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Individual transport emissions and the built environment: A structural equation modelling approach

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ABSTRACT

Increasing CO_2 emissions from the transport sector have raised substantial concerns among researchers and policy makers. This research examines the impact of the built environment on individual transport emissions through two mediate variables, vehicle usage and vehicle type choice, within a structural equation modelling (SEM) framework. We find that new-urbanism-type built environment characteristics, including high density, mixed land use, good connectivity, and easy access to public transport systems help reduce transport CO_2 emissions. Such mitigating effect is achieved largely through the reduced vehicle miles travelled (VMT) and is enhanced slightly by the more efficient vehicles owned by individuals living in denser and more diverse neighborhoods, all else being equal. Our research findings provide some new evidence that supports land use policies as an effective strategy to reduce transport CO_2 emissions.

1. Introduction

Transport has been a major contributor to the dramatic rise of carbon emissions worldwide (Dulal et al., 2011). According to the data in 2011, CO_2 generated from transport has increased from 4605 million tonnes in 2009 to 7001 million tonnes in 2011, accounting for approximately 22% of global CO_2 emissions (IEA, 2013). The rapid growth in transport emissions was mainly driven by emissions on the road, which increased by 52% since 1990 (IEA, 2013). The International Energy Agency (IEA) expects global transport-related CO_2 emissions to increase by 50% by 2030, and by more than 80% by 2050 (IEA, 2009). Approaches to reducing carbon emissions from transport thus have received considerable attention. In addition to technology innovations to improve the energy efficiency of vehicles and economic approaches to increase the cost of driving, land use control policies that aim to reduce vehicle dependence by changing the built environment have been widely considered an effective means to reduce transport emissions.

The amount of CO_2 emissions generated from urban transport is determined by multiple factors, such as vehicle usage, vehicle efficiency, and fuel type (Schipper et al., 2000). The dramatic increase in vehicle usage, often measured in vehicle miles travelled (VMT), is suggested to be one of the most important factors affecting transport emissions (Cervero and Murakami, 2010; Millard-Ball and Schipper, 2011). This has sparked numerous studies into the influence of the built environment on VMT, especially in the context of global warming (Grazi et al., 2008; Aditjandra et al., 2013). However, VMT is not equivalent to CO_2 emissions due to the substantial heterogeneity in vehicle emission levels. For example, the Tesla Model

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S is claimed to be a zero emission vehicle while the CO_2 emissions from a Sport Utility Vehicle (SUV) could be hundreds of grams of CO_2 per kilometer travelled. Ignoring the vehicle type effect might yield significant bias in transport CO_2 emission studies. In the meantime, many existing studies targeting directly on transport CO_2 emissions use an aggregate approach to investigate the relationship between the built environment and transport energy consumption or emissions at the neighborhood, city, or country levels (e.g. Newman and Kenworthy, 1989; Lindsey et al., 2011). Such studies have provided useful insights into transport emission reduction by revealing the general trends in the land use and transport interactions. However, statistical analyses based on aggregate measures generally ignore the individual heterogeneity within a specific area and do not allow for an exploration of the underlying mechanisms by which the built environment may influence individual decisions.

Our study aims to fill the gaps by discerning the complex interactions among the various factors that could influence individual transport emissions using Structural Equation Modelling (SEM). Specifically, our study examines the effects of the built environment and socio-demographic characteristics on individual transport CO_2 emissions through two mediate variables – vehicle usage and vehicle type choice. We find that new-urbanism-type built environment characteristics including high density, mixed land use, good connectivity, and easy access to public transport systems help reduce transport CO_2 emissions. Such mitigating effect is achieved largely through the reduced VMT and is enhanced slightly through the more efficient vehicles owned by individuals living in denser and more diverse neighborhoods, all else being equal. The SEM techniques allow researchers to decompose the total effect of one variable on another into direct effect and indirect effect through other intermediate variables. We find that by considering all the direct and indirect effects, the built environment has a larger impact on VMT and a smaller impact on vehicle type choice compared to that of individual socio-demographic characteristics. Overall, the built environment affects transport emissions to a larger extent than that of individual socioeconomic and demographic attributes. Our research findings provide some new evidence to support the design of policies aiming to relieve transport emissions.

The remainder of this paper is structured as follows. Section 2 briefly reviews the research on the relationship between land use and transport CO_2 emissions. Section 3 introduces the study area, methodology, data sets and variables in the empirical analysis. Section 4 presents the main empirical results. The last section summarizes research findings and proposes future research directions.

2. Literature review

The connection between the built environment, socio-demographic attributes and transport CO_2 emissions has been widely investigated in transportation research. In this section, we review the related literature to provide a proper context for our study.

2.1. The impact of the built environment on vehicle usage and vehicle type choice

In the transportation field, a large number of studies have focused on the impact of the built environment on vehicle usage often measured in VMT. The underlying assumption is that given the stable improvement of vehicle technology, the less VMT generated, the less carbon will be released from automobiles. The theoretical foundation for the built environment effect on VMT can be found in the theory of utilitarian travel demand (Lancaster, 1957). This theory postulates that travelers do not derive their utilities from the trips per se, but from the need to engage in activities located at different places. Therefore, land use configuration could affect travel patterns (Boarnet and Crane, 2001). In general, new-urbanism-type built environment characteristics such as high density, mixed land use, good connectivity, and easy access to public transport are expected to encourage travelers to shift from driving to walking, bicycling, or taking public transportation (Cervero, 2002; Brownstone, 2008; Cao et al., 2009). For example, using data from 370 urbanized areas in the US, Cervero and Murakami (2010) found that denser urban settings with better retail and transit accessibility lead to a reduction in individual VMT. Using a difference-in-differences analysis, Zhu and Diao (2016) found that the inauguration of a new urban rail transit line in Singapore has reduced the levels of car dependence in wealthy households living in the proximity of new rail stations. Sun et al. (2009) compared the influence of the built environment and a household's lifecycle stages on vehicle usage. They found that the built environment has a larger explanatory power on the differences in the share of automobile trips, whereas the lifecycle stages explain the number of trips being made. Diao and Ferreira (2014) indicated that built environment factors not only play an important role in explaining the intra-urban variation of VMT in Metro Boston, but may also be underestimated by previous studies that use more aggregate built environment measures.

