

DIGITALES ARCHIV

Su, Qing

Article

Travel demand management policy instruments, urban spatial characteristics, and household greenhouse gas emissions from travel in the US urban areas

Provided in Cooperation with:

International Journal of Energy Economics and Policy (IJEPP)

Reference: Su, Qing (2017). Travel demand management policy instruments, urban spatial characteristics, and household greenhouse gas emissions from travel in the US urban areas.

This Version is available at:

<http://hdl.handle.net/11159/1227>

Kontakt/Contact

ZBW – Leibniz-Informationszentrum Wirtschaft/Leibniz Information Centre for Economics
Düsternbrooker Weg 120
24105 Kiel (Germany)
E-Mail: [rights\[at\]zbw.eu](mailto:rights[at]zbw.eu)
<https://www.zbw.eu/econis-archiv/>

Standard-Nutzungsbedingungen:

Dieses Dokument darf zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden. Sie dürfen dieses Dokument nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, aufführen, vertreiben oder anderweitig nutzen. Sofern für das Dokument eine Open-Content-Lizenz verwendet wurde, so gelten abweichend von diesen Nutzungsbedingungen die in der Lizenz gewährten Nutzungsrechte.

<https://zbw.eu/econis-archiv/termsfuse>

Terms of use:

This document may be saved and copied for your personal and scholarly purposes. You are not to copy it for public or commercial purposes, to exhibit the document in public, to perform, distribute or otherwise use the document in public. If the document is made available under a Creative Commons Licence you may exercise further usage rights as specified in the licence.



Travel Demand Management Policy Instruments, Urban Spatial Characteristics, and Household Greenhouse Gas Emissions from Travel in the US Urban Areas

Qing Su*

Department of Economics and Finance, Northern Kentucky University, BC 338, Nunn Drive, Highland Heights, KY 41099, USA.
*Email: suq1@nku.edu

ABSTRACT

This paper examines the impact of travel demand management (TDM) policy instruments and a wide variety of measures of urban spatial characteristics on CO₂ emissions from household travel based on more than 27,000 observations from the 2009 National Household Travel Survey. The regression results indicate that TDM instruments and urban spatial characteristics affect CO₂ emissions from household travel in a complicated way. Population-weighted density, rail availability, and TDM instruments such as parking management, promotion of transit use and carpool, and employer-based TDM programs have a moderate but negative impact on CO₂ emissions from household travel. On the other hand, employment and population distribution imbalance and major road network density have a moderate but positive impact on CO₂ emissions from household travel.

Keywords: Parking Management, Promotion of Transit Use and Carpool, Employer-based Travel Demand Management Program, CO₂ Emissions from Household Travel, Population-weighted Density, Employment and Population Distribution Imbalance

JEL Classifications: Q2, Q5

1. INTRODUCTION

The U.S. federal government has proposed to curb greenhouse gas (GHG) emissions by 17% below 2005 emission levels by 2020 and 26-28% by 2025 (US Department of State 2010). This climate-stabilizing target requires an annual reduction rate of 1.2% for the period of 2005-2020 and 2.3-2.8% for the period of 2020-2025. Since 2010, many policies relying on technology improvement and pricing solutions have been implemented and much progress has been made. The newly released report from the US Environmental Protection Agency on inventory of US GHG, however, suggests that the US will have to implement additional policies to reach its 2025 target. One of the areas requiring additional actions is the transportation sector. According to the US Environmental Protection Agency (2016), among the total CO₂ emissions of 5564.3 million metric tons (MMT), 31.22% (1737.4 MMT) were from transportation. The CO₂ emissions from transportation have been declining consistently and slowly from 2005 until 2012 (Table 1), after which the CO₂ emissions from transportation increased again (2.4% increase in 2014) (US EPA 2016, Table ES-2). This

increase in the emissions from transportation represents a challenge in achieving the overall goal of reducing GHG emissions, which makes it compelling to address this issue.

Transportation emissions are affected by many long-term and short-term factors including, but not limited to: Population growth, economic growth, energy prices, technology improvement, and fuel choices. Most of the existing policy measures aimed at reducing transportation emissions focus on improving fuel economy of vehicles. Although improved fuel efficiency could reduce emissions from travel, it may also induce more travel due to lower monetary cost per mile, which could partially offset the saving of energy consumption due to enhanced fuel economy of the vehicle. Additionally, it takes time to increase the overall fuel economy of a vehicle fleet considering the fact that vehicles are durable goods. Together with the fact that motor vehicle travel is derived from other economic activities, the overall trend of growing population and economy in the US makes it challenging to reduce emissions from travel without moderating travel demand from end users.

Table 1: US GHG emission 2010-2014 (MMT CO₂ equation)

Gas/source	2005	2010	2011	2012	2013	2014
CO ₂	6132.6	5698.2	5568.6	5361.0	5513.2	5564.3
Fossil fuel combustion	5747.1	5538.3	5227.7	5024.7	5157.6	5208.7
Transportation	1887.0	1728.3	1707.6	1696.8	1713.0	1737.4
CH ₄	735.4	720.8	711.8	703.8	704.0	707.9
N ₂ O	406.4	415.2	423.8	419.4	411.0	411.4
Other	154.4	176.2	183.6	181.4	182.9	189.1
Total	7428.8	7010.5	6887.8	6665.7	6811.2	6872.6

This is the simplified version of Table 2 and 1, Draft Inventory of US Greenhouse Gas Emission and Sinks 1990-2014, EPA (2016), GHG: Greenhouse gas

In view of the importance of reducing GHG emissions from transportation through moderating travel demand and fuel consumption, and building upon existing literature of determinants and management of travel demand, this paper investigates the impact of a wide variety of urban spatial characteristics and travel demand management (TDM) strategies on household GHG emissions from travel in the US urban areas.

