring census tracts) and the other with a large window size (100 census tracts). Among the clusters of density peaks as defined by the significant differentials, only those with more than 10,000 jobs as employment centers qualified (for a detailed description of the procedure, see Lee (2007)).

Finally, urbanized characteristics use numerous sources. Both population density and population-weighted density are calculated based on the CENSUS (2010) data. To identify intra-urban population and employment distributions, the location information for job centers is used based on CENSUS (2010), the CENSUS boundary file (2010), and LODES (2009). The major source of land use mix variables is LODES (2009), and urbanized area level freeway lane miles come from Federal Highway Administration (FHWA, 2009). Both ‘vehicle revenue mile’ and ‘public transit subsidy’ variables come from the National Transit Database (NTD, 2009).

Table C.1. Definitions of dependent and explanatory variables.

	Variable	Description	Source
Dependent	**Annual vehicle mile traveled [lnVMT]**	■ Natural logarithm of annual vehicle mile traveled per household	NHTS 2009
	Annual CO_2 emission from private vehicle and public transit ride [lnTCO_2]	■ Natural logarithm of annual CO_2 emissions per household • Annual CO_2 [TCO_2] = CO_2 Private vehicle use [VCO_2] + CO_2 Public transit ride [PCO_2] • 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.	NHTS 2009 NTD 2009 EIA
Household (Level 1)			
	Age [AGE1] [AGE2] … [AGE6]	■ Household Head Age 5 different dummy variables: [AGE1] under 20; [AGE2] 21~30; [AGE3] 31~40; [AGE4] 41~50; [AGE5] 51~64; [AGE6] larger than 65.	NHTS 2009
	Education [EDU1] [EDU2] … [EDU5]	■ Education level of household head 5 different dummy variables: [EDU1] less then high school graduate; [EDU2] high school graduate; [EDU3] some college or associate's degree; [EDU4] bachelor's degree (BA, AB, BS); [EDU5] graduate or professional degree.	NHTS 2009
	Household income [INC1] [INC2] … [INC5]	■ Total Household Income 5 different dummy variables: [INC1] under $20,000; [INC2] $20,000~$35,000; [INC3] $35,000~$55,000; [INC4] $55,000~$80,000; [INC5] higher than $80,000	NHTS 2009
	Race [White] [Black] [Asia] [Other]	■ Race 4 different dummy variables: [White] White; [Black] African American; [Asia] Asian, [Other] all other races.	NHTS 2009
	Household size [lnHHSIZE]	■ Natural logarithm of the number of household member	NHTS 2009
	Number of worker [lnWRK]	■ Natural logarithm of the number of worker	NHTS 2009
Census Tract (Level 2)			
	Population density [lnC_PDEN]	■ Natural logarithm of population density at the level of census tract (pop. density = # of pop. / sq. miles)	NHTS 2009
	Land use mix [lnC_LUMIX]	■ Natural logarithm of entropy index Entropy Index : $-1 \times \{[\sum(p_i)\ln(p_i)] \;/\; \ln(k)\}$ *where pi=land use i's % of total land area* *k=number of categories of land use* 4 different land areas are considered as follows: Residential; Commercial; Industrial; Office districts. • The proportion of each districts are re-defined as the same proportion of number of worker who works at the census tract. (Entropy index range: b/w 0 to 1)	LODES 2009
	Beta index [lnBETA]	■ Natural logarithm of Beta Index • Beta index is defined as the ratio of links to nodes as follows; $\beta = e \;/\; v$, e: number of links, v: number of nodes	CENSUS 2009 (Tiger file)
	Distance to the closest transit terminal [lnC_DTT]	■ Natural logarithm of 4 way intersection density • The density is defined as 4 way intersection divided by street length (mile) at the targeted census tract	CENSUS 2009 (Tiger file)
	Distance to downtown [lnC_DCBD]	■ Natural logarithm of distance (mile) from Central Business District (CBD) to each census tract	LODES 2009
	Distance to the closest subcenter [DSUBD]	■ $1 \;/\; \sqrt{Dist.of\ the\ closest\ subcenter\ from\ each\ census\ tract}$ (based on shepard's method (Gordon & Wixom, 1978))	LODES 2009
	Compactness Index [lnC_SPW]	■ Natural logarithm of compact. index at the census tract level Compactness index comes from Hamidi & Ewing (2014)	Hamidi & Ewing, 2014
	[continue to the next page]		

Table C.1. (cont.).

Urbanized Area (Level 3)		
Population density [lnU_PDEN]	■ Natural logarithm of urbanized area pop density Population density = urbanized area pop. / sq. mile	CENSUS 2010
Population-weighted density [lnU_PWDEN]	■ Natural logarithm of population-weighted density (PWD) • PWD is estimated as the weighted mean of census block group level density with each block group's population	CENSUS 2010
Centrality index [lnU_CENp]	■ Natural logarithm of population centrality index • Centrality index is summarized as principle component analysis (PCA) from the 4 indices as follows; 1) Central business district (CBD) population share 2) The area-based centrality index (ACI) 3) The ratio of weighted to unweighted average distance (WUAD) 4) The population density gradient. The CBD population share is estimated as the share of the UA population in the CBD (Lee, 2007; Lee and Lee, 2014).	CENSUS 2010 & LODES 2010
Job accessibility [lnU_JTH10b]	■ Natural logarithm of population weighted jobs-to-housing index of census tracts in 10 mile buffer. Jobs-to-housing index: $-1 \times \{[\sum(p_i)\ln(p_i)] \,/\, \ln(2)\}$ *where* p_1=# *employment* / $\sum(\#household + \#emp.)$ p_2=# *household* / $\sum(\#household + \#emp.)$	LODES 2010
Total lane miles [lnU_TLMpt]	■ Natural logarithm of total lane miles per 1,000 persons	FHWA 2009
Transit service supply [lnU_VRMp]	■ Natural logarithm of vehicle revenue miles (VRM) per 100 persons; VRM is defined as the miles that vehicles travel (public transit) while in revenue service	NTD 2009
Compactness Index [lnU_SPW]	■ Natural logarithm of compact. index at the UA level Compactness index comes from Hamidi & Ewing (2014)	Hamidi & Ewing, 2014

Table C.2. Characteristics of dependent and independent variables.