However, studies focusing on vehicle usage generally ignore the role of vehicle type choice in individual transport CO_2 emissions, which could bring significant biases to transport emission research due to the substantial heterogeneity in vehicle emission levels measured in grams of CO_2 per mile travelled.[1] Researchers have found that the built environment can also influence transport CO_2 emissions through individual vehicle type choice (Brownstone and Golob, 2009; Lindsey et al., 2011;

[1] In European countries, vehicle emissions have been increasingly heavily regulated, which could reduce the variation of emission factors among vehicles that are approved by the same standard.

Liu and Shen, 2011). The association between the built environment and vehicle type choice could be explained by multiple factors, such as land use characteristics, commuting distance, outdoor spaciousness, and density. For example, Potoglou (2008) found that in Hamilton Canada, households living in areas with heterogeneous land uses are more likely to purchase fuel-efficient vehicles, after controlling for travel attitudes and socio-demographic characteristics of individuals and households. Using a sample in Northern California, Cao et al. (2006) found that outdoor spaciousness and commuting distance are positively associated with the preference for bigger and less efficient cars. Other studies also indicated that households in denser urban areas are less likely to own and drive low-fuel-efficiency vehicles, such as SUVs and light trucks (Bhat and Sen, 2006; Fang, 2008; Bhat et al., 2009). Given the potential significant role of vehicle usage and vehicle type choice in transport emission generation, it is necessary to incorporate both VMT and vehicle emission factors into the analysis when assessing the effect of the built environment on transport CO_2 emissions (Lee and Lee, 2014).

2.2. The association between the built environment and transport energy consumption and emissions

Unlike studies that examine the linkage between the built environment and certain aspects of individual travel behavior such as vehicle type choice and vehicle usage, another line of research directly focuses on the effect of the built environment on transport energy consumption and emissions. Many previous studies investigated transport energy consumption and/or emissions at certain geographic scales, such as the neighborhood, city or country levels. One of the most influential aggregate studies was conducted by Newman and Kenworthy (1989), which established a negative linkage between land use density and transport energy consumption per capita based on historical data of 32 megacities. A more recent work by Makido et al. (2012) analyzed the relationship between urban form and CO_2 emissions in 50 cities in Japan. They showed that CO_2 emissions from the residential and passenger transport sectors in a city are closely associated with the spatial metrics of the city such as compactness and urban complexity. In an analysis conducted at the transportation analysis zone level, Ferreira et al. (2013) estimated the transport emission implications of alternative urban growth scenarios in Metro Boston. They found that while urban growth management can significantly reduce transport emissions, it alone will not be sufficient to achieve the emission reduction targets set by the State government. Such aggregate studies provide useful insights into transport emission reduction. However, they mainly capture the relationship between land use and transport energy consumption or emission at the neighborhood, city, or country levels, thus neglecting the substantial heterogeneity in individual travel behavior within the specific area.

Such a glaring problem has not gone unnoticed. There has been an increasing number of studies investigating transport emissions at disaggregate (individual or household) levels. For example, Frank et al. (2000) analyzed the relationship between land use and household vehicle emissions in Seattle, accounting for household demographic factors. They estimated trip emissions carefully by considering network distance of each trip, travel speed and the mode of engine operation. The results confirmed the potential role that land use strategies could play in transport emissions mitigation. Barla et al. (2011) investigated the influence of individual socioeconomic attributes, land use, and public transport supply on travel greenhouse gas emissions in Quebec City, Canada. The estimation of trip emissions took into account distance travelled, vehicle make/year, speed and number of passengers. Their linear regression results indicated that individuals living in the city periphery produce 70% more emissions on average than individuals located at the city center. A more recent work by Waygood et al. (2014) compared the transport CO_2 emissions produced over a family's life cycle stages across five land use types in the Osaka metropolitan area, Japan. The energy consumed by each trip was estimated using the average energy consumption rates for different transport modes, adjusted further for cold start. The results revealed that there are over three times more emissions in less developed areas than their central urban counterparts.

Previous disaggregate studies provide valuable insights into the impact of the built environment on transport emissions at individual or household levels. However, many of them are based on single-equation regressions (e.g. Frank et al., 2000; Barla et al., 2011) or analysis of variance (e.g. Waygood et al., 2014), thus being insufficient to account for the complex interactions among socio-demographic characteristics, the built environment, travel behavior, and transport emissions. To address this issue, Brownstone and Golob (2009) developed a set of structural equation models of residential density, vehicle use and transport fuel consumption. Based on the California subsample of the 2001 National Household Travel Survey (NHTS) in the US, they found that a lower development density could lead to an increase of household vehicle usage and a decrease of vehicle fuel economy, thus higher fuel consumption. Using the same analytical approach, Kim and Brownstone (2013) extended the California subsample to the national sample of the 2001 NHTS, and obtained similar results. However, due to data limitations, density has been used as the only proxy for the built environment in their studies despite the multidimensionality of the built environment (Handy et al., 2002; Brownson et al., 2009; Cervero and Murakami, 2010). Liu and Shen (2011) carefully developed multiple built environment measures in their analysis, and applied SEM to disentangle the interrelationships among urban form, household socioeconomic characteristics, vehicle choice, household travel and energy consumption using the Baltimore subsample of 2001 NHTS. Their results showed that the built environment does not have a direct effect on VMT or energy use, but affects them indirectly through other factors, such as vehicle choice and ownership. In the meantime, these three NHTS-based studies only focused on the energy consumption and emissions from private cars while omitting that from other transport modes. Therefore, they only provided a glimpse of the complete picture of individual transport emissions.

2.3. The role of socio-demographic characteristics

In addition to the built environment, socio-demographic characteristics have been found to be an important determinant of house hold residential location, vehicle type choice, and vehicle usage, thus affecting individual transport emissions. For example, Krizek (2006) found that in the US, large households with four or more family members are prone to live in suburban environments and tend to drive more. Choo and Mokhtarian (2004) explored the influence of demographics, travel attitudes, lifestyle, and mobility on individual vehicle type choice. Their result suggested that respondents' age, gender, education, income and household size are significantly associated with vehicle type choice. Generally, households with higher income and more children are more likely to own large vehicles, such as SUVs or light trucks. Beige and Axhausen (2012) found that turning points in life (e.g., household composition change and occupation change) have a bearing on the long-term mobility decisions (e.g., vehicle ownership and vehicle type choice) of the family.