This paper adds to the existing literature on the analysis of travel and greenhouse emissions, contributing two major improvements. First, this paper examines whether and how public policies of TDM affect GHG emissions from travel. This paper examines the impact of three TDM instruments (including programs promoting transit use and shared ride, employer-base TDM strategies, and parking management) on the GHG emissions at the household level. Second, this paper examines the impact of different dimensions of urban spatial characteristics such as population weighted density, population centrality, population dispersion, imbalance between population and employment, spatial size of urban area, city shape, median distance to city center, and transit supply and rail availability to reduce the omitted variable bias generated by using population density as a catch-all variable of urban spatial characteristics.

2. LITERATURE REVIEW

Since the 1980s, TDM has been focusing on improving the efficiency of road system. As a cost-effective alternative to build more roads, TDM applies different strategies or policy instruments to reduce auto trips and vehicle miles traveled by increasing travel options (bike, walk, rideshare, transit), encouraging alternative modes of driving alone, and providing incentives and facilities to help people modify their travel behavior in terms of mode choice (Brownstone and Golob 1991; Peng et al., 1996; Zhou et al. 2009; Su and Zhou, 2012), route choice, and time choice. Many local governments and regional agencies in the states such as California, Washington, Colorado, Maryland, Virginia, Oregon, and Massachusetts have implemented TDM programs. Contrary to its popularity in the US, there are few studies directly examining the impact of TDM instruments on GHG emissions despite the strong connection between travel and GHG emissions. It is, therefore, important for us to investigate and better understand the impact of these policy instruments on GHG emissions from travel.

On the other hand, there is a vast body of literature examining the relationship between built environment and travel behavior in terms of mode choices, travel demand, and travel pattern as

shown by the comprehensive reviews for this broad topic (Badoe and Miller, 2000; Crane, 2000; Ewing and Cervero, 2001; Handy, 2005; Cao et al., 2008). The section below highlights only those studies most relevant to this paper.

During the past 20 years, urban and transportation planners have proposed using density as a planning tool to reduce motor vehicle travel. Transportation planners believe density can be a feasible and useful planning tool to reduce vehicle miles traveled. The idea is that by modifying the design of neighborhoods aimed at increasing population density and being transit-oriented, the need or desire to use automobiles can be reduced, which in turn lowers overall travel demand. This “smart growth” movement has been observed across the country during the past 20 years (Cervero and Kockelman 1997, Chen et al., 2007). Empirical evidence on the impact of population density, however, is not consistent.

Some studies find density plays a negligible role in affecting people’s travel behavior and travel pattern (Boarnet and Crane, 2001; Boarnet and Sarmient, 1998; Mindali et al., 2004; Schimek, 1996; Miller and Ibrahim, 1998; Liu and Shen, 2011). On the other hand, some studies find a negative impact of density on the probability of using auto (Frank and Pivo, 1996; Cervero, 1994; Zhang, 2004) and fuel consumption (Newman and Kenworthy, 1989; Ewing and Cervero 2010; Su, 2011; Brownstone and Golob, 2009; Kim and Brownstone, 2013; Lee and Lee, 2014). Even among those who find that density does matter, the magnitude of the impact of density is wide-ranging from -0.04 to -0.986 (Ewing and Cervero, 2010; Cervero and Murakami, 2010; Brownstone and Golob, 2009; Kim and Brownstone, 2013; Lee and Lee, 2014).

Using aggregate city-level data, Newman and Kenworthy (1989) find a higher level of vehicle utilization is associated with lower population density. Mindali et al. (2004) apply a different method with the same dataset and find urban density does not have a statistically significant impact. Karathodorou et al. (2010) examine the same issue with a larger dataset and conclude that urban density affects total fuel consumption with a very mild magnitude. The impact of urban density, however, seems to be larger on vehicle ownership and per vehicle VMT.

Among all the studies based on individual data, Bento et al. (2005) find the impact of population density is not statistically significant. They find that urban measures such as population centrality, job-housing imbalance, road density, and rail supply have a significant but very small impact on annual household VMT. Differing from Bento et al (2005) using a national sample, Boarnet and Sarmiento (1998) and Brownstone and Gobb (2009) use a sample from the state

of California while Liu and Shen (2011) use samples in Baltimore. Boarnet and Sarmiento find that the land use variables are not jointly statistically significant as a group and rarely individually significant. Liu and Shen find that urban form does not directly affect vehicle miles traveled and energy consumption, but indirectly through other channels. Brownstone and Golob (2009) find that population density at the tract level has a very small impact on the VMT. Kim and Brownstone (2013) expand the study of Brownstone and Golob (2009) and their findings on the impact of residential density are consistent with Brownstone and Golob (2009).

Lee and Lee (2014), however, find a much larger impact of population density on household travel and GHG emissions from travel while controlling for population centrality, polycentric structure, transit subsidy, and population size, and road network. They find that GHG emissions from household travel will be reduced by 48% and 18% if population-weighted density and per capita transit subsidy double.

In addition to population density, road density is another variable that has been identified as an important factor affecting travel demand. The so-called induced travel has been tested in a variety of studies based on data at both macro and micro levels. It seems that studies based on aggregate data (Fulton et al., 2000; Hansen, 1997; Noland, 2001; Noland and Lem, 2002; Noland and Cowart, 2000; Small and Van Dender, 2007; Su, 2010; Su, 2012) find the evidence to support the view. Empirical evidence using individual data, however, is not consistent. Bento et al. find that road density does not have a statistically significant impact on VMT by households owning two or more vehicles. On the other hand, Barr (2000) and Su (2011) find that highway capacity improvements induce more travel.