	Mean	Median	S.D.	Categories (%)					
Dependent **: 56,373 Households**									
lnVMT	**9.63**	9.79							
└ VMT (miles)	**19,844**	16,516							
lnTCO$_2$	**9.53**	9.80							
└ TCO$_2$ (lbs/CO$_2$)	**21,222**	17,367							
└ VCO$_2$ (lbs/CO$_2$)	**21,098**	17,269							
└ PCO$_2$ (lbs/CO$_2$)	**124**	0							
Household (Level 1) **: 56,373 Households**									
Age	**54**	57	22	AGE1	AGE2	AGE3	AGE4	AGE5	AGE6
└ **AGE** (Categories)				3.5%	4.5%	7.9%	11.8%	27.6%	36.4%
Edu (Categories)				EDU1	EDU2	EDU3	EDU4	EDU5	
				5.9%	19.4%	34.2%	22.7%	17.9%	
Income ($)	**71,887**	57,500	50,388	INC1	INC2	INC3	INC4	INC5	
└ **INC** (Categories)				13.8%	13.1%	18.7%	22.5%	31.9%	
Race (Categories)				White	Black	Asia	Other		
				79.6%	8.6%	3.2%	4.2%		
lnHHSIZE	**0.75**	0.69	0.52						
└ HHSIZE	**2.41**	2.00	1.29						
lnWRK	**0.33**	0.00	0.39						
└ WRK	**0.97**	1.00	0.90						
Census Tract (Level 2) **: 16,695 Census Tracts**									
lnC_PDEN	**8.31**	8.01	0.94						
└ C_PDEN	**6,107**	3,000	6,031						
lnC_LUMIX	**0.48**	0.47	0.21						
└ LUMIX	**−0.86**	−0.75	0.55						
lnC_BETA	**0.20**	0.19	0.09						
└ BETA	**1.22**	1.21	0.11						
lnC_DTT	**1.22**	1.36	0.94						
└ DTT	**4.77**	3.88	3.59						
lnC_DCBD	**2.13**	2.26	0.99						
└ DCBD	**12.90**	9.76	10.83						
DSUBD	**1.06**	0.63	2.04						
└ DSUB	**3.18**	2.52	2.59						
lnC_SPW	**4.59**	4.54	0.28						
└C_SPW	**101.24**	100.74	19.37						
Urbanized Area (Level 3) **: 121 Urbanized Areas**									
lnU_PWDEN	**8.60**	8.47	0.72						
└ U_PWDEN	**7,419**	4,764	7,744						
lnU_PDEN	**7.82**	7.86	0.48						
└ U_PDEN	**6,317**	3,646	13,069						
lnU_CENp	**4.53**	4.49	0.24						
└CENp	**90.36**	86.99	21.29						
lnU_JTH10b	**4.48**	4.48	0.05						
└ JTH10b	**88.08**	88.13	3.93						
lnU_TLMpt	**2.74**	2.72	0.64						
└ TLM	**3.96**	4.01	1.53						
lnU_VRMp	**10.54**	10.61	0.79						
└ VRMp	**18.56**	15.11	11.39						
lnU_SPW	**4.60**	4.61	0.19						
└U_SPW	**102.95**	93.95	28.96						

APPENDIX D
FULL MODEL RESULTS OF VMT ELASTICITIES (CHAPTER 3)

Table D.1. VMT elasticities (Model 3.1-3.4).

	Model 3.1			**Model 3.2**			**Model 3.3**			**Model 3.4**		
	Beta	**t-value**		**Beta**	**t-value**		**Beta**	**t-value**		**Beta**	**t-value**	
Fixed Effect												
Intercept	**9.173**	449.8	***	**9.32**	55.2	***	**9.159**	445.3	***	**9.341**	54.8	***
Urbanized Area Level (Level 3)												
Pop.-weighted Density	**−0.108**	−4.0	***				**−0.090**	−3.2	***			
Population Density				**−0.066**	−2.5	**				**−0.099**	−2.1	**
Centrality Index				**−0.031**	−1.8	*				**−0.038**	−2.2	**
Jobs-to-housing ratio	**−0.264**	−1.8	*	**−0.171**	−1.9	*				**−0.115**	−0.6	
Transit Service Supply	**−0.104**	−2.6	***	**−0.043**	−3.1	***				**−0.034**	−2.4	**
Total Lane Miles	**−0.016**	−1.1		**−0.053**	−1.0					**−0.017**	−0.3	
Census Tract Level (Level 2)												
Population Density	**−0.058**	−10.7	***	**−0.058**	−10.5	***						
Land-use Mix	**−0.031**	-4.3	***	**−0.031**	−4.3	***						
Street Design (Beta Index)	**−0.057**	−1.1		**−0.074**	−1.4							
Dist. to Closest Transit Stop	**0.033**	5.8	***	**0.034**	6	***						
Dist. to Downtown	**0.051**	9.7	***	**0.05**	9.3	***						
Prox. to Closest Subcenter	**−0.002**	−1.0		**−0.002**	−0.9							
Compactness Index (H&E)							**−0.527**	−23.4	***	**−0.539**	−23.5	***
Household Level (Level 1)												
Age1 (Under 20)	**0.067**	3.9	***	**0.065**	3.7	***	**0.065**	3.8	***	**0.063**	3.6	***
Age2 (21 ~ 30)	**0.09**	5.6	***	**0.087**	5.3	***	**0.089**	5.5	***	**0.086**	5.3	***
Age3 (31 ~ 40)	**0.012**	0.9		**0.012**	0.9		**0.012**	0.9		**0.012**	0.9	
Age5 (51 ~ 64)	**0.111**	11.2	***	**0.113**	11.3	***	**0.111**	11.3	***	**0.114**	11.4	***
Age6 (larger than 65)	**−0.014**	−1.2		**−0.015**	−1.3		**−0.014**	−1.2		**−0.015**	−1.3	
Race1 (White)	**0.028**	2.1	**	**0.026**	1.9	*	**0.037**	2.7	***	**0.034**	2.5	**
Race2 (African American)	**−0.035**	−1.9	*	**−0.040**	−2.1	**	**−0.037**	−2.0	**	**−0.042**	−2.2	**
Race3 (Asian)	**−0.074**	−3.4	***	**−0.076**	−3.5	***	**−0.066**	−3.0	***	**−0.068**	−3.1	***
Edu1 (Under High School)	**−0.061**	−3.1	***	**−0.061**	−3.0	***	**−0.067**	−3.4	***	**−0.067**	−3.3	***
Edu2 (High School Graduate)	**−0.013**	−1.2		**−0.016**	−1.4		**−0.013**	−1.2		**−0.016**	−1.4	
Edu4 (Bachelor's degree)	**−0.006**	−0.6		**−0.007**	−0.7		**−0.007**	−0.7		**−0.008**	−0.8	
Edu5 (Graduate)	**−0.007**	−0.7		**−0.009**	−0.8		**−0.013**	−1.2		**−0.014**	−1.3	
Income1 (Under $20,000)	**−0.307**	−17.8	***	**−0.305**	−17.5	***	**−0.314**	−18.2	***	**−0.313**	−17.9	***
Income2 ($20,000 ~$35,000)	**−0.149**	−10.1	***	**−0.146**	-9.8	***	**−0.148**	−10.1	***	**−0.145**	−9.7	***
Income4 ($55,000 ~$80,000)	**0.126**	11	***	**0.125**	10.8	***	**0.127**	11.1	***	**0.126**	10.9	***
Income5 ($80,000~)	**0.237**	21.6	***	**0.238**	21.5	***	**0.238**	21.6	***	**0.238**	21.5	***
Household Size	**0.487**	54.1	***	**0.487**	53.6	***	**0.489**	54.4	***	**0.489**	53.8	***
# Worker	**0.338**	33.2	***	**0.336**	32.7	***	**0.338**	33.2	***	**0.337**	32.7	***
Random Effect	**V.C.**			**V.C.**			**V.C.**			**V.C.**		
Int. level 3 (UA)	**0.003**	0.051		**0.003**	0.057		**0.003**	0.055		**0.003**	0.059	
Int. level 2 (census tract)	**0.009**	0.096		**0.009**	0.097		**0.01**	0.1		**0.01**	0.101	
Int. level 1 (household)	**0.435**	0.659		**0.436**	0.66		**0.435**	0.659		**0.436**	0.66	
Sum (level 1+2+3)	**0.446**			**0.448**			**0.448**			**0.449**		
Pseudo R-Sq (level 3)	**70.10%**			**62.60%**			**65.40%**			**60.50%**		
Pseudo R-Sq (level 2)	**88.60%**			**88.50%**			**87.60%**			**87.50%**		
Pseudo R-Sq (level 1)	**49.80%**			**49.70%**			**49.70%**			**49.60%**		