Due to the heterogeneity in the choices on daily mobility patterns, vehicles, and residential locations, individuals with different socioeconomic characteristics produce different levels of transport emissions. Susilo and Stead (2009) investigated the extent to which socioeconomic characteristics explain the differences in transport-related CO_2 emissions in the UK and the Netherlands. They found that, in both countries, men, higher income groups, smaller households, full-time employment, and accessibility to private cars are associated with higher transport emissions. Ko et al. (2011) examined the relationship between transport emissions and the emitters' socioeconomic attributes in Seoul metropolis area, and found that male adults produce 2.5 times more CO_2 than female adults. For people entering their 40 s or 50 s and being in professional or administrative occupations, their transport emissions are also higher than others. Mathez et al. (2013) used travel survey to identify the highest emitter group among those commuting to McGill University downtown campus, and found that job, gender, age, and residential location are all related with their commuting emissions.

Because individuals with certain socio-demographic traits and travel patterns may purposely choose to live in certain types of neighborhood, it is necessary to incorporate both built environment and individual socio-demographic characteristics into analytic models to disentangle their effects on travel behavior and transport emissions.

2.4. Structural equation modelling

Methodologically, SEM is a powerful statistical modelling technique to investigate the complicated interactions among multiple factors. The main advantages of SEM compared to simple regression analysis include: (1) modelling intermediate variables, thus decomposing the total effect into direct and indirect effect; (2) accounting for measurement error in all observed variables for accuracy; and (3) discerning the causal relations rather than simple regression coefficients (Kline, 2011).

SEM has been adopted by a number of studies to investigate the impact of land use on travel behavior (Cao et al., 2007; van Acker et al., 2007; Brownstone and Golob, 2009; van Acker and Witlox, 2010). For example, Cao et al. (2007) developed a longitudinal SEM for recent movers in eight neighborhoods in Northern California. They found that changes in the built environment have a significant impact on changes in travel behavior after controlling for self-selection. van Acker et al. (2007) also employed SEM to explore the relationships among land use, socio-demographic characteristics, and travel behavior. Their results indicated that socioeconomic characteristics influence travel behavior to a greater extent than that of land use.

In this study, we aim to fill some gaps in the literature by examining the influence of the built environment and socio-demographic characteristics on individual transport emissions using SEM to partly control for residential self-selection. The study benefits from a refined estimation of transport CO_2 emissions at an individual level, which takes into account multiple factors that could influence emission levels including trip mode, travel distance, vehicle type and some particular attributes of the vehicle. This approach enables us to estimate individual transport CO_2 emissions with a degree of precision and coherence unavailable to most previous researchers. In the meantime, this research also benefits from a variety of spatial variables, covering a wide range of dimensions in the built environment such as diversity, connectivity, accessibility and walkability, which enables us to fully explore the potential impact of the built environment on transport emissions.

3. Data and methodology

In this section, we introduce the study area, data sources, statistical techniques and key variables used in our empirical analysis.

3.1. Study area and data sources

Greater Boston is the study area of the empirical analysis. Located at the eastern part of Massachusetts, Greater Boston encompasses a diverse range of built environment characteristics across urban and suburban settings, thus providing a proper background for the study. The Metropolitan Area Planning Council (MAPC) is the regional planning agency for Metro Boston. It classifies cities and towns in Metro Boston into four types according to their land use characteristics, housing patterns and growth trends, including inner core, regional urban centers, maturing suburbs, and developing suburbs (Fig. 1).

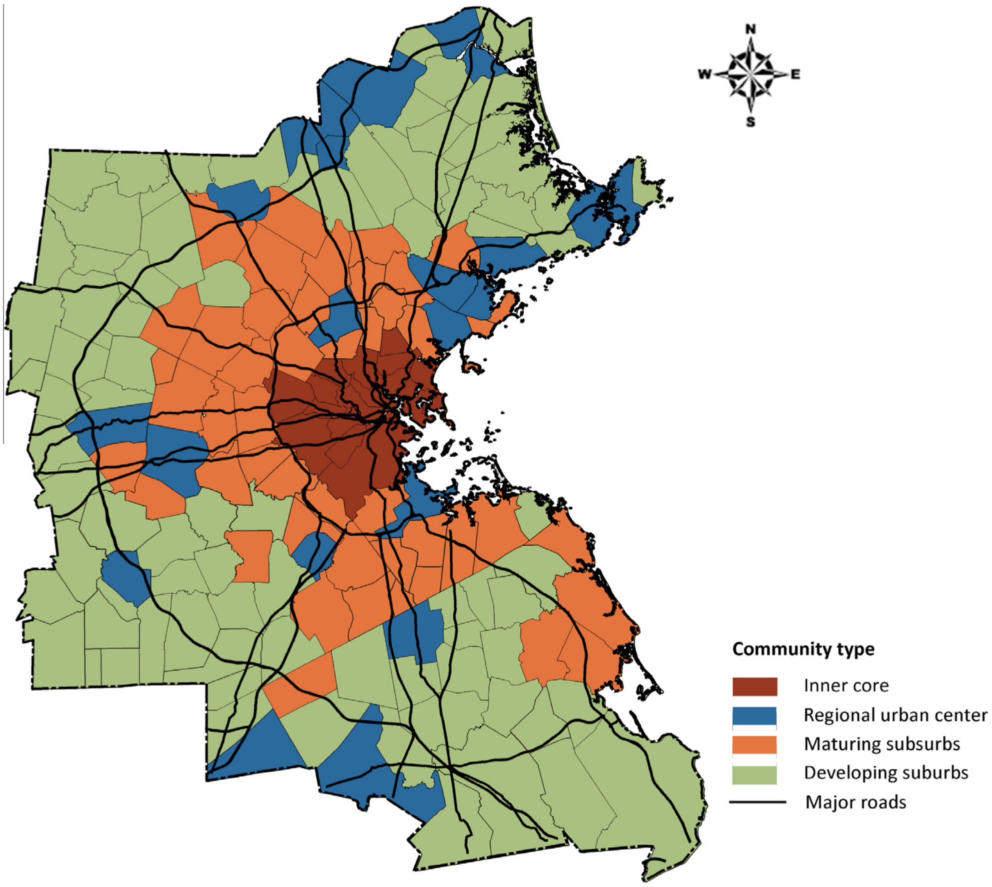

Fig. 1. Cities and towns in Greater Boston.