3. DATA AND VARIABLES USED

The major source of the data used in this paper is the 2009 National Household Travel Survey (NHTS) conducted by the Federal Highway Administration. Measures of urban spatial characteristics are derived based on those variables used in Bento et al. (2005) and Malpezzi and Guo (2001). Supplementary data have been obtained from the Highway Statistics in 2009 published by the Federal Highway Administration.

The 2009 NHTS is used because this survey was collected during a unique period in which gasoline prices reached historically high levels and fluctuated wildly. Among all the observations from NHTS' vehicle file, only those vehicles that use gasoline are selected as the base sample. Additionally, considering the volatile fluctuation of gasoline prices in the survey period covered¹, the final sample includes only those surveyed before September 2008 when financial turmoil shocked the market. This is necessary to reduce the potential bias from inconsistency across observations from the dramatic change in economic expectation and fuel prices. This dataset enables us to observe the impact of TDM instruments and spatial characteristics on GHG emissions from household travel in a period of high fuel prices.

1 The average price at the pump for unleaded regular gasoline was \$4.09 a gallon in July, and was below \$1.70 in December 2008.

Following Glaeser and Kahn (2010) and Lee and Lee (2014), this paper uses a similar approach to estimate household GHG emissions in the 40 largest urban areas for which the geographic locations for household in the NHTS are reported and sufficient information is available to derive the variables reflecting different aspect of spatial characteristics. The following procedure has been used. First, based on the annual vehicle miles and vehicle fuel economy from the NHTS' vehicle mile, annual gasoline consumption is derived and then aggregated at the household level. Second, the annual household CO₂ emission from driving is derived by multiplying the household gas consumption by an emission factor of 23.46 lbs. per gallon used by Glaeser and Kahn (2010) and Lee and Lee (2014). The emission from travel is further adjusted by emissions from public transit. This adjustment, however, only applies to those households with at least one member using transit. The household annual emissions from public transit ride are derived as multiplying annual household transit rides (aggregated from personal files) by average passenger trip length and emission factor per passenger mile at the urbanized area level. Average passenger trip length is derived as dividing total passenger miles by unlinked passenger trips obtained from Urban Mobility Report. Following Lee and Lee, the emission factor per passenger mile at the urban area level is estimated using data on annual fuel consumption by source and mode at the transit agency level reported by National Transit Database², total passenger mile, and CO₂ emission factor reported by Energy Information Administration³.

The variables of interest are a wide variety of measures reflecting inter-area differences in TDM instruments and urban spatial characteristics. In order to single out the effect of the variables of interest, we also control for household demographic, economic characteristics, and fuel cost of travel.

3.1. Variables of Interest

3.1.1. TDM instruments

Three dummy variables are used to capture whether the local governments have the TDM instruments in place: Programs that promote transit use and carpooling, employer-based TDM strategies, and parking management.

Several instruments fall into the category of promoting transit use and carpooling: Increasing transit service routes and frequency by transit agencies, getting low-cost or free transit passes subsidized by public agencies, improving and distributing real time transit information, supporting transit use and carpooling by public agencies through park-and-ride and high-occupancy lanes. A dummy variable is used to capture those strategies that have been implemented by local governments or local public agencies.

Employer-based TDM programs include a variety of instruments implemented by employers to reduce driving alone to work, including the tools such as providing incentive, information and facilitation for employees to use alternative mode, supplementary support of additional transportation options to commute (carpool

2 <http://www.ntdprogram.gov/ntdprogram/data.htm>.

3 <http://www.eia.gov/oiaf/1605/coefficients.html> - tb12.

and vanpool match, guaranteed ride home, shower facilities for bikers and walkers), and congestion relief instruments (compressed work week, telecommuting). A dummy variable is used to capture whether such a program has been implemented.

Parking management includes many policy tools aimed at encouraging more efficient use of existing parking facilities, shifting travel to non-drive alone modes, and reducing “parking search” traffic. The instruments that fall into this category include cost-based parking price for single-occupancy vehicle and reduced pricing for ride-sharing vehicles, parking cash-out options to commuters, maximum parking space for new developments, and electronic parking guidance system. A dummy variable is used to capture those instruments that are put in place by local public agencies. The data are collected for the 40 urbanized areas included in the sample. The data sources include websites of department of transportation for the states in which the urbanized areas are located, the relevant metropolitan planning organizations, and local governments. For those areas with such policy instruments in place, although the exact implementation time is different, all those instruments have been put in place by 2000.

3.1.2. Spatial characteristics

Based on existing literature on travel demand, the important urban spatial factors identified can be categorized into four groups: The distribution of population, the distribution of employment within the area, the road network, and public transportation availability and services.

The impact of population distribution can be captured by three variables. Average population density is one of the most commonly used variables in the literature. In this paper, population-weighted density per square mile at the urbanized area is used to reflect the impact of average population distribution⁴. In addition, the variation of population density at the tract level is used as a measure of population dispersion. The third variable in this group is the measure of population centrality based on the same method used by Bento et al. (2005). A higher value of population centrality indicates a higher percentage of the population living near the CBD.

The impact of the distribution of employment can be captured by the variable measuring the level of imbalance between the employment and housing; employment and housing imbalance index borrowed directly from Bento et al. (2005). This variable is used to capture the degree of imbalance between jobs and residence. The less even distribution between jobs and residences will have a higher value of this index.

