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How built environment affects travel behavior: A comparative analysis of the connections between land use and vehicle miles traveled in US cities

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Abstract: Mixed findings have been reported in previous research regarding the impact of built environment on travel behavior—i.e., statistically and practically significant effects found in a number of empirical studies and insignificant correlations shown in many other studies. It is not clear why the estimated impact is stronger or weaker in certain urban areas and how effective a proposed land use change/policy will be in changing certain travel behavior. This knowledge gap has made it difficult for decision makers to evaluate land use plans and policies according to their impact on vehicle miles traveled (VMT), and consequently, their impact on congestion mitigation, energy conservation, and pollution and greenhouse gas emission reduction.

This research has several objectives: (1) re-examine the effects of built-environment factors on travel behavior, in particular, VMT in five US metropolitan areas grouped into four case study areas; (2) develop consistent models in all case study areas with the same model specification and datasets to enable direct comparisons; (3) identify factors such as existing land use characteristics and land use policy decision-making processes that may explain the different impacts of built environment on VMT in different urban areas; and (4) provide a prototype tool for government agencies and decision makers to estimate the impact of proposed land use changes on VMT.

The four case study areas include Seattle, WA; Richmond-Petersburg and Norfolk-Virginia Beach, VA; Baltimore, MD; and Washington, DC. Our empirical analysis employs Bayesian multilevel modeling method with various person-level socioeconomic and demographic variables, and five built-environment factors including residential density, employment density, entropy (measuring level of mixed-use development), average block size (measuring transit/walking friendliness), and distance to city center (measuring decentralization and level of infill development).

Our findings show that promoting compact, mixed-use, small-block, and infill developments can be effective in reducing VMT per person in all four case study areas. However, the effectiveness of land use plans and policies encouraging these types of land development is different both across case study areas and within the same case study area. We have identified several factors that potentially influence the connection between built environment shifts and VMT changes including urban area size, existing built environment characteristics, transit service coverage and quality, and land use decision-making processes.

Keywords: Built environment, land use change, travel behavior, vehicle miles traveled (VMT), multilevel Bayesian model, US urban transportation planning policy

1 Introduction

In 2007, a total of 3 trillion vehicle miles traveled (VMT) was recorded on all US roads, which led to 176,000 million gallons of fuel consumption (NAS 2009). For several decades, urban transportation researchers and policymakers have been trying to understand and potentially exploit the relationship between land use and travel behavior. The topic has received enormous attention, especially in terms of its connection to energy consumption, traffic congestion, and environmental quality (Cervero 1991, 1996, 1998; Kitamura et al. 1997; Frank et al. 2000; Hanson and Genevieve 2004; Cao et al. 2006; Levinson and Krizek 2008; Zhang et al. 2009; among others). In addition, several policies focusing on transportation rules that target environmental and sustainability issues have been recently suggested. These policies acknowledge that urban transportation produces about 30 percent of the nation's total carbon emissions (EPA 2006, Ewing et al. 2008; Frumkin 2002) and attempt to mitigate or stop the degradation of environmental quality. Low-density land use patterns, urban sprawl, lack of mixed land use, neighborhoods unfriendly to transit and nonmotorized transportation, and the continual expansion of urban area boundaries have been identified as some of the most important factors contributing to dominant

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automobile travel and auto-dependency in the United States (NAS 2009). Not surprisingly, policymakers have considered land use policies long-term solutions to urban transportation problems (Neuman 2005).

There have been many published results on the impacts of built environment on travel behavior in and outside of the United States, which are summarized in the Literature Review section. However, few previous studies have compared these impacts in different urban areas with consistent models and datasets. Since mixed findings have been reported in the literature, additional in-depth and comparative studies on the connection between built environment and travel behavior are required (Cervero 1996; Cervero and Kockelman 1997; Boarnet and Sarmiento 1998; Boarnet and Crane 2001; Frank et al. 2007). It is unclear to what extent the reported differences in the estimated impacts of built environment on travel behavior can be attributed to the different existing land use patterns and/or land use policies in urban areas analyzed in previous studies.