Detailed individual travel data are extracted from the Massachusetts Travel Survey (MTS) supported by the Massachusetts Department of Transportation (MassDOT) and the Metropolitan Planning Organizations (MPOs) from May 2010 to October 2011. Surveys of this kind are usually conducted every 10 years, and the MTS 2010–2011 is the most recent dataset of individual travel records in the study area. The MTS consists of four files: *personal* file, *household* file, *place* file and *vehicle* file. The first two documents provide personal and household information of each member from 15,033 households in Massachusetts. One shortcoming of the MTS survey is that it does not reveal individuals' travel attitudes, which are an important source of residential self-selection. Thus the influence of travel attitudes on residential location choice and travel behavior could not be captured in the analysis. In addition to personal attributes, all respondents were asked to complete a travel diary for a random weekday. This included each place visited during the specified weekday, the exact time the respondent arrived and left each place, the travel mode and the purpose of each trip. The MTS encompasses detailed vehicle information of the household under investigation and the vehicle used in each trip, thus providing a sound basis for estimating individual transport CO_2 emissions. All the MTS respondents living in Greater Boston are included in our sample regardless of their travel modes of transportation, as long as they are above 16 years old and the information on all key variables is present. The final dataset consists of 11,037 individuals. All trips made by these respondents including both motorized and non-motorized trips are included in our analysis.

3.2. Modelling approach

In this study, SEM is utilized to examine the complex interactions between various factors and transport CO_2 emissions. Based on previous literature, some possible relationships can be postulated between the built environment, socio-demographic characteristics, vehicle usage, vehicle type choice, and transport CO_2 emissions. The conceptual framework is shown in Fig. 2. In this framework, vehicle usage and vehicle type choice are directly influenced by the built environment and socioeconomic and demographic characteristics. Both vehicle usage and vehicle type choice affect individual CO_2 emissions generated from transport. We establish a path from socioeconomic and demographic characteristics to the built environment considering the potential role of these factors on household location. In this way, the indirect impact of individual

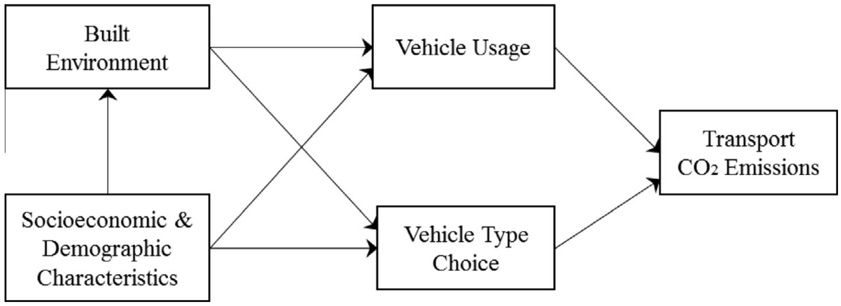

Fig. 2. Conceptual framework for modelling transport CO_2 emissions.

socio-demographic attributes on vehicle usage and vehicle type choice through the built environment can be captured despite that the attitudinal residential self-selection is not fully controlled due to the data limitation. Within this framework, the impact of the built environment and individual socio-demographic characteristics on transport CO_2 emissions through vehicle usage and vehicle type choice can be identified.[2]

Based on the conceptual framework, a series of equations are specified in the SEM. Firstly, two measurement models are developed to verify whether the observed variables correctly measure the latent variables – the built environment (*BE*) and socioeconomic and demographic characteristics (*SD*). Secondly, a system of structural models is established to specify the possible causations in the conceptual framework. The proposed structural models are presented below.

$$
\begin{aligned}
TE_i &= a_1 VMT_i + b_1 EF_i + \varepsilon_{i1} \\
VMT_i &= a_2 BE_i + b_2 SD_i + \varepsilon_{i2} \\
EF_i &= a_3 BE_i + b_3 SD_i + \varepsilon_{i3} \\
BE_i &= a_4 SD_i + \varepsilon_{i4}
\end{aligned}
$$

where a and b are coefficient matrices; TE_i denotes the transport emissions of individual i from all trips made during the day by all transport modes; VMT_i is the daily VMT by private car, which measures individual i's vehicle usage; EF_i measures the emission factor of the private car used by individual i, serving as an indicator of individual's vehicle type choice; SD_i is a set of socioeconomic and demographic characteristics of individual i; BE_i is a vector of the built environment variables representing the neighborhood where individual i lives in; and ε is a vector of residuals with an unrestricted correlation structure. The analysis is performed in LISREL 9.1 using the maximum likelihood (ML) estimation method. ML assumes multivariate normality of continuous outcome variables. Hence, we transformed the variables that are not normal distributed by taking the logarithm of the original values.

3.3. Key variables

Three sets of key variables are generated for the empirical analysis, including built environment variables, socioeconomic and demographic variables, and transport related variables.

3.3.1. Built environment variables

In the field of urban planning, the built environment is normally measured along five dimensions: density, diversity, design, destination accessibility, and distance to transport (Cervero and Murakami, 2010). In this study we compute a set of 18 built environment variables at the block group level, covering all the five dimensions mentioned above (Table 1). Some built environment variables are likely to be closely correlated. For example, areas with higher density tend to have more diverse land uses and better access to public transport systems. The multicollinearity among built environment variables could lead to biased estimates (Kline, 2011). To address this problem, we conduct a principal component analysis (PCA) with orthogonal varimax to the built environment variables, following Diao and Ferreira (2010, 2014). The PCA can convert a large set of correlated variables into a smaller set of linearly uncorrelated principal components to address the multicollinearity issue, while retaining as much as possible of the variations in the original dataset. The results of the PCA are shown in Table 2. We keep the four components whose eigenvalues are greater than 1. They can explain 76.41% of the variance in the original 18 built environment variables. We label the four built environment components as "development density", "connectivity", "infrastructure inaccessibility", and "land use mix", respectively, and integrate them into the SEM (see Table 2).

[2] We also tested the model specification that allow the interactions between vehicle usage and vehicle type choice. But the model did not pass the goodness-of-fit standards for SEM.

Table 1
Summary of travel, built environment and socioeconomic variables.