Additionally, three more variables are used to capture other characteristics that distribution of population and employment cannot reflect. Since larger areas are more likely to have more entertainment facilities, the spatial size of an area is also

included and expected to have an impact on travel demand. City shape may also affect people’s travel. As discussed by Bento et al., travel distance in a more circular city may be different compared to that in a long and narrow city. The third variable is the median distance to the center (CBD) weighted by tract population, a measure used by Malpezzi and Guo (2001) and Glaeser (2000) as a proxy variable for appealingness of city center. As discussed by Glaeser, people with higher income are attracted to live close to the city center in the large cities because of the appealingness of city centers for their cluster of leisure activities, public amenities, and consumption. The cities with lower levels of appealingness of the city center, thus, are expected have a higher median distance to the center, other things equal.

Road network is identified as an important factor that affects travel behavior and fuel demand. The measure used in this paper is major road network density calculated as the average primary road lane-miles per square mile. This measure is obtained from the 2009 Highway Statistics⁵ and used given its relatively low correlation with other variables used.

In the areas included in our sample, public transit is available as an alternative mode of travel. Transit revenue miles per 1000 residents are used to capture the inter-area difference in public transportation supply. This variable is derived from the 2009 Urban Mobility Report. Additionally, a dummy variable is used to reflect whether rail is available for public transit service.

Weather and geographic characteristics of an area may also affect motor vehicle travel demand and associated GHG emissions. Four variables are used as control variables. The mean cooling-degree days and mean heating-degree days are used to capture the impact of weather. Physical barriers of an area such as high mountains may serve as a boundary for urban expansion while rugged terrain may encourage scattered urban development, which may indirectly affect travel demand and GHG emissions from household travel. The range in elevation and a terrain ruggedness index used by Burchfield et al. (2006) are included to capture the impact of inter-area difference in geographic characteristics. The summary of statistics is reported in Table 2, while the correlation matrix of selected spatial characteristics is presented in Table 3.

3.2. Household Demographic and Economic Characteristics

The monetary price of travel is also an important variable. Since the gasoline prices reported by NHTS are based on weekly regional gasoline prices depending on the survey date, the data may not accurately capture the overall fuel cost for the survey period. This paper uses the average gasoline prices at the state level for the period of 12 months before the survey dates in order to be more compatible with the dependent variable of annual VMT and annual CO₂ emissions at the household travel. This variable is obtained from the Bureau of Transportation Statistics.

4 Kim and Brownstone measure population density at the census tract level. Given the concern of self-selection, they apply 3SLS to address the issue. As discussed in their conclusion, their model cannot reject the null hypothesis that there is no significant self-selection effect. Since our measure is at the level of urban area, it is expected to be exogenous.

5 Other measures including total road density and freeway road density have been experimented with in the regressions, but the major findings of this paper remain unchanged.

The control variables in this group include household structure, income, and other characteristics such as race, occupation, and education level. NHTS reports combined gross household income of previous year in 18 ranges. Four dummy variables are created to reflect categories of household income: <\$20,000, between \$20,000 and \$35,000, between \$35,000 and \$55,000, and above \$55,000. The base category is between \$35,000 and \$55,000.

Other household characteristics are captured through twelve dummy variables. Two dummy variables of race are created: African-American and white. The base is the other. Three dummy variables of education level are created: Associate degree, bachelor’s degree, and graduate degree. The base category is high school and below. Household member’s occupation may also influence people’s travel demand. Four dummy variables are created to capture whether any household member is in the category of sales/service, administrative support, manufacture/construction/maintenance/farming, and professional/managerial. The base category is the other. The last group of dummy variables is used to reflect respondents’ age: Younger than 21, between 21 and 30, between 31 and 40, between 41 and 50, between

51 and 65, and above 65. The base is between 31 and 40. Household size and number of workers are also used as control variables.

4. METHODOLOGY

Since household VMT and household CO₂ emissions from travel are jointly determined, a simultaneous equation model is used. As discussed in the section of data and variables, this model has two endogenous variables in natural log: Ln (household VMT) and ln (household CO₂ emissions from travel). The variables of interest include three variables capturing the impact of TDM instruments and ten variables reflecting different dimensions of urban spatial characteristics including population weighted density, population centrality, population dispersion, employment and population imbalance index, median distance to the CBD (a proxy for appealingness of city center), the spatial size of an urban area, city shape, rail availability, transit supply per 1000 residents, and major road density. The control variables include monetary price of travel, as well as geographic, weather, and household economic and

Table 2: Summary statistics of selected variables

Variable	Frequency (%)	Variable	Frequency (%)
Promotion of transit and carpooling	5.09	Parking management	16.84
Employer-based program	17.13	Sales	5.43
Manufacturing/construction	11.27	Professional/Managerial	23.93
Age below 21	0.58	Age between 21 and 30	3.14
Age between 41 and 50	17.79	Age between 51 and 65	32.50
Age above 65	30.96	Income below \$20,000	13.17
Income between \$20,000 and \$35,000	10.15	Income between \$35,000 and \$55,000	20.52
Income above \$55,000	38.60	Household w/o Children	31.95
Household w/youngest child aged below 5	11.69	Household w/youngest child between 16 and 21	5.76
Retired	36.7	Associate Degree	26.45
Bachelor degree	22.63	Graduate	17.17
Rail availability	36.2		
Variable	Mean±SD	Minimum	Maximum
ln (population weighted density)	8.71±0.69	7.52	10.35
Population centrality	0.353±1.050	-1.88	2.02
Population dispersion	84.98±22.087	56.6	153.4
Employment and job imbalance index	0.67±0.89	-1.66	2.61
Median distance to CBD	17.40±4.17	8.9	26.8
Spatial size	6.984±0.64	4.26	8.146
City shape	0.61±0.17	0.04	0.99
ln (transit mile per 1000 residents)	-1.67±0.85	-4.127	0.15
ln (major road density)	1.73±0.37	1.05	2.83
Elevation range index	1247.28±1154.30	4	4367
Ruggedness index	12.45±10.83	0.0487	47.01
ln (gas prices)	1.04±0.05	0.89	1.13
N	27168		