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:

1) Model 3.1-3.4 are adopted by 3-level random intercept model with different independent variables.
2) Dependent and all continuous independent variables except distance to the closest subcenter are in natural logarithm, so estimated coefficients can be interpreted as elasticities.
3) Reference categories for dummy variables are as follows: Age4 (household head age 41~50); Race4 (all other races); Education3 (some college or associate's degree); Household annual income3 ($35,000~$55,000).

Table D.2. VMT elasticities with various interaction terms (Model 3.5-3.6).

	Model 3.5			Model 3.6		
	Beta	t-value		Beta	t-value	
Fixed Effect						
Intercept	**9.171**	444.30	***	**9.181**	446.50	***
Urbanized Area Level (Level 3)						
Population Weighted Density (P.W.D.)	**−0.099**	−3.50	***	**−0.123**	−4.40	***
Jobs-to-housing ratio (10 mile Buffer)	**−0.242**	−2.03	**	**−0.227**	−1.98	**
Transit Service Supply (VRM / pop)	**−0.088**	−2.10	**	**−0.097**	−2.30	**
Total Lane Miles (TLM / pop)	**−0.008**	−0.60		**−0.013**	−0.80	
Census Tract Level (Level 2)						
Compactness Index	**−0.499**	−22.20	***			
Population Density (Tract Level)				**−0.047**	−8.50	***
Land-use Mix (Entropy Index)				**−0.037**	−5.10	***
Street Design (Beta Index)				**−0.074**	−1.40	
Distance to the Closest Transit Stop				**0.026**	4.50	***
Distance to Downtown				**0.055**	10.50	***
Proximity to the Closest Subcenter				**−0.002**	−1.00	
Interaction Effect(Level 3 × Level2)						
[UA] P.W.D. × [CT] Compactness Index	**−0.251**	−10.30	***			
[UA] P.W.D. × [CT] Pop. Density				**−0.029**	−4.00	***
[UA] P.W.D. × [CT] Land-use Mix				**0.008**	0.70	
[UA] P.W.D. × [CT] Street Design				**0.006**	0.10	
[UA] P.W.D. × [CT] Dist. to Transit Stop				**0.016**	2.00	**
[UA] P.W.D. × [CT] Dist. to Downtown				**0.036**	4.80	***
[UA] P.W.D. × [CT] Prox. to Subcenter				**−0.005**	−1.70	*
Household Level (Level 1)						
<Skip>						
Random Effect	**V.C.**			**V.C.**		
Int. level 3 (UA)	0.003	0.056		0.003	0.052	
Int. level 2 (Census Tract)	0.008	0.089		0.007	0.082	
Int. level 1 (individual Household)	0.435	0.660		0.435	0.660	
Sum (level 1+2+3)	0.447			0.445		
Pseudo R-Sq (level 3)	63.59%			68.64%		
Pseudo R-Sq (level 2)	90.17%			91.68%		
Pseudo R-Sq (level 1)	49.67%			49.68%		

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:
1) Model 3.5-3.6 are adopted by 3-level random coefficient model with interaction terms (random coefficients) between level 3 (UA level) and level 2 (census tract level).
2) Dependent and all continuous independent variables except distance to the closest subcenter are in natural logarithm, so estimated coefficients can be interpreted as elasticities.
3) Individual household level results are not described because of the limit of the space, but they are same with Model 3.1 in Table D.1 and the results are similar with the outputs of Model 3.1 to Model 3.4.
4) All interacted variables are used after centering for the ease of interpretation.

Table D.3. VMT elasticities with various interaction terms (Model 3.7-3.9).

	Model 3.7			Model 3.8			Model 3.9		
	Beta	t-value		Beta	t-value		Beta	t-value	
Fixed Effect									
Intercept	**9.36**	54.2	***	**9.367**	54.07	***	**9.339**	53.73	***
Urbanized Area Level (Level 3)									
Population Density (UA Level)	**−0.044**	−2.51	**	**−0.076**	−2.74	***	**−0.085**	−1.84	*
Centrality Index	**−0.041**	−2.26	**	**−0.039**	−2.18	**	**−0.034**	−1.87	*
Jobs-to-housing ratio (10 mile Buffer)	**−0.232**	−2.49	**	**−0.149**	−1.80	*	**−0.195**	−2.22	**
Transit Service Supply (VRM / pop)	**−0.024**	−1.63		**−0.041**	−2.82	***	**−0.035**	−2.44	**
Total Lane Miles (TLM / pop)	**−0.016**	−0.30		**−0.056**	−1.02		**−0.053**	−0.99	
Census Tract Level (Level 2)									
Compactness Index (H&E)	**−0.504**	−21.01	***						
Population Density (Tract Level)				**−0.055**	−9.89	***	**−0.047**	−8.31	***
Land-use Mix (Entropy Index)				**−0.034**	−4.64	***	**−0.035**	−4.82	***
Street Design (Beta Index)				**−0.076**	−1.37		**−0.072**	−1.31	
Distance to the Closest Transit Stop				**0.033**	5.6	***	**0.028**	4.83	***
Distance to Downtown				**0.053**	9.91	***	**0.054**	9.85	***
Proximity to the Closest Subcenter				**−0.002**	−2.00	**	**−0.002**	−1.33	
Interaction Effect (Level 2 × Level3)									
[UA] Pop. Density × [CT] Compactness Index	**−0.307**	−6.72	***						
[UA] Pop. Density × [CT] Pop. Density				**−0.029**	−2.38	**	**−0.015**	−1.25	
[UA] Pop. Density × [CT] Land-use Mix				**0.007**	0.4		**0**	0.02	
[UA] Pop. Density × [CT] Street Design				**−0.021**	−0.17		**−0.046**	−0.37	
[UA] Pop. Density × [CT] Dist. Transit Terminal				**0.021**	1.58		**0.016**	1.14	
[UA] Pop. Density × [CT] Dist. to Downtown				**0.051**	4.12	***	**0.05**	4.1	***
[UA] Pop. Density × [CT] Dist. to Subcenter				**−0.008**	−2.03	**	**−0.007**	−1.73	*
[UA] Centrality × [CT] Compactness Index	**−0.478**	−5.54	***						
[UA] Centrality × [CT] Pop. Density							**−0.068**	−3.00	***
[UA] Centrality × [CT] Land-use Mix							**0.092**	2.89	***
[UA] Centrality × [CT] Street Design							**0.042**	0.18	
[UA] Centrality × [CT] Dist. to Transit Stop							**0.075**	3.11	***
[UA] Centrality × [CT] Dist. to Downtown							**0.053**	2.82	***
[UA] Centrality × [CT] Prox. to Subcenter							**0.002**	0.26	
Household Level (Level 1)									
<Skip>									
Random Effect	**V.C.**			**V.C.**			**V.C.**		
Pseudo R-Sq (level 3)	**58.24%**			**58.95%**			**63.77%**		
Pseudo R-Sq (level 2)	**89.30%**			**90.02%**			**91.08%**		
Pseudo R-Sq (level 1)	**49.62%**			**49.62%**			**49.61%**		