Code	Variables	Mean	Std. Dev.
Travel			
VMT	Vehicle miles travelled by individual (miles)	27.25	25.97
TE	Transport CO_2 emissions (kilograms)	13.39	49.79
EF	Emission factors of private cars (grams of CO_2 per mile)	430.92	95.32
Socioeconomic and demographic variables (SD)			
Gend	Gender (female = 1)	0.53	0.50
Age	Age	48.52	15.17
HHsize	Household size (count)	3.04	1.29
HHbic	Household bicycles (count)	1.98	1.81
HHveh	Household vehicles (count)	2.25	0.99
HHchild	Number of children in household (count)	0.93	1.09
Income[a]	Household income (ordinal)	6.11	1.77
Employ	Employment (yes = 1)	0.74	0.44
Lic	Valid driver's license (yes = 1)	0.97	0.17
Trans	Have transit pass or not? (yes = 1)	0.22	0.41
Edu[b]	Level of education completed (ordinal)	4.45	1.59
Built environment variables (BE)			
Pop_den	Population density (10 k/km^2)	0.38	3.51
HH_den	Household density (10 k/km^2)	0.15	1.08
Job_den	Job density (k/km^2)	0.67	1.24
Busi_den	Business establishment density (k/km^2)	0.08	0.13
Hut_den	Housing unit density (10 k/km^2)	0.16	1.03
Entropy	Entropy type land use mix indicator	0.35	0.22
Ndden	Road intersection density (10/km^2)	5.66	4.55
Nden_3	Density of 3-way intersections (10/km^2)	3.71	3.03
Nden_4	Density of 4-way intersections (10/km^2)	0.89	1.20
Rdden_M	Road density (km/km^2)	9.67	5.45
Avg_sw	Average sidewalk width (m)	4.00	3.73
Dis_subway	Distance to subway stations (km)	16.91	13.24
Dis_exit	Distance to highway exit (km)	3.46	2.45
Dis_cbd	Distance to CBD (km)	27.51	14.80
Dis_open	Distance to open space (km)	0.21	0.23
Dis_nonwk	Distance to non-work destinations (km)	2.11	1.08
Dis_crail	Distance to commuter rail stations (km)	3.81	3.27
Jobacc	Job accessibility (10 k)	20.96	15.73

[a] Income is classified into eight categories. They are 1 (less than \$15,000); 2 (\$15,000–\$24,999); 3 (\$25,000–\$34,999); 4 (\$35,000–\$49,999); 5 (\$50,000–\$74,999); 6 (\$75,000–\$99,999); 7 (\$100,000–\$149,999); and 8 (\$150,000 or more).
[b] Education is classified into six categories. They are 1 (not a high school graduate); 2 (high school graduate); 3 (some college credit but no degree); 4 (associate or technical school degree); 5 (bachelor's or undergraduate degree); and 6 (graduate degree).

Table 2
Principal component analysis for built environment variables.

BE variable	Factor loadings			
	Comp1: development density	Comp2: connectivity	Comp3: infrastructure inaccessibility	Comp4: land-use mix
Pop_den	0.5793			
HH_den	0.5769			
Hut_den	0.5752			
Ndden		0.4236		
Nden_3		0.4044		
Nden_4		0.4140		
Rdden_M		0.3929		
Avg_sw		0.3302		
Dis_subway			0.4922	
Dis_cbd			0.4726	
Dis_open			0.3463	
Dis_crail			0.3942	
Jobacc			−0.3437	
Entropy				0.6836
Job_den				0.5043
Busi_den				0.3654
Dis_exit				−0.3009
Dis_nonwk				
Cumulative	16.63%	45.62%	66.75%	76.41%

Note: we suppress factor loadings with an absolute value less than 0.3 for interpretation convenience.

3.3.2. Socioeconomic and demographic variables

Similar to the built environment variables, a PCA is conducted for the 11 socioeconomic and demographic variables listed in Table 1 to address multicollinearity. Four components with eigenvalue greater than 1 are retained, which explain 61.61% of the variance in the original variables. They are labelled "unemployed female", "young family with children", "car free", and "highly educated and employed", respectively (see Table 3). It should be noted that the PCA is an approach to reveal the underlying dimensions in a set of correlated observed variables, but not an approach for data aggregation. Although the PCA is applied to the built environment and individual socio-demographic variables, our study still examines the travel behavior and transport emissions at an individual level. On the contrary, aggregate studies use the mean values of transport and socio-demographic attributes in the neighborhood/city/country in their analyses, thus ignoring individual heterogeneity.

3.3.3. Transport related variables

The estimation of CO_2 emissions from transport is fundamental to research on the relationship between the built environment and transport emissions. In previous studies, researchers often rely on aggregate measures of transport emissions, for example, the total transport energy consumption by geographic zones or the product of average VMT and average fuel economy/emission factor of vehicles at certain spatial levels (Dhakal, 2009; Cai et al., 2012). However, individual transport emissions could vary considerably due to the substantial heterogeneities in both individual VMT and fuel economy/emission factor of vehicles. To overcome the shortcomings of aggregate transport emission estimates, we compute CO_2 emissions from transport at the individual level in this study. Because it is infeasible to do direct measurements, we adapt the approach used by Mui et al. (2007) to generate our own estimates of individual transport emissions. We first compute the amount of CO_2 emissions of a trip by multiplying the emission factor (grams of CO_2 per mile travelled) associated with the trip mode and trip distance, then aggregate the CO_2 emissions from all trips made by an individual using all transport modes in the survey day, including both motorized and non-motorized trips, to get the total transport emission for this individual. This approach is different from that of previous studies based on the NHTS data and SEM, such as Brownstone and Golob (2009), Kim and Brownstone (2013), and Liu and Shen (2011). They only considered the energy consumption and transport emissions from trips by private cars, which might lead to biased estimates on the overall built environment effect on transport emissions.

The MTS dataset does not report actual distance of each trip, but contains geographic IDs of both the origin and destination blocks for each trip. Such location information enables us to geocode each pair of origin and destination to form a basis for trip distance estimation. Unlike previous studies that use the straight-line distance between each origin and destination pair as the proxy of trip distance (Lindsey et al., 2011), we compute network distances, taking advantage of the detailed road network dataset from MassGIS, the State's Office of Geographic Information. For trips using private cars or taxis, the travel distance is the shortest network distance between the origin and destination. For individuals taking subway or buses, the travel distance is measured based on the specific subway line or bus route, respectively. The shortest network distance is calculated between each pair of origin and destination for every individual using the Network Analyst extension in ArcGIS 10.1.

Emission factor differs significantly across transport modes. Table 4 shows the emission factors of all modes of transport except private cars. The emission factor of non-motorized trips such as walking and bicycling is set to zero. Emission factors for transit bus, commuter rail, ferryboat, paratransit and taxi are extracted from a report prepared by M.J. Bradley & Associates (2014) and submitted to the American Bus Association. According to the American School Bus Council, average fuel economy for school bus is 7 miles per gallon (MPG). The CO_2 emissions rate is 10,180 g/gallon (USEPA, 2014). The average number of students transported by each school bus is 54. Therefore, the average emissions level for school bus is 26.9 g/passenger$*$mile. According to USEPA (2014), the emission factors for subway and motorcycle are 133.0 g/passenger$*$mile and 197.0 g/passenger$*$mile, respectively.