This research has several objectives: (1) Re-examine the effects of built-environment factors on travel behavior, in particular, vehicle miles traveled (VMT) in five US metropolitan areas grouped into four case study areas; (2) Develop consistent models in all case study areas with the same model specification and datasets to enable direct comparisons; (3) Identify factors such as existing land use characteristics and land use policy decision-making processes that may explain the different impacts of built environment on VMT in different urban areas; and (4) Provide a prototype tool for government agencies and decision makers to estimate the likely impact of proposed land use changes on VMT.

The four case study areas include Seattle in Washington State, Richmond-Petersburg and Norfolk-Virginia Beach in Virginia, Baltimore in Maryland, and Washington, DC. The case study in Virginia represents small to medium-sized urban areas with <1 million population. The other three cases all involve large urban areas on the East and West Coasts of the United States, with Washington, DC. being the largest urban area in this study. Seattle has relatively more progressive land use policies than the other cases and in most other urban areas in the US. Washington, DC, has some unique downtown land use patterns with very good transit and subway access and a large number of transit-oriented development projects. In the three cases along the East Coast, local government agencies have dominant control on land use development decisions, which is different from the decision process in Seattle.

In terms of methodology, a Bayesian multilevel modeling approach is employed to quantify the relationship between built environment measures and VMT. As mentioned above, consistent models and datasets are developed for all four case study areas. In addition, we have included five built environment variables that reflect diverse aspects of urban form: residential density, employment density, entropy (measuring the level of mixed development), average block size (measuring transit/walking friendliness), and distance to city center (measuring decentralization).

The following section summarizes previous research on the connection between built environment and travel behavior. Section 3 presents the data and modeling methodology in detail. Results are presented and interpreted in Section 4. Section 5 offers conclusions and recommendation for future research.

2 Literature review

The linkage between built environment and travel behavior was not highlighted or intensively analyzed until the 1980s. In theory, built environment characteristic can influence travel behavior on different time scales and through various mechanisms. Boarnet and Crane (2001) suggested that the built environment influences the price/generalized cost of travel through its short-run impact on travel time and other factors, which then influences the consumption of travel. In the long run, the built environment can also influence the location choices of households and businesses, and consequently. their travel decisions. Last but not least, land use dynamics can also have a less immediate and more indirect effect on travel behavior through their impact on activity-travel attitudes over time.

Early studies focused on the connection between land use density and transit use (Pushkarev and Zupan 1977). Driven by recent policy debates related to new urbanism and smart growth, a number of studies have examined the effect of built environment on travel behavior at a disaggregate level. In general, these studies attempted to quantify the correlation and understand the causal structure between the two. Plenty of studies have found statistically significant impacts of various built environment factors on travel behavior, such as mode choice, trip generation, trip length, trip chaining, and VMT (Cervero 1996; Cervero and Kockelman 1997; Ewing and Cervero 2001; Frank et al. 2007; McMullen et al. 2008). Built environment characteristics examined include density, diversity, block size, sprawl indicators, and network connectivity. In contrast, a number of studies have shown insignificant or negligible impacts of certain land use patterns on certain travel behavior (Boarnet and Sarmiento 1998; Boarnet and Crane 2001). Other studies have empirically examined the reverse impact of transportation on land use (e.g., Hanson and Genevieve 2004; Zhang 2010), which is not the focus of this research.

Census block, tract, and Traffic Analysis Zone (TAZ) are often used as the geographic units of analysis in most previous studies probably because land use and travel data are usually available at these levels. Several studies have shown that land use patterns measured at different geographic resolutions can produce different empirical estimates (Zegras 2010; Boarnet and Crane 2001). It is conceivable that some significant effects may only be found at certain geographic levels. For instance, while nonmotorized trips are sensitive mostly to local neighborhood characteristics, the characteristics of auto commuting trips are influenced more by regional land use patterns. We have chosen to use TAZ and census tract (in one case) as the spatial units of analysis for data and model consistency. The census tracts used in one case study area are approximately similar in size to TAZs in the remaining three cases.