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:

1) Model 3.7-3.9 are adopted by 3-level random coefficient model with interaction terms (random coefficients) between level 3 (UA level) and level 2 (census tract level).
2) Dependent and all continuous independent variables except distance to the closest subcenter are in natural logarithm, so estimated coefficients can be interpreted as elasticities.
3) Individual household level results are not described because of the limit of the space, but they are same with Model 3.1 in Table D.1 and the results are similar with the outputs of Model 3.1 to Model 3.4.
4) All interacted variables are used after centering for the ease of interpretation.

APPENDIX E

FULL MODEL RESULTS OF CO_2 ELASTICITIES (CHAPTER 3)

Table E.1. CO_2 elasticities (Model 3.10-3.11).

	Model 3.10		Model 3.11	
	Beta	**t-value**	**Beta**	**t-value**
Fixed Effect				
Intercept	**9.032**	349.20***	**9.077**	366.00***
Urbanized Area Level (Level 3)				
Population Weighted Density (P.W.D.)	**−0.126**	−2.80***	**−0.152**	−3.80***
Centrality Index				
Jobs-to-housing ratio (10 mile Buffer)	**−0.369**	−1.60	**−0.362**	−1.80*
Transit Service Supply (VRM / pop)	**−0.168**	−2.50**	**−0.133**	−2.20**
Total Miles (TLM / pop)	**−0.052**	−2.10**	**−0.054**	−2.50**
Census Tract Level (Level 2)				
Neighborhood Compactness Index (H&E)	**−0.935**	−33.10***	**−0.778**	−28.20***
Interaction Effect (Level 2 × Level3)				
[UA] P.W.D. × [CT] Compactness Index			**−0.751**	−26.70***
Household Level (Level 1)				
Age1 (**Under 20**)	**0.042**	2.10**	**0.045**	2.30**
Age2 (**21 ~ 30**)	**0.068**	3.60***	**0.064**	3.40***
Age3 (**31 ~ 40**)	**−0.003**	−0.20	**0.001**	0.10
Age5 (**51 ~ 64**)	**0.151**	13.30***	**0.150**	13.30***
Age6 (**larger than 65**)	**0.055**	4.10***	**0.049**	3.70***
Race1 (**White**)	**0.098**	6.40***	**0.084**	5.50***
Race2 (**African American**)	**−0.091**	−4.30***	**−0.093**	−4.50***
Race3 (**Asian**)	**−0.062**	−2.40**	**−0.071**	−2.80***
Edu1 (**Less then High School Graduate**)	**−0.190**	−8.50***	**−0.194**	−8.80***
Edu2 (**High School Graduate**)	**−0.001**	0.00	**−0.002**	−0.10
Edu4 (**Bachelor's degree** (BA, AB, BS))	**−0.021**	−1.90*	**−0.022**	−1.90*
Edu5 (**Graduate or Professional Degree**)	**−0.041**	−3.20***	**−0.044**	−3.50***
Income1 (**Under $20,000**)	**−0.623**	−32.50***	**−0.630**	−33.20***
Income2 (**$20,000 ~$35,000**)	**−0.207**	−12.20***	**−0.215**	−12.80***
Income4 (**$55,000 ~$80,000**)	**0.134**	10.00***	**0.135**	10.20***
Income5 (**higher than $80,000**)	**0.267**	20.80***	**0.268**	21.10***
Household Size (**# members**)	**0.574**	55.40***	**0.572**	55.70***
# Worker	**0.337**	28.40***	**0.338**	28.70***
Random Effect	**V.C.**		**V.C.**	
Int. level 3 (UA)	**0.010**	0.101	**0.007**	0.086
Int. level 2 (Census Tract)	**0.054**	0.232	**0.036**	0.190
Int. level 1 (individual Household)	**0.570**	0.755	**0.573**	0.757
Sum (level 1+ 2+3)	**0.634**		**0.616**	
Pseudo R-Sq (level 3)	**63.36%**		**73.49%**	
Pseudo R-Sq (level 2)	**82.03%**		**87.90%**	
Pseudo R-Sq (level 1)	**53.52%**		**53.31%**	

***: significant at 1%, **: significant at 5%, *: significant at 10%

Note:

1) Model 3.10 is adopted by random intercept model, while Model 3.11 is adopted by random coefficient model.
2) Dependent and all continuous independent variables except distance to the closest subcenter are in natural logarithm, so estimated coefficients can be interpreted as elasticities.
3) Reference categories for dummy variables are as follows: Age4 (household head age 41~50); Race4 (all other races); Education3 (some college or associate's degree); Household annual income3 ($35,000~$55,000).

APPENDIX F
MODEL SPECIFICATION (CHAPTER 4)

OLS Analysis

As a preliminary test, OLS analysis is applied before more sophisticated regression models. The dependent variable is the monthly VMT per capita and the key independent variable is the urban form such as population density or the compactness index. Other factors affecting the monthly VMT are also included as control variables (equation 1). Gasoline prices change dramatically with time for the study period and I will analyze how the impacts of urban form on VMT change with gasoline prices. Thus, the sample will be divided by 120 months, and the same regression model will be repeatedly run with each period sample. The purpose of the analysis is to compare the elasticity of the VMT w.r.t. density (β_1) with the changes in gasoline price level. If the absolute values of the density coefficient (β_1) and gasoline prices move in the same direction over time, it validates my hypothesis of the complementarity between pricing and density.

OLS Model Specification:

$$\ln VMT = \beta_1 \cdot \ln DEN + \beta_2 \cdot \ln FWLYph + \beta_3 \cdot \ln VRMpt + \beta_4 \cdot \ln EMP + \beta_5 \cdot \ln POP + \varepsilon \quad (1)$$

where the *DEN* variable is designated as 1) traditional population density at the UA level, 2) UA population-weighted density, or 3) the compactness index; all dependent and independent variables are in the natural logarithm form, thus all coefficients can be interpreted as a point elasticity. The sample size is 115 for all periods.