Table 3
Principal component analysis based on socioeconomic and demographic variables.

SD variable	Factor loading			
	Comp1: unemployed female	Comp2: young family with children	Comp3: car free	Comp4: highly educated and employed
Gend	0.7001			
Employ	−0.4582			0.3144
Age		−0.3349		
HHsize		0.5269		
HHbic		0.4537		
HHchild		0.5487		
HHveh			−0.5256	
Lic			−0.3003	0.5398
Trans			0.7455	
Income				0.3348
Edu				0.6238
Cumulative	11.06%	35.83%	46.82%	61.61%

Note: we suppress factor loadings with an absolute value less than 0.3 for interpretation convenience.

Table 4
CO_2 emission factors by Transport Modes.

Travel mode	CO_2 emission factor (g/passenger*mile)
Walk	0.0
Bike	0.0
Transit bus	136.0[a]
Transit rail	
Subway	133.0[c]
Commuter rail	183.0[a]
Ferryboat	819.0[a]
Paratransit	1,151.0[a]
Taxi	256.0[a]
School bus	26.9[b]
Motorcycle	197.0[c]

[a] Source: M.J. Bradley & Associates (2014).
[b] Computed based on American School Bus Council assumptions on the fuel economy of school buses and CO_2 emission level from USEPA (2014).
[c] Source: Emission Factors for Greenhouse Gas Inventories (USEPA, 2014).

For a trip using a private car (not listed in Table 4) in our data sample, the emission factor is derived from the published vehicle emission data by the U.S. Environmental Protection Agency (USEPA) and the U.S. Department of Energy (DOE) according to the manufacturer, model, production year, and fuel type of the vehicle used in the trip.

The individual daily VMT by private car, the emission factor of private cars, and the individual daily transport CO_2 emission are the three key transport-related variables in the SEM framework. To visualize the spatial patterns of the three variables across Greater Boston, we link individual level measures to their corresponding home locations and use the interpolation tools in ArcGIS to generate a series of surfaces of the three key variables in Greater Boston (Fig. 3). It can be observed that both VMT and transport CO_2 emissions by private cars are lower near the city center, and higher in the suburban areas. The VMT and transport emissions also vary within suburbs. For areas closer to sub-regional centers such as Lawrence and Lowell, the VMT and emissions are lower. In contrast, the spatial pattern of car efficiency in Greater Boston is less obvious.

In addition to visual explorations of the spatial patterns, we run a series of t-tests to test whether the means of the three variables differ between urban and suburban areas. The urban areas include cities and towns designated as “inner core” and “regional urban centers” by the MAPC (Fig. 1). Accordingly, the suburban area is defined as cities and towns labelled “maturing suburbs” and “developing suburbs”. The results as presented in Table 5 show significant differences between the suburban and urban areas in all three variables. Individual daily transport CO_2 emissions are much higher in suburban areas

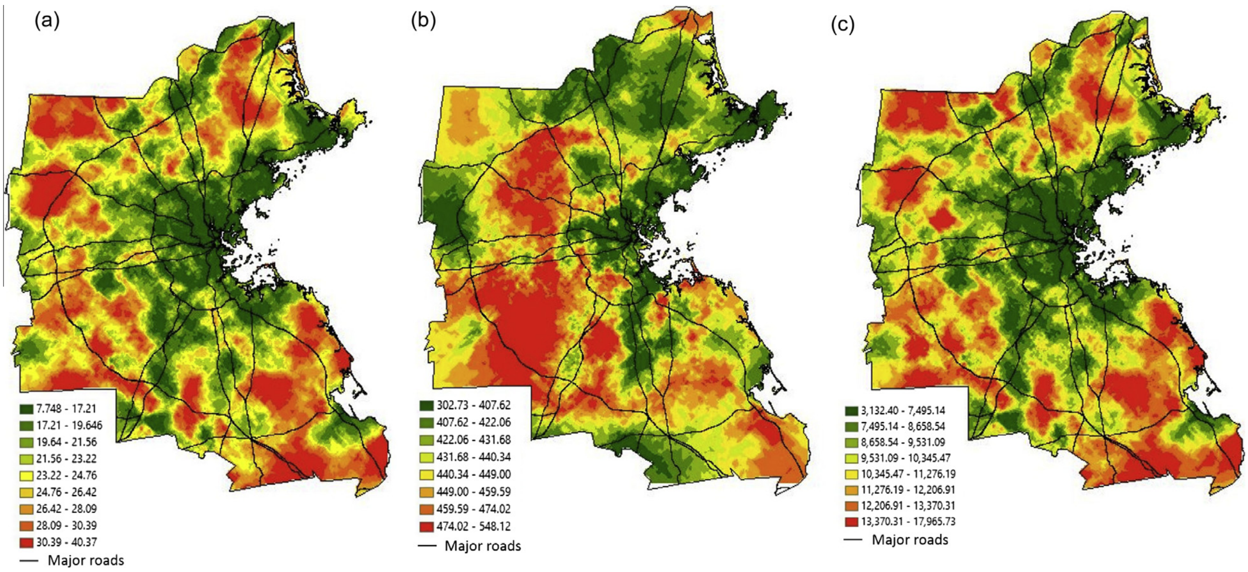

Fig. 3. (a) Individual daily VMT by private cars (unit: miles); (b) emission factor of private cars (unit: g/mile); (c) individual daily transport CO_2 emissions (unit: g).

Table 5
T-test for individual daily VMT, transport CO_2 emissions and emission factor.

Neighborhood type	Transport indicator		
	VMT (miles)	Emission factor (g/mile)	Transport CO_2 emissions (g)
Urban	23.568	422.471	9963.169
Suburban	29.770	436.836	12962.110
p-value	0.000	0.000	0.000

compared with urban areas. The high emission level could be explained by both the longer distances travelled and the less efficient cars owned by residents in suburban neighborhoods.