SD: Standard deviation

Table 3: Correlation matrix of Urban spatial characteristics

	Population weighted density	Population centrality	Population density variation	Employment housing imbalance	Median distance to CBD	Spatial size	City shape
Population weighted density	1.00						
Population centrality	0.59	1.00					
Population dispersion	0.09	0.22	1.00				
Employment housing imbalance index	0.04	0.36	-0.44	1.00			
Median distance to CBD	0.16	-0.11	-0.25	0.27	1.00		
Spatial size	0.08	0.03	-0.01	0.02	-0.001	1.00	
City shape	-0.14	-0.34	0.25	-0.43	-0.07	-0.06	1.00

social characteristics. Since the rich literature of travel demand has identified almost all of the above-mentioned variables as important factors that affect household VMT, they are included in the equation of household VMT. On the other hand, the specification of the equation of household CO₂ emissions from travel relies on a few tests.

The selection process starts with identifying other variables in addition to population density, used by Lee and Lee (2014) as the only explanatory exogenous variable for household CO₂ emissions from travel. Population-weighted density works as a catch-all variable reflecting underlying land use mix and urban design elements. Since this paper includes more measures of spatial characteristics that capture different dimensions of urban form, the specification tests start with including all the explanatory variables reflecting different spatial characteristics in the equation of household CO₂ emissions from travel. Based on the preliminary results, those variables that are not individually or jointly statistically significant at the level of at least 0.1 are then excluded from the equation. As the result, the equation of household CO₂ emissions from travel include nine explanatory variables: Household VMT, population weighted density, population dispersion, employment and population distribution imbalance, major road density, elevation index, terrain ruggedness index, the mean cooling-degree days, and mean heating-degree days.

Since a simultaneous equation model can also be run using structural equation model command with benefits of reporting direct and indirect effects (Huber, 2013), this specification is run using Stata command (sem).

5. REGRESSION RESULTS

The regression results are reported in Table 4. The direct, indirect, and total effects of the variables of interest are reported in Table 5. The discussions will focus on those variables that are statistically significant at the level of at least 0.1.

Parking management, promotion of transit use and carpool, and employment-based TDM programs are the three dummy variables used to capture the impact of TDM policy instruments. The regression results indicate that they all indirectly affect CO₂ emissions from household travel. The overall impacts of parking management, promotion of transit use and carpool, and employer-based TDM programs are -0.16, -0.14, and -0.05 respectively. This finding suggests that, other things equal, the average household CO₂ emissions from travel in the areas with such policy instruments in place are 16.77%, 14.45%, and 4.6% lower than those households located in the areas without implementing the policy instruments of parking management, promotion of transit use and carpool, and employer-based TDM programs respectively.

The impact of population distribution is captured by three variables: Population-weighted density, population dispersion measured by variation of population density at the tract level, and population centrality. The regression results indicate the coefficients of population-weighted density are negative and statistically significant at the level of at least 0.01 in both equations. This finding suggests that, on average, household GHG emissions from travel are lower in the areas with higher population-weighted

density. Combining the direct and indirect effects, the regression results indicate that a 10% increase in population-weighted density is associated with a 1.8% decrease in household CO₂ emissions from travel in the urban areas.

The overall impact of population-weighted density is split unevenly between the indirect effect through the household vehicle miles traveled (-0.13, 72%) and direct effect (-0.05, 28%). The direct effect of population-weighted density may be captured through other modes of travel. Firstly, people living in the areas of higher population-weighted density normally have more choices to satisfy their needs of transportation since the existence of rail or subway system heavily depends on density. As to bus services, bus routes and frequency can also be positively related to higher level of population density, which eventually affect passenger ridership and per passenger-mile CO₂ emissions. The impact of population-weighted density on household emissions from travel may also be captured through owning more fuel-efficient vehicles to lower congestion cost.

The magnitude of the estimated population weighted density on VMT is consistent with existing evidence ranging from -0.04 to -0.3 (Ewing and Cervero, 2010; Ewing et al., 2008). When the average population density is used, its elasticity of -0.086 is very close to the results obtained by Kim and Brownstone (2013) (-0.08). While population-weighted density is considered a more accurate measure of the urban characteristics of built-environment than the average population density used by most existing studies (Lee and Lee 2014), the magnitude of this variable on CO₂ emissions from household travel in absolute value is smaller than that obtained by Lee and Lee (0.48). This difference may be because of several factors combined. First, the data used in this paper are based on observations surveyed before September 2008 when gasoline prices were very high while Lee and Lee use data in 2001 when gasoline prices were much lower. Second, given the importance of fuel costs on travel, this paper includes average gasoline prices on a 12-month basis to capture the impact of energy prices. Energy prices, however, are not controlled in Lee and Lee (Table 2). Third, in addition to several additional spatial characteristics used, this paper also includes TDM policy instruments.

The variation of population density at the tract level is the variable used to capture the dispersion of population. This variable is positive and statistically significant at the level of at least 0.01 in both equations although both coefficients are very small. The higher level of variation of population density may be the result of poor urban planning and land use management or fragmentation of local governments in terms of land use regulation. Its overall impact on CO₂ emissions from household travel is 0.0024. The variable of population centrality only affects CO₂ emissions from household travel indirectly through the vehicle miles traveled equation with an overall impact of 0.02.