Panel Analysis

The second empirical model is a panel analysis with interaction terms between the gasoline price and land use variables to statistically test the presence of complementary or potential synergic effects (see equations 2 & 3). Multiplicative interaction models are popular in testing a conditional hypothesis, which typically assumes that X affects Y depending on the condition of Z (Brambor, Clark & Golder, 2006; Friedrich, 1982; Wright, 1976). A negative coefficient of the interaction term in this analysis will corroborate the main research hypothesis – an increase in gasoline prices has a greater stimulating effect on reducing the VMT in urban areas that have more transit-friendly land uses and policies such as transit oriented development (TOD) in comparison to sprawling areas that are less transit friendly. To ease in interpretation, all interacting variables are centered by subtracting the mean values. The centered coefficients explain the change in the response variable by one unit change of each explanatory variable when the other interacting variable is at the average level. Additionally, dependent and interacting variables are converted to the log transformations in order to focus on the per capita VMT elasticity and compare the results to previous studies.

This research analyzes a unique panel data set covering 115 UAs for 120 time periods, which produces more generalizable findings than in previous cross-sectional or time-series studies. As mentioned above, ordinary least squares (OLS) regression models would produce biased and inconsistent estimates of key coefficients since monthly VMT per capita is affected by both time- and space-variant elements. The gasoline price is a time variant variable, but the price changing patterns are relatively similar among the UAs. Instead, population density and urban compactness tend to ratchet down for 10 years, but the UA densities are substantially different. Thus, the range of density variations among the UAs is far larger than that of the time-series variations. To cover both the cross-section and time-series effects, panel analysis is applied in this research.

In general, a one-way fixed effects model that controls for unobserved area-specific but time-invariant effects could best fit this analysis. However, it is possible that the UA fixed effects might swamp the effects of other UA-specific land use variables because these key variables do not vary much over a short time span. Therefore, both fixed effects and random effect models are employed, leading to more robust results. All regression models are estimated with heteroskedasticity consistent standard errors. Finally, including time trend and month dummy variables, controls for time and seasonal effects are in place. To choose the best model, an incremental F-test, Breusch-Pagan test, and Hausman test (Breusch & Pagan, 1980; Hausman, 1978) are conducted.

Fixed Effect Model: $Y_{it} = \sum_k \beta_k \cdot X_{itk} + \sum_i \beta_i \cdot D_i + \alpha + \varepsilon_{it}$ (2)

where Y_{it} is the monthly per capita VMT for the i-th urbanized area at t-th time; X_{itk} is the k-th independent variable such as real gasoline price, population densities, population size, freeway lane miles, transit service supply, unemployment rate, post-peak or monthly dummy, with interaction terms between gasoline price and urban form variables; D_i denotes 114 dummies for all UAs except the one reference UA, Yongstown, OH; β_k and β_i are the coefficient of independent and dummy variables, respectively; α is the intercept of the model; ε_{it} is random error. All dependent and independent variables are the natural logarithm form, so all coefficients can be interpreted as point elasticity.

Random Effect Model: $Y_{it} = \sum_k \beta_k X_{kit} + \beta_{0i} + \varepsilon_{it},$

$$\beta_{0i} = \beta_i + \nu_i,$$

$$\therefore Y_{it} = \sum_k \beta_k X_{kit} + \beta_i + \varepsilon_{it} + \nu_i, \quad (3)$$

where Y_{it} and X_{kit} are the major dependent and independent variables, same as with the Fixed model; intercept β_{0i} is a random outcome variable among the 114 UAs, and it is composed of a mean value β_i and random error ν_i; random error ν_i indicates the deviation from the constant of the 114 UAs (heterogeneity among 114 UAs); random error ε_{it} is specific to observations for general independent variables (X_{kit}). To estimate variance components, Wallace and Hussain's method is applied (Wallace & Hussain, 1969). As with the fixed model, all coefficients can be interpreted as point elasticity.

P-LOESS Analysis

The third approach to testing the interaction effects relies on a locally weighted regression covering fixed panel model (P-LOESS). Although the panel analysis with an interaction term can test the complementary effects with statistical inference, it inevitably assumes a linear relationship. However, the extent of synergistic effects can be larger (or smaller) under very high gasoline prices or in high density cities. The P-LOESS does not impose a linear relationship to capture the potential variation in the interaction effects.

The conventional locally weighted model (LOESS) analysis is a popular technique for fitting a regression model to data through multivariate smoothing (Cleveland, 1979; Cleveland & Devlin, 1988). At each data point, a regression model is fit to a subset of the data, which is composed of observations near the data point being estimated. P-LOESS follows the concept of the original LOESS but it covers a fixed panel model. The fixed panel model is fitted to only one third of the sample that is similar in gasoline price level with the estimation points and more weights are given to closer data points in the dimension of the gas price. A 20% window size and the bi-square weight function are used. The estimation results of both the panel with interaction terms and the LOESS are compared. The specific model is as follows (equations 4 through 7):

$$y_i = \sum_k X_{ik}\beta_{ik} + \varepsilon_i \tag{4}$$

$$\hat{\beta} = [X'W(i)X]^{-1} X'W(i)Y \tag{5}$$

$$\hat{\sigma}_{si}^2 = X'[XW(i)X]^{-1} X'W(i)X[X'W(i)X]^{-1} X\sigma_s^2(i) \tag{6}$$

$$W_j(i) = \begin{cases} (1-(d_{ij}^2/q(i))^2)^2, & if \;\; d_i \le d(i), i = 1,2,3, \dots , n, \\ 0, & if \;\; d_i > d(i) \end{cases} \tag{7}$$

where the varying parameters at a target data point, I, are estimated by a weighted regression as in equation 4. W(*i*) is the weighting matrix for regression point, I, of which the diagonal elements are the weights given to n observations, $W_j(i)$; the off-diagonal elements are zero.

APPENDIX G
MEASURES OF DEPENDENT AND INDEPENDENT VARIABLES (CHAPTER 4)

Geographic Area with Time Trend and Data Source

The spatial scopes in this research are the 115 largest UAs in the U.S. with more than 250,000 residents, based on U.S. Census 2000 data. In the continental U.S., there are 125 urbanized areas as of 2000, but 10 UAs are excluded from the sample in this research mainly due to missing values. New Orleans, LA is excluded to remove the Hurricane Katrina impacts. Although the metropolitan area defined by economic activity can be considered for this study, it contains large areas in which no people live, such as the desert. Thereby, the areas can cause biased results. The term *urbanized area* is defined as densely settled core and surrounding census blocks that meet minimum population density. In other words, the boundary is based on number of residents rather than economic performance such that the urbanized area is suitable. This study covers 120 time periods for the monthly data from January 2002 through December 2011.

There are seven data sources used for this study - Highway Performance Monitoring System (HPMS, 2002-2011), Oil and Gas Journal (OGJ, 2002-2011), CENSUS (2000, 2010), Longitudinal Employer-Household Dynamics (LODES, 2002-2011), National Transit Database (NTD, 2002-2011), Bureau of Labor Statistics (BLS, 2002-2011), and Compactness index from Ewing & Hamidi (2014). HPMS provides annual vehicle miles traveled (VMT) with population information at the urbanized area level. Additionally, Federal Highway Administration (FWHA) delivers monthly traffic volume trends using HPMS sources at the State level. Therefore, monthly vehicle miles traveled per capita is accounted for by multiplying both terms.