4. Modelling results

In this section, we present the major findings from the SEM analysis. Table 6 reports model fit statistics in order to evaluate if the proposed model is compatible with the sample data. The most basic statistic is the model chi-square (χ^2) test, which measures the discrepancy between the model-implied and sample covariance matrices. However, the value of χ^2 tends to increase along with the sample size. In large samples, it is common to ignore a failed model chi-square test and refer to other fit indices in order to justify the model (Kline, 2011). As shown in Table 6, all other fit indices for our model indicate a good model fit. Thus, with a large data sample consisting of 11,037 observations, we conclude that our model fit is acceptable in spite of the relatively high χ^2 value.

Table 7 summarizes the estimation results of both the measurement model and the structural model. Fig. 4 plots the significant relationships among the key variables based on the estimation results. They demonstrate the benefits of using SEM to investigate the complicated interactions among the built environment, socio-demographic characteristics, vehicle usage, vehicle type choice, and transport CO_2 emissions. In the measurement model, the latent variable "built environment" is positively related with development density, connectivity and land use mix, but negatively associated with infrastructure inaccessibility. Hence in the remainder of this paper including Table 7, we use "built environment" to represent new-urbanism-type built environment, which is characterized by high development density, well-connected road network, diverse land uses, and easy access to public transport systems. The latent variable "socioeconomic and demographic characteristics" has positive factor loadings on "young family with children" and "highly educated and employed", but negative factor loading on "car free" and "unemployed female". Thus we use "socioeconomic and demographic characteristics" to denote high-income family with large household size and more cars.

We partly control for the issue of residential self-selection by treating the built environment as endogenous and estimating the influence of socioeconomic and demographic characteristics on the type of neighborhoods to live in. In contrast, previous studies that used single-equation regression models or ANOVA (e.g. Frank et al., 2000; Barla et al., 2011; Waygood et al., 2014) treated the built environment characteristics as exogenous variables, therefore they may overestimate the effect of the built environment on transport emissions. As can be seen from Table 7 and Fig. 4, the two latent variables "built environment" and "socioeconomic and demographic characteristics" are negatively correlated (−0.327), which means that higher income households are more likely to live in sprawl-type suburban neighborhoods with lower density and more homogenous land uses. This result is consistent with the findings of previous research on other cities (e.g. Cao et al., 2009; van Acker and Witlox, 2010). This pattern is reasonable considering the preference of richer households with larger family size to live in more spacious houses with better environment (often in suburbs). These households also tend to have access to private cars and tend to rely on driving to meet their travel demand.

Table 6
Measures of fit for the structural equation model.

Model fit indices	Description	Value
df	Degrees of freedom	29
χ^2	Maximum Likelihood Ratio Chi-Square: measuring the discrepancy between data and model-based covariance matrices. If $\chi^2 = 0$, the model perfectly fits the data.	750.828
RMSEA	Root Mean Square Error of Approximation: measuring the discrepancy between model-implied and sample covariance corrected by the expected value of *df* or χ^2. RMSEA $\leqslant$ 0.05 indicates "good fit".	0.0478
RMR	Root Mean Square Residual: measuring the mean absolute covariance residual. RMR = 0 indicates perfect fit.	0.0086
SRMR	Standardized Root Mean Square Residual: measuring the mean absolute correlation residual. If SRMR $\leqslant$ 0.08, the model is acceptable.	0.0331
GFI	Goodness of Fit Index: estimating the proportion of covariance in the sample data matrix explained by the model. GFI = 1 indicates best fit.	0.988
CFI	Comparative Fit Index: measuring the relative improvement in the fit of the implied model over that of a baseline model. CFI $\geqslant$ 0.95 indicates acceptable fit.	0.986

Table 7
Estimation results of SEM (significant at α = 0.05).

	Direct effect	Indirect effect	Total effect
Measurement model			
Development density			
Built environment	0.972	–	–
Connectivity			
Built environment	0.834	–	–
Infrastructure inaccessibility			
Built environment	−0.943	–	–
Land use mix			
Built environment	0.462	–	–
Unemployed female			
Socioeconomic & demographic characteristics	−0.502	–	–
Young family with children			
Socioeconomic & demographic characteristics	0.183	–	–
Car free			
Socioeconomic & demographic characteristics	−1.002	–	–
Highly educated and employed			
Socioeconomic & demographic characteristics	0.257	–	–
Structural model			
Effect on built environment			
Socioeconomic & demographic characteristics	−0.327	–	−0.327
Effect on VMT			
Socioeconomic & demographic characteristics	0.090	0.073	0.163
Built environment	−0.224	–	−0.224
Effect on emission factor			
Socioeconomic & demographic characteristics	0.081	0.026	0.107
Built environment	−0.080	–	−0.080
Effect on CO_2 emissions			
Socioeconomic & demographic characteristics	–	0.179	0.179
Built environment	–	−0.230	−0.230
VMT	0.946	–	0.946
Emission factor	0.228	–	0.228

1. Standardized estimates are reported.
2. The variable "built environment" refers to new-urbanism-type built environment; and the variable "socioeconomic and demographic characteristics" refers to high-income households with large family size and easy access to private vehicles.

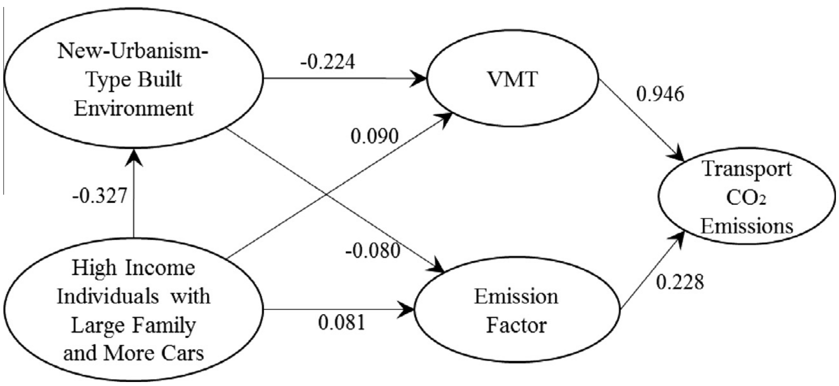

Fig. 4. Significant relationships among key variables (standardized estimates are reported; significant at α = 0.05).