The impact of employment distribution is captured by the employment and housing imbalance index. Its coefficients are positive and statistically significant at the level of at least 0.01 for both equations. This finding suggests that CO₂ emissions from household travel are higher in those areas with a higher level of

Table 4: Regression results

Variable	Equations	
	ln (CO ₂ emissions from travel)	ln (VMT)
ln (VMT)	0.62 (162.8)***	
ln (PopW density)	-0.050 (5.40)***	-0.21 (4.90)***
Pop centrality		0.034 (2.57)***
Pop dispersion	0.002 (5.38)***	0.0013 (1.84)*
Employment and pop. imbalance	0.05 (6.68)***	0.094 (5.45)***
Median distance to city center		-0.015 (5.43)***
ln (spatial size)		0.024 (0.96)
City shape		0.11 (1.83)*
Rail		-0.13 (3.70)***
ln (transit supply)		-0.011 (0.49)
ln (major road density)	0.07 (3.42)***	0.035 (0.81)
Parking management		-0.249 (2.11)***
Promotion of transit use and carpool		-0.22 (2.10)***
Employer-based TDM programs		-0.073 (1.74)*
Elevation range	0.00004 (4.53)***	0.00008 (4.82)***
Ruggedness index	-0.009 (7.62)***	-0.012 (4.68)***
Cooling days	-0.00008 (5.46)***	-0.00006 (2.42)**
Heating days	-0.00004 (6.04)***	-0.00003 (2.30)**
ln (gas prices)		-0.126 (1.68)*
African American		-0.054 (2.12)**
White		0.064 (3.91)***
Associate degree		0.0045 (0.35)
Bachelor degree		0.022 (1.52)
Graduate degree		-0.03 (2.05)**
Manufacturing		0.02 (1.28)
Sales/service		0.12 (5.24)***
Professional		-0.03 (7.10)***
Household w/o children		0.154 (4.00)***
Household w/youngest Aged<5		-0.083 (4.00)***
Household w/youngest Aged 16-21		0.118 (4.63)***
Retired w/o children		0.096 (4.18)***
Household income below \$20,000		-0.584 (29.74)***
Household income \$20,000-\$35,000		-0.247 (13.78)***
Household income \$55,000-\$80,000		0.223 (13.87)***
Household income above \$80,000		0.409 (26.81)***
Household size		0.187 (27.21)***
Number of workers		0.213 (24.50)***
Age<21		-0.167 (2.53)**
Age (21-30)		0.101 (3.30)***
Age (41, 50)		-0.024 (1.36)
Age (51-65)		0.024 (1.37)
Age>65		-0.219 (10.48)***
Constant	4.30 (45.80)***	11.12 (25.67)***
CF1: 0.93	SRMR: 0.048	RMSEA: 0.040

***significant at the level of at least 0.01; **significant at the level of at least 0.05; *significant at the level of at least 0.1.

imbalance between population and employment distribution. Its overall impact on CO₂ emissions from household travel is 0.11

The impact of other spatial characteristics beyond population and employment distribution is captured by the spatial size of an area, city shape index, and median distance to city center (used to capture the appealingness of city center). Among these three variables, the coefficients of the city shape are positive and statistically significant at the level of at least 0.01 in the household VMT equation. It indirectly affects household CO₂ emissions from travel with an overall impact of 0.11. Median distance to city center is a proxy to reflect the impact of appealingness of city center. The coefficient is negative and statistically significant at the level of at least 0.01 in the household VMT equation. This variable indirectly affects household CO₂ emissions from travel with an

overall impact of 0.009. This finding suggests that household CO₂ emissions from travel are higher in those areas with appealing city centers, although the magnitude of the impact is quite small.

Road network density has been identified by many studies as an important factor affecting travel demand. Its overall impact is 0.09, suggesting that a household’s CO₂ emissions from travel is 0.9% higher with a 10 increase in major road density. Rail availability variable indirectly affects CO₂ emissions from household travel with an overall impact of -0.09, suggesting that CO₂ emissions from household travel are lower in those areas with rail available.

The average gasoline price during the 12-month period before the survey data is used to capture the impact of variable monetary cost of travel. Its coefficient is negative and statistically significant at

the level of at least 0.1 in the household VMT equation. It indirectly affects household CO₂ emissions from travel with an overall impact of -0.08, suggesting the CO₂ emissions from household travel are lower by 0.8% if gasoline prices increase by 10%.

Among all the control variables, four variables are used to control for weather and geographic conditions: The mean cooling-degree days and mean heating-degree, physical barriers of an area such as high mountains, and rugged terrain. The regression results indicate that their coefficients are statistically significant. Their overall impact, however, are very limited.

5.1. Robustness Check

Robustness check is conducted to test whether the major findings of this paper remain unchanged. The first robustness check is to see whether the major findings are sensitive to control variables measured in alternative way. In this robustness check, the household income enters the regression as a continuous variable while household structure is measured by 19 dummy variables based on different combinations of number of adults and number of children (based on the household size, number of adults and number of children, 16 dummy variables are created to reflect inter-household structure differences. For one-adult households, four dummy variables are created with respect to the number of children ranging from zero to three. For two-adult households, the number of children ranges from one to

four. For three-adult and four-adult households, the number of children ranges from zero to four. The base category is two-adult households without children). The second robustness check is to run the regressions using the simultaneous equation model (with stata command reg3 (3SLS)) and structured equation model with different estimation methods (maximum likelihood and maximum likelihood with missing values) based on variables used in this paper and alternative measures used in the first robustness check. The results from the above robustness check are summarized in Table 6.