To determine the fuel price, the real gasoline price is adopted as reflected on regional living cost level to exclude the effect of regional living cost level on fuel prices. Information from the OGJ is used for the nominal gasoline price. The OGJ gathers a sample of gasoline stations at the city level at weekly intervals (OGJ, 2009). Consumption price index (CPI) and living cost index (CLI) come from the BLS. Various land use variables are considered in the research: population density, population-weighted density, centrality index, polycentricity index, compactness index, and population size. To find the complementary effect, interaction terms are also considered. All land use variables and the gasoline price variable are interacted and they are used after centering for ready interpretation. Freeway lane miles, transit service supply, the unemployment rate, gasoline price peak dummy and monthly dummies are used as control variables. Summaries of dependent and explanatory variables are given in Table G.1.

Table G.1. Descriptions of variables in the analyses.

Variable	Description	Major Source
Dependent variable		
Monthly vehicle mile traveled [lnVMT]	■ Natural logarithm of monthly vehicle mile traveled (VMT) per capita.	HPMS (2002-11)
Key Independent variable 1: Gas Price		
Real gasoline price [clnGAS83]	■ Centered logarithmic term of monthly real gasoline price. Real gasoline price (1983 real $) = PR / (CPI × CLI). • PR: monthly gasoline price for each time and urban area • CPI: consumer price index (CPI,1983=1) for each time and urban area • CLI: cost of living index among UAs (Rochester, NY=1) for each time and urban area.	OGJ (2002-11) & BLS (2002-11)
Key Independent variable 2: Urban Form Variables		
Population density [clnPDEN]	■ Centered logarithmic term of monthly urbanized area pop density for each time and urban area. • Population density = urbanized area pop. / sq. mile.	HPMS (2002-11)
Population-weighted density [clnPWDEN]	■ Centered logarithmic term of monthly UA population-weighted density (PWD). PWD is estimated as the weighted mean of census tract level density with each block group's population.	CENSUS (2000, 10)
Centrality index [clnCEN]	■ Natural logarithm of centrality index.	LODES (2002-11)
Polycentricity index [clnPOL]	■ Natural logarithm of polycentricity index.	LODES (2002-11)
Compactness Index [clnSPW]	■ Natural logarithm of sprawl index at the UA level. The index comes from Hamidi & Ewing (2014).	Hamidi & Ewing, 2014
Population size [lnPOP]	■ Natural logarithm of UA population size.	CENSUS
Interaction Terms (Gas Price × Urban Form Variables)		
Pop. density interaction [ilnPDEN]	■ Interaction gasoline price and population density. = **[clnGAS83] × [clnPDEN]**	
PWD interaction [ilnPWDEN]	■ Interaction gasoline price and population-weighted density. = **[clnGAS83] × [clnPWDEN]**	
Centrality interaction [ilnCEN]	■ Interaction gasoline price and centrality index. = **[clnGAS83] × [clnCEN]**	
Polycentricity interaction [ilnPOL]	■ Interaction gasoline price and polycentricity index. = **[clnGAS83] × [clnPOL]**	
Compactness index interaction [ilnSPW]	■ Interaction gasoline price and compactness index. = **[clnGAS83] × [clnSPW]**	
Control variables		
Freeway lane miles [lnFWYLph]	■ Natural logarithm of freeway lane miles per 100 people.	FHWA (2002-11)
Transit service supply [lnVRMpt]	■ Natural logarithm of vehicle revenue miles (VRM) per 100 people; VRM is defined as the miles that vehicles travel (public transit) while in revenue service.	NTD (2002-11)
Employment Rate [lnEMP]	■ Natural logarithm of monthly employment divided by working age non-industrialized population (UA level).	BLS (2002-2011)
Trend [lnTREND]	■ Natural logarithm of Trend. Trend is defined as follows: Jan 2002 = 1, Feb 2002 = 2, … , Dec 2011 = 120	
Postpeak dummy [POSTPEAK]	■ Dummy variable showing whether each month is before or after the gasoline price peak (June 2008).	
Month dummies	■ 11 dummy variables for each month except May (Reference Month).	

Table G.2. Descriptive statistics of key variables in 115 UAs.

Variable		Unit	Mean	Median	S.D.	Max	Min
Monthly VMT	[VMT]	(mile/person)	769	751	189	136	1,833
Nominal gas price	[GAS]	(cent/gallon)	213	214	75	65	446
Real gasoline price	[GAS83]	(1983 real cent/gallon)	104	103	31	37	203
Real gasoline price (living cost of UAs) Ref. Rochester, NY	[GAS83cl]	(1983 real cent/gallon)	92	90	30	22	200
Population density	[PDEN]	(pop./sqmile)	2,531	2,267	1,010	1,196	7,073
Pop-w.g.t. density	[PWDEN]	Σ[(pop.wgt)×(pop./sqm)]	4,435	3,910	3,251	1,591	33,249
Centrality index	[CEN]		100	94	24	59	191
Polycentricity index	[POL]		100	103	23	34	155
Sprawl index	[SPW]		99	96	23	37	184
Freeway lane miles	[FWYLph]	(FWYL/ 100 people)	0	0	0	0	0
Transit service supply	[VRMpt]	(VRM / 100 people)	1,012	880	723	0	6,673
Employment rate	[EMP]	(emp./total working age)	62.69	62.61	4.93	45.02	78.67

APPENDIX H
CLUSTER ANALYSIS (CHAPTER 4)