The estimation results show that the direct effect of new-urbanism-type built environment on VMT is negatively and significant (−0.224). It suggests that people who live in an area with mixed land use, high density, good connectivity, and easy access to transit tend to drive less compared with those living in sprawl-type neighborhoods with opposite characteristics. The result is different from Liu and Shen (2011) who did not find a direct effect of the urban from on VMT in Baltimore, but found a significant indirect effect through other channels. The socioeconomic and demographic characteristics have a positive direct impact on VMT as expected (0.090), indicating that people with higher income and larger household size are more dependent on automobiles. The socio-demographic characteristics can also influence VMT indirectly through the built environment (0.073) as wealthy households are more likely to live in sprawl-type neighborhoods, thus driving more. This indirect effect is generally comparable to the direct effect of socio-demographic characteristics on VMT. The total effect of socioeconomic and demographic characteristics on VMT amounts to 0.163, which is smaller in magnitude compared with the built environment effect.

The new-urbanism-type built environment has the potential to influence vehicle emission factor through vehicle type choice, which can be explained by multiple factors. For example, some previous studies suggest that households in denser areas are more likely to choose and drive high efficiency vehicles due to the space constraints in these neighborhoods for large vehicles such as SUVs and pick-up trucks (Fang, 2008; Brownstone and Golob, 2009). Cao et al. (2006) argue that people living far away from urban centers may require larger-capacity vehicles considering the greater home improvement demands as well as the inconvenience for shopping activities. Similarly, in Greater Boston we find that new-urbanism-type neighborhoods are associated with vehicles with lower emission levels as reflected by the small and negative coefficient (−0.080) in the model. Moreover, socio-demographic characteristics have a direct positive effect of similar magnitude (0.081) on individuals' vehicle type choices. This reveals that higher income households generally have less environment-friendly cars. As family size increases, large vehicles, such as vans or pick-up trucks, are more likely to be purchased than other types of vehicles. The total effect of socio-demographic characteristics on vehicle type choice is estimated to be 0.107, which is larger in magnitude than that of the built environment.

In summary, socioeconomic and demographic characteristics influence transport CO_2 emissions through the two mediate variables: vehicle usage and vehicle type choice. The estimation results suggest that CO_2 emissions increase with personal income, household size and car ownership rate. The total effects (0.179) can be decomposed into three parts: socioeconomic demographics influence CO_2 emissions through vehicle choice (0.018), VMT (0.085) and the built environment (0.075), respectively. New-urbanism-type built environment has the presumed negative impact (−0.230) on transport CO_2 emissions, which means that higher density, mixed land use and easier access to public transport could help reduce transport emission levels. The results are generally in line with previous research on individual transport emissions, such as Frank et al. (2000), Barla et al. (2011) and Waygood et al. (2014). The SEM approach further enriches the findings by enabling the understanding of the direct and indirect effects of the built environment and socio-economic characteristics on transport emissions and by allowing quantitative assessment of their impacts on the two intermediate variables, vehicle type choice and vehicle usage. The research finding justifies the effectiveness of implementing planning strategies in relieving transport emissions. Residents living in neighborhoods with high density, mixed uses, good connectivity, and easy access to public transport systems not only tend to own cars with lower emission levels, but also drive less compared with residents living in sprawl-type neighborhoods, hence reduce transport CO_2 emissions. Moreover, the effect of the built environment on transport CO_2 emissions through VMT (−0.212) is much larger than that through vehicle choice (−0.018). In this regard, the built environment helps reduce transport emissions largely through changing people's vehicle usage and to a less extent by influencing their vehicle type choices. When comparing the influence of socio-demographic variables and built environment variables on transport CO_2 emissions, we find that the built environment (−0.230) has a slightly larger effect than individual characteristics (0.179). Our finding provides some new evidence that supports land use planning as a policy option to mitigate transport emissions.

5. Conclusions

Using a 2010 household travel survey dataset of Greater Boston, USA, this study examines the impact of the built environment and socio-demographic characteristics on transport CO_2 emissions through two mediate variables, vehicle usage and vehicle type choice. Unlike some of the previous studies that mainly rely on aggregate measures of transport emissions, we compute carbon emissions from transport at an individual level, considering trip mode, travel distance, and the manufacturer, model, production year, and fuel type of vehicles used in individual trips, which enables us to investigate transport CO_2 emissions at a degree of precision and coherence that is unavailable to most previous researchers. The SEM approach adopted in this study allows us to discern the complicated interactions among the built environment, individual characteristics, travel behavior, vehicle type choice and transport emissions.

We find that individual socio-demographic characteristics play a significant role in transport CO_2 emissions as we would expect. Wealthier households with larger family size and higher car ownership rate are more likely to purchase less-efficient cars and drive more compared with households with opposite characteristics, thus producing more transport emissions. We also find that the new-urbanism-type of built environment characterized by high density, mixed land use, good connectivity, and easy access to transit is negatively associated with transport CO_2 emissions. Such mitigating effect is achieved largely through the reduced VMT and is enhanced slightly by the more efficient vehicles owned by households living in denser and more diverse neighborhoods, all else being equal. Moreover, the built environment factors influence transport emissions to a greater extent than that of socio-demographic characteristics, which adds further support to the effectiveness of land use policies to reduce transport CO_2 emissions.

The empirical results could inform the design of proactive land use and transport policies aimed at transport emission mitigation. As suggested by the results, creating new-urbanism-type neighborhoods would help discourage vehicle usage. In the meantime, people living in such neighborhoods are less prone to drive large-capacity cars such as SUVs or light trucks, indicating a taste for urban living is associated with the desire for fuel-efficient cars as new urbanism proponents might expect. However, the effectiveness of land use control policies in promoting fuel-efficient cars might be limited based on our results, because socio-demographic characteristics have a larger impact on vehicle type choice than the built environment. Thus other policy measures such as financial incentives might be necessary in order to encourage the purchase of fuel-efficient cars.

This research can be effectively extended in a number of directions in the future. By allowing socioeconomic and demographic characteristics to affect the built environment in the SEM, this study partly controls for residential self-selection. The issue of residential self-selection can be better handled by integrating longitudinal design with SEM to investigate the behavior changes of recent movers or by incorporating psychological variables such as travel attitudes and life style preferences into the analysis. Furthermore, although we have considered the heterogeneity of emission factors across diffident vehicle types in the estimation of individual transport emissions, some other factors that could influence vehicle emission such as the real-time driving condition, speed, acceleration and road slope are not captured. A better estimation or direct measurement of individual transport emissions that take into account such factors could strengthen our analysis. In the meantime, the current research focuses solely on Greater Boston. Similar analysis can be performed for other metropolitan areas to understand the variations in the interactions between the built environment and transport emissions and provide a more complete picture on this complicated yet critical linkage.

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