While the robustness check suggests that the results are encouraging, one important limitation of this paper is the fact that we use 1-year cross sectional data, which does not allow us to capture the impact of those variables of interest over time. This is definitely an area worth further investigation.

6. CONCLUSION AND POLICY IMPLICATIONS

This paper examines the impact of a wide variety of measures of TDM policy instruments and urban spatial characteristics on household CO₂ emissions from travel based on more than 27,000 observations from the 2009 NHTS surveyed before the most recent financial crisis. The regression results indicate that TDM instruments and urban spatial characteristics affect household CO₂ emissions from travel in a complicated way. Population-weighted density, rail availability, and TDM instruments such as parking management, promotion of transit use and carpool, and employer-based TDM programs have a moderate but negative impact on household CO₂ emissions from travel. On the other hand, employment and population distribution imbalance and major road network density have a moderate but positive impact on household CO₂ emissions from travel.

The regression results indicate that doubling population-weighted density is associated with a decrease of household CO₂ emissions from travel by 18%. Given the fact that transit route and frequency are highly dependent on population density, urban design aimed at increasing population-weighted density, coupled with public policies such as parking management and promotion of transit use and shared ride could help curbing household CO₂ emissions from travel furthermore. If local governments also make efforts to reduce the imbalance between employment and population distribution through combining mixed land use and entrepreneur-

Table 5: Direct, indirect, and total effect of spatial characteristics and travel demand management instruments on household CO₂ emissions from travel

Variable	Direct	Indirect	Total
Population weighted density	-0.05	-0.21	-0.18***
Population centrality		0.034	0.021***
Population dispersion	0.002	0.0013	0.0024***
Employment and population imbalance	0.050	0.094	0.108***
Median distance to city center		-0.015	-0.009***
City shape		0.11	0.068*
Rail		-0.13	-0.082***
Major road density	0.069	0.035	0.091**
Parking management		-0.249	-0.155**
Promotion of transit use and carpool		-0.216	-0.135**
Employer-based TDM programs		-0.073	-0.045*
Gasoline prices		-0.126	-0.079*

TDM: Travel demand management, *** significant at the level of at least 0.01; ** significant at the level of at least 0.05; * significant at the level of at least 0.1.

Table 6: Robust check results of the total effect on household CO₂ emissions from travel

Variable	Minimum	Maximum	Mean	Sign +	Sign -
Population weighted density	-0.207	-0.169	-0.186		100
Population centrality	0.017	0.026	0.023	100	
Population dispersion	0.0016	0.0029	0.0022	100	
Employment and population imbalance	0.087	0.126	0.113	100	
Median distance to city center	-0.0094	-0.0084	-0.0094		100
City shape	0.068	0.087	0.075	100	
Major road density	0.079	0.134	0.106	100	
Parking management	-0.164	-0.126	-0.152		100
Promotion of transit use and carpool	-0.139	-0.128	-0.134		100
Employer-based TDM programs	-0.044	-0.041	-0.043		100

TDM: Travel demand management

friendly actions, compact urban design could be more meaningful in reducing household CO₂ emissions from travel.

Considering the federal goal of reducing US GHG emissions and the trend of increasing emissions from transportation since 2012, the findings of this paper present evidence that TDM instruments and urban spatial design or improvement could play a supplemental yet important role in mitigating GHG emissions. Changing spatial characteristics, however, requires a long-term effort by all levels of government. For those areas focusing on urban renewal and redevelopment, urban design of meaningful density threshold, mixed land use, and transit oriented is of essence. For those areas at the urban fringe, state policies and support are necessary to avoid the fragmented development, which is especially true in those areas with different levels of land use regulations.