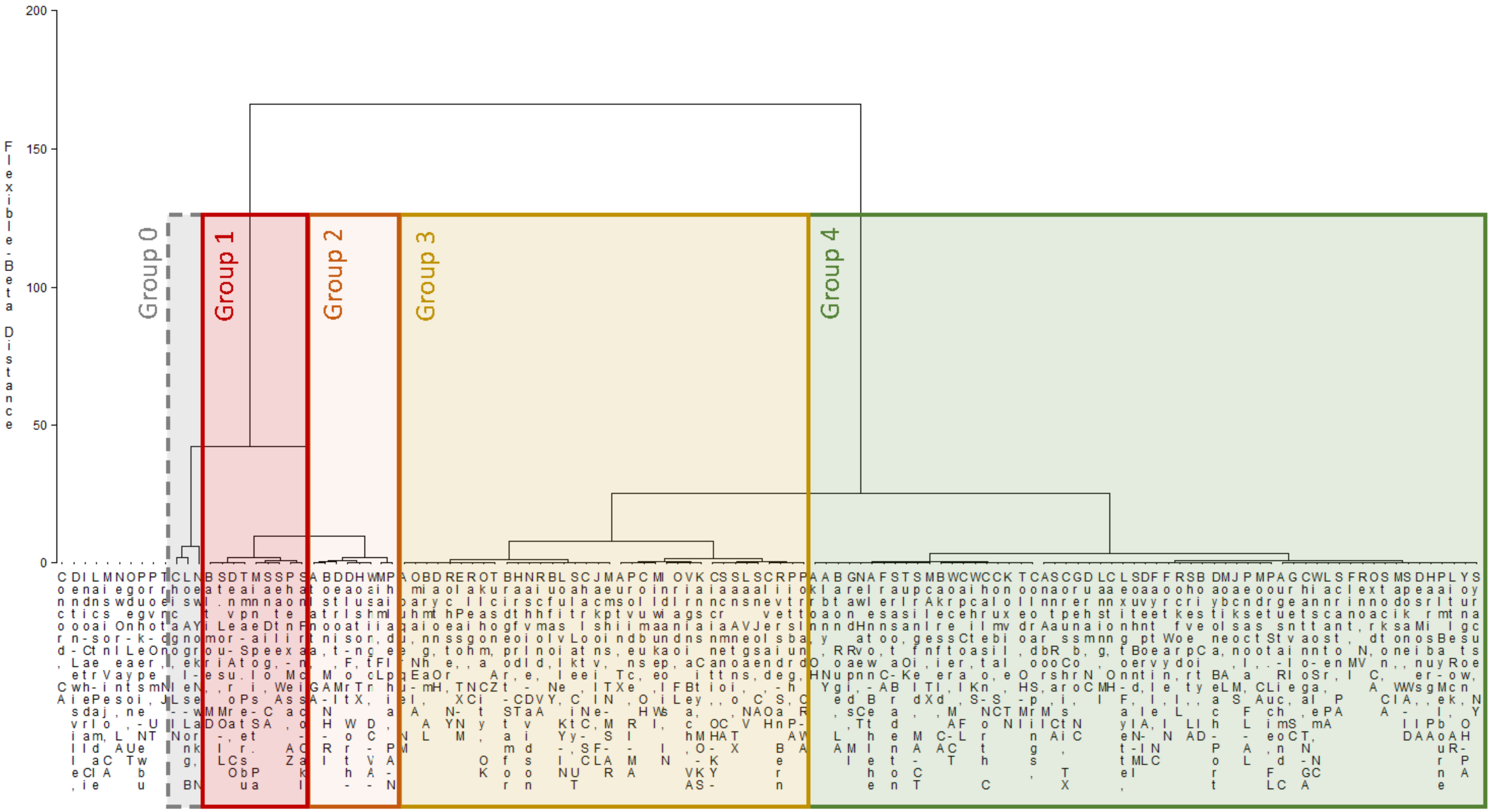


Figure H.1. The output of cluster analysis.

APPENDIX I

DESCRIPTIVE COMPARATIVE ANALYSIS RESULTS (CHAPTER 4)

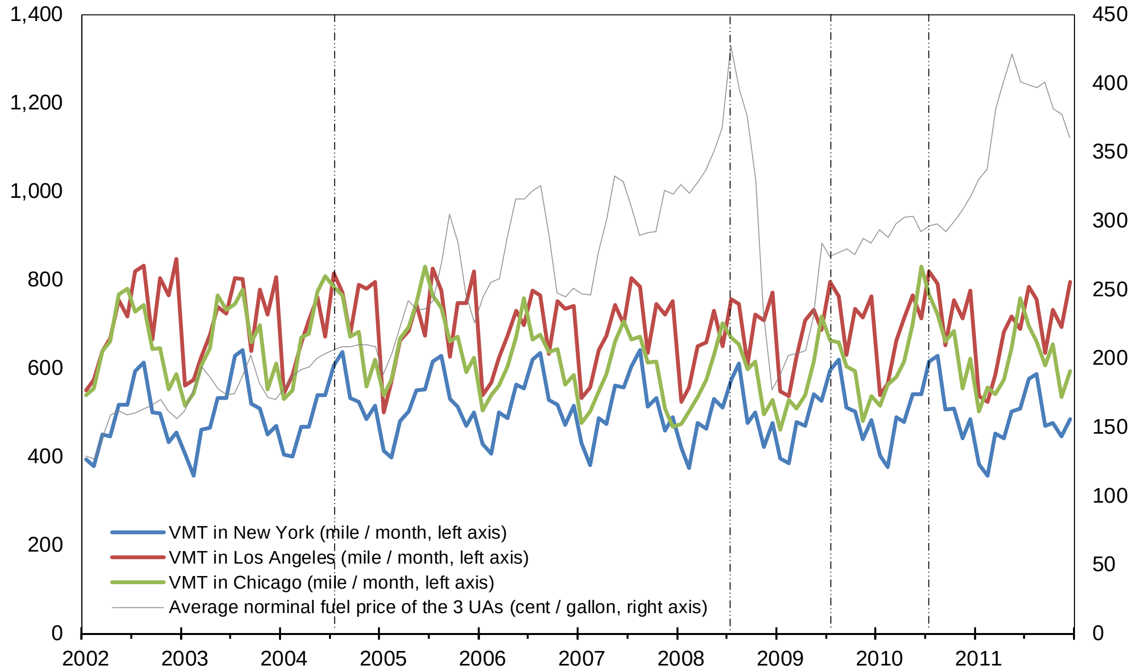


Figure I.1. The monthly per capita VMTs in New York, Los Angeles, and Chicago, and their monthly fuel prices (right axis, cent per gallon).

APPENDIX J
FULL MODEL RESULTS OF VMT ELASTICITIES (CHAPTER 4)

Table J.1. Analysis of monthly per capita VMT between urban form and gasoline price (fixed effects panel models).

Dep. Variable	**Model 4.1F**				**Model 4.2F**				**Model 4.3F**			
Monthly per capita VMT	**Std. Coef.**	**Coef.**	**t-value**		**Std. Coef.**	**Coef.**	**t-value**		**Std. Coef.**	**Coef.**	**t-value**	
Real gasoline price	−0.066	**−0.046**	−2.67	***	−0.093	**−0.065**	−3.58	***	−0.096	**−0.067**	−3.75	***
Population-weighted density	−0.440	**−0.222**	−4.96	***								
× gasoline price	−0.045	**−0.003**	−1.72	*								
Population density					−0.371	**−0.245**	−5.60	***				
× gasoline price					−0.112	**−0.009**	−1.33					
Population centrality					−0.189	**−0.207**	−6.71	***				
× gasoline price					0.290	**0.038**	4.35	***				
Polycentricity					0.015	**0.013**	0.95					
× gasoline price					−0.183	**−0.024**	−2.59	***				
Sprawl index									−0.300	**−0.288**	−6.09	***
× gasoline price									−0.049	**−0.006**	−1.86	*
Population size	0.308	**0.079**	2.42	**	0.408	**0.105**	−5.60	***	−0.091	**−0.023**	−0.69	
Freeway lane miles	0.284	**0.165**	23.15	***	0.293	**0.17**	−1.33		0.278	**0.161**	22.39	***
Transit service supply	−0.004	**−0.001**	−0.20		−0.015	**−0.004**	−6.71	***	0.002	**0.001**	0.12	
Employment rate	0.033	**0.022**	3.63	***	0.027	**0.018**	−1.61		0.032	**0.021**	3.43	***
Trend	0.104	**0.026**	11.14	***	0.106	**0.027**	0.95		0.113	**0.029**	12.01	***
Post-peak dummy	−0.061	**−0.030**	−6.62	***	−0.060	**−0.030**	−2.59	***	−0.050	**−0.025**	−5.47	***
Monthly dummies												
January	−0.240	**−0.206**	2.42	**	−0.240	**−0.206**	−42.81	***	−0.231	**−0.199**	−39.99	***
February	−0.282	**−0.242**	23.15	***	−0.282	**−0.242**	−50.42	***	−0.280	**−0.240**	−48.53	***
March	−0.086	**−0.074**	−0.20		−0.086	**−0.074**	−15.60	***	−0.083	**−0.072**	−14.59	***
April	−0.071	**−0.061**	3.63	***	−0.071	**−0.061**	−12.95	***	−0.070	**−0.060**	−12.30	***
June	−0.005	**−0.004**	11.14	***	−0.005	**−0.004**	−0.86		−0.005	**−0.004**	−0.92	
July	0.077	**0.066**	−6.62	***	0.078	**0.066**	14.04	***	0.075	**0.064**	13.14	***
August	0.041	**0.035**	−42.60	***	0.041	**0.035**	7.48	***	0.038	**0.033**	6.68	***
September	−0.083	**−0.071**	−50.19	***	−0.083	**−0.071**	−15.06	***	−0.087	**−0.075**	−15.25	***
October	−0.030	**−0.026**	−15.53	***	−0.030	**−0.026**	−5.46	***	−0.029	**−0.025**	−5.08	***
November	−0.113	**−0.097**	−12.89	***	−0.114	**−0.098**	−20.32	***	−0.112	**−0.096**	−19.44	***
December	−0.118	**−0.101**	−0.91		−0.119	**−0.102**	−20.95	***	−0.116	**−0.100**	−19.83	***
UA dummies					< Skip >							
Constant		**7.792**	16.76	***		**8.854**	17.49	***		**8.761**	16.34	***
R-square	0.775				0.777				0.776			
F-test	128.24***				123.62***				141.23***			
Breush-Pagan Test	200,493***				187,849***				201,103***			

***: significant at 1%, **: significant at 5%, *: significant at 10%.

Note:

1) 'Std. Coef.' indicates the coefficient of standardized regression for each independent variable, so we can compare the relative impacts of different independent variables on monthly per capita VMT.
2) Dependent and all continuous independent variables are in natural logarithm, so estimated coefficients (Coef.) can be interpreted as elasticities. The elasticity is defined as the ratio of the percent change in dependent variable to the percent change in each independent variable.

Table J.2. Analysis of monthly per capita VMT between urban form and gasoline price (random effects panel models).

Dep. Variable	Model 4.1R				Model 4.2R				Model 4.3R			
Monthly per capita VMT	**Std. Coef.**	**Coef.**	**t-value**		**Std. Coef.**	**Coef.**	**t-value**		**Std. Coef.**	**Coef.**	**t-value**	
Real gasoline price	−0.069	**−0.048**	−2.79	***	−0.094	**−0.066**	−3.64	***	−0.098	**−0.068**	−3.82	***
Population-weighted density	−0.580	**−0.292**	−10.95	***								
× gasoline price	−0.044	**−0.003**	−1.69	*								
Population density					−0.470	**−0.310**	−9.90	***				
× gasoline price					−0.087	**−0.007**	−1.04					
Population centrality					−0.221	**−0.242**	−8.87	***				
× gasoline price					0.274	**0.036**	4.14	***				
Polycentricity					0.016	**0.014**	1.03					
× gasoline price					−0.189	**−0.025**	−2.68	***				
Compactness index									−0.367	**−0.352**	−10.23	***
× gasoline price									0.014	**0.002**	0.54	
Population size	0.325	**0.083**	5.83	***	0.292	**0.075**	5.23	***	−0.051	**−0.013**	−1.03	
Freeway lane miles	0.282	**0.164**	23.62	***	0.293	**0.17**	24.24	***	0.277	**0.161**	22.88	***
Transit service supply	−0.003	**−0.001**	−0.14		−0.020	**−0.006**	−1.05		−0.001	**0**	−0.08	
Employment rate	0.03	**0.02**	3.3	***	0.026	**0.017**	2.85	***	0.028	**0.018**	3.04	***
Trend	0.103	**0.026**	11.3	***	0.107	**0.027**	11.91	***	0.113	**0.029**	12.22	***
Post-peak dummy	−0.060	**−0.030**	−6.74	***	−0.058	**−0.029**	−6.47	***	−0.048	**−0.024**	−5.31	***
Monthly dummies												
January	−0.240	**−0.206**	−42.66	***	−0.240	**−0.206**	−42.83	***	−0.231	**−0.198**	−40.00	***
February	−0.282	**−0.242**	−50.24	***	−0.282	**−0.242**	−50.44	***	−0.280	**−0.240**	−48.54	***
March	−0.086	**−0.074**	−15.53	***	−0.086	**−0.074**	−15.59	***	−0.083	**−0.071**	−14.58	***
April	−0.071	**−0.061**	−12.91	***	−0.071	**−0.061**	−12.96	***	−0.070	**−0.060**	−12.31	***
June	−0.005	**−0.004**	−0.87		−0.005	**−0.004**	−0.87		−0.005	**−0.004**	−0.89	
July	0.078	**0.066**	14	***	0.078	**0.066**	14.04	***	0.075	**0.064**	13.16	***
August	0.041	**0.035**	7.47	***	0.041	**0.035**	7.48	***	0.038	**0.033**	6.68	***
September	−0.083	**−0.071**	−14.99	***	−0.083	**−0.071**	−15.08	***	−0.087	**−0.075**	−15.27	***
October	−0.030	**−0.026**	−5.40	***	−0.030	**−0.026**	−5.48	***	−0.029	**−0.025**	−5.11	***
November	−0.114	**−0.097**	−20.22	***	−0.114	**−0.098**	−20.34	***	−0.113	**−0.097**	−19.48	***
December	−0.118	**−0.102**	−20.83	***	−0.119	**−0.102**	−20.98	***	−0.116	**−0.100**	−19.90	***
UA dummies					< Skip >							
Constant		**8.523**	41.36	***		**10.104**	35.13	***		**9.103**	37.36	***
R-square	0.385				0.388				0.38			
Hausman Test	16.94				23.38				22.77**			
Breush-Pagan Test	203,029***				190,675***				203,631***			

***: significant at 1%, **: significant at 5%, *: significant at 10%.

Note:

1) The results are similar to Table J.1, but the results are not outputs of fixed effects model, but those of random effects model.
2) 'Std. Coef.' indicates the coefficient of standardized regression for each independent variable, so we can compare the relative impacts of different independent variables on monthly per capita VMT.
3) Dependent and all continuous independent variables are in natural logarithm, so estimated coefficients (Coef.) can be interpreted as elasticities. The elasticity is defined as the ratio of the percent change in dependent variable to the percent change in each independent variable.