REFERENCES

- Available from: http://www.pubs.its.ucdavis.edu/publication_detail.php?id=1194.
- Badoe, D., Miller, E. (2000), Transportation - Land use interaction: Empirical findings in North America and their implications for modeling. *Transportation Research Part D*, 5(4), 235-263.
- Barr, L. (2000), Testing for the significance of induced highway travel demand in metropolitan areas. *Journal of the Transportation Research Board*, 1706, 1-8.
- Bento, A., Cropper, M., Mobarak, A., Vinha, K. (2005), The impact of urban spatial structure on travel demand in the United States. *The Review of Economics and Statistics*, 87, 466-478.
- 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.
- Brownstone, D., Golob, T. (1991), *The Effectiveness of Ridesharing Incentives: Discrete-Choice Models of Commuting in Southern California*. Irvine: University of California Transportation Center, University of California.
- Brownstone, D., Golob, T.F. (2009), The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics*, 65, 91-98.
- Burchfield, M., Overman, H., Puga, D., Turner, M. (2006), Causes of sprawl: A portrait from space. *Quarterly Journal of Economics*, 121, 587-633.
- Cao, X., Mokhtarian, P., Handy, S. (2008), Examining the Impacts of Residential Self-Selection of Travel Behavior: Methodologies and Empirical Findings. Research Report UCD-ITS-RR-08-25. Davis: Institute of Transportation Studies, University of California.
- Cervero, R. (1994), Transit-based housing in California: Evidence on ridership impacts. *Transportation Policy*, 1(3), 174-183.
- Cervero, R., Kockelman, K. (1997), Travel demand and three DS: Density, diversity, and design. *Transportation Research Part D*, 2(3), 199-219.
- 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.
- Chen, C., Hongmian, G., Paaswell, R. (2007), Role of the built environment on mode choice decisions: Additional evidence on the impact of density. *Transportation*, 35, 285-299.
- Crane, R. (2000), The influence of urban form on travel: An interpretive review. *Journal of Planning Literature*, 15(1), 3-23.
- Ewing, R., Cervero, R. (2001), Travel and the built environment: A synthesis. *Transportation Research Record*, 1780, 87-114.
- Ewing, R., Cervero, R. (2010), Travel and built environment. A meta analysis, *Journal of American Planning Association*, 76(3), 265-294.
- Ewing, R., Keith, B., Winkelman, S., Walters, J., Chen, D. (2007), *Growing Cooler: The Evidence on Urban Development and Climate Change*. Washington, DC: Urban Land Institute.
- Frank, L., Pivo, G. (1996), Impacts of mixed use and density on utilization of three modes of travel: Single occupant vehicle, transit, walking. *Transportation Research Record*, 1466, 44-52.
- Fulton, L., Meszler, D., Noland, R., Thomas, J. (2000), A Statistical Analysis of Induced Travel Effects in the US Mid-Atlantic Region, The 79th Annual Meeting of the Transportation Research Board, Paper No. 00-1289.
- Glaeser, E.L., Kahn, M.E. (2010), The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics*, 67, 404-418.
- Glaeser, E. (2000), The future of urban economics: Non-Market interactions, *Brookings-Wharton Papers on Urban Affairs*, 1, 101-150.
- 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.
- Hansen, M. (1997), Road supply and traffic in California urban areas. *Transportation Research Part A*, 31, 205-218.
- Huber, C. (2013), *Generalized Structural Equation Modeling Using Stata*. Available from: http://www.stata.com/meeting/italy13/abstracts/materials/it13_huber.pdf.
- Karathodorou, N., Graham, D., Noland, R. (2010), Estimating the effect of urban density on fuel demand. *Energy Economics*, 32(1), 86-92.
- Kim, J., Brownstone, D. (2013), The impact of residential density on vehicle usage and fuel consumption: Evidence from national samples. *Energy Economics*, 40, 196-206.
- Lee, S., Lee, B. (2014), The influence of urban form on GHG emissions in the US household sector. *Energy Policy*, 68, 524-549.
- Liu, C., Shen, Q. (2011), An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment, and Urban System*, 35(5), 347-357.
- Malpezzi, S., Kuo, W. (2001), *Measuring "Sprawl": Alternative Measures of Urban Form in U.S Metropolitan Areas*. Madison, WI: Center for Urban Land Economics Research, University of Wisconsin.
- Miller, E., Ibrahim, A. (1998), Urban forms and vehicular travel: Some empirical findings. *Transportation Research Record*, 1617, 18-27.
- Mindali, O., Raveh, A., Salomon, I. (2004), Urban density and energy consumption: A new look at old statistics. *Transportation Research Part A*, 38, 143-162.
- Newman, P., Kenworthy, J. (1989), *Cities and Automobile Dependence: An International Source Book*. England: Avebury Technical.
- Noland, R. (2001), Relationships between highway capacity and induced vehicle travel. *Transportation Research Part A*, 35, 47-72.
- Noland, R., Cowart, W. (2000), Analysis of metropolitan highway capacity and the growth in vehicle miles of travel. *Transportation*, 27(4), 363-390.
- Noland, R., Lem, L. (2002), A review of the evidence for induced travel and changes in transportation and environmental policy in the US and the UK. *Transportation Research Part D*, 7(1), 1-26.
- Peng, Z., Dueker, K., Strathman, J. (1996), Residential location, employment location, and commuter responses to parking charges. *Transportation Research Record*, 1556, 109-118.
- Schimek, P. (1996), Household vehicle ownership and use: How much does residential density matter? *Transportation Research Record*, 1552, 120-130.
- Small, K., Van Dender, K. (2007), Fuel efficiency and motor vehicle travel: The declining rebound effect. *The Energy Journal*, 28(1), 25-51.
- Su, Q. (2010), Travel demand in the U.S. Urban areas: A system dynamic

- panel data approach. *Transportation Research Part A*, 44(2), 100-107.
- Su, Q. (2011), Induced motor vehicle travel from improved fuel efficiency and road expansion. *Energy Policy*, 39(11), 7257-7264.
- Su, Q., Zhou, L. (2011), Parking management, financial subsidies to alternatives to drive alone and commute mode choices in Seattle. *Regional Science and Urban Economics*, 42, 88-97.
- Su, Q. (2012). A quantile regression analysis of the rebound effect: evidence from the 2009 National household transportation survey in the United States, *Energy Policy*, 45, 368-377.
- Su, Q., Zhou, L. (2012), Parking management, Financial subsidies to alternatives to drive-alone and commute mode choices in Seattle, *Regional science and urban economics*, 42(1-2), 88-97.
- U.S. Bureau of Transportation Statistics. (2009), National Household Travel Survey. Available from: http://www.bts.gov/programs/national_household_travel_survey.
- US Environmental Protection Agency. (2016), Draft US Greenhouse Gas Inventory Report 1990 - 2014. Available from: <http://www3.epa.gov/climatechange/ghgemissions/usinventoryreport.html#fullreport>.
- Zhang, M. (2004), The role of land use in travel mode choice - Evidence from Boston and Hong Kong. *Journal of American Planning Association*, 70(3), 344-360.
- Zhou, L., Su, Q., Winters, P. (2009), Telecommuting as a component of a commute trip reduction program: Trend and determinants analyses. *Journal of Transportation Research Record*, 2009, 2135, 151-159.