There are also several well-known methodology issues when the impacts of built environment on travel behavior are examined. First, the correlation between travel behavior and neighborhood characteristics is at least partially explained by residential self-selection (Kitamura et al. 1997; Krizek 2003a; Schwanen and Mokhtarian, 2005; Handy et al. 2005; Mokhtarian and Cao 2008). Spatial self-selection is defined as the tendency for individuals and businesses to locate in areas that meet their travel preferences (e.g., those who tend to drive less are more likely to choose to live in transit-friendly neighborhoods). With self-selection, it is difficult to ascertain to what extent the observed correlation between built environment and travel behavior also represents a causal effect. Studies have also found that the connection between built environment and travel behavior is weakened after considering residential self-selection. Self-selection can be controlled for with travel attitudinal variables, structural models that consider two-way effects, longitudinal behavior data, and/or carefully selected socioeconomic and demographic variables that correlate with travel attitudes. In our research, only one case study area has behavior data (e.g., attitudinal factors) that allow for the direct control of self-selection effects. For data and model consistency, we address the residential self-selection issue indirectly by including a rich set of socioeconomic and demographic information of individual travelers. This is not the most desirable approach, but it enables comparative analysis in multiple urban areas.

In addition to self-selection problems, other issues that can possibly confound the relationship between built environment and travel behavior include spatial auto-correlation, inter-trip dependency, and geographic scales (Krizek 2003b; Bottai et al. 2006; Chen et al. 2008; Frank et al, 2008). Spatial auto-correlation is a problem in geographic analysis, since individuals and firms located in the same spatial unit are likely to be similar in ways not accounted for by their observable characteristics. Spatial heterogeneity is also an issue in geography wherein relationships between variables differ across spatial contexts. Ignoring these issues can result in model misspecification and biased estimates of standard errors in linear models. We address the spatial auto-correlation issue in the chosen methodology, which will be detailed in Section 3.2.

Finally, it is interesting to note that Burchell and Lahr (2008) studied land use policies for several major US cities and found that the institutional structure for land use decision making is different in each of these cities. For instance, in some cases, cities and other local governments have autonomous and dominant control over land use decisions (e.g., Maryland, Virginia, and many other East Coast and New England states), while in other cases state and regional governments have much stronger control on land-use policies. It is reasonable to hypothesize that centralized and decentralized land use decision-making processes can lead to different impacts of land use on travel behavior.

3 Methodology

3.1 Data and Built Environment Measures

Several data sources in the four case study areas are employed for this study. For Seattle, the 2006 Household Activity Survey (HAS) and 2005 building and parcel land use data are used. The Puget Sound Region Council (PSRC) has conducted several travel surveys since 1985. Our data includes 4746 households—approximately 0.5 percent of all households in the metropolitan area. The HAS contains household/person-level activity and travel information over two days.

The data for the DC and Baltimore cases are obtained from the Metropolitan Washington Council of Governments (MWCOG) and the Baltimore Metropolitan Council (BMC), respectively. The travel and land-use datasets in these two cases are similar to each other. The travel surveys containing travel behavior information were conducted in 2007 by the Transportation Planning Board (TPB), part of the MWCOG, and the Baltimore Metropolitan Council (BMC), which included 11,000 households in DC and 4650 households in the Baltimore metropolitan area. Land use information in the same survey year was collected for both cases.

For the Virginia case that includes two metropolitan areas (Richmond-Petersburg and Norfolk-Virginia Beach), we use the 2009 National Household Travel Survey (NHTS) add-on data and the matching 2009 land-use data from the Virginia Department of Transportation (VDOT). The NHTS add-on data contains 5428 households in the two chosen metropolitan areas in Virginia.

After removing household and person observations with missing variable values, we have 6582 persons in Seattle, 7215 persons in Virginia, 6089 persons in Baltimore, and 12,963 persons in DC cases for subsequent modeling tasks. The home location information for all persons is available at the TAZ, census tract, or even smaller geographic levels and is used to link built environment measures to travel behavior in GIS. For each of the four cases, all continuous variables are standardized by the sample mean and two standard deviations in that case study area. We use two standard deviations rather than one (which is more common) because it ensures coherence with binary covariates in our analysis (Gelman & Hill 2007).

We measure weighted VMT by dividing total travel distance for each reported trip by the number of people in the vehicle used for the trip. In other words, we calculate VMT per person to capture the effects of switching to public transit or High Occupancy Vehicle (HOV) from Single Occupancy Vehicle (SOV). For travelers who reported bus trips, we divided the trip distance by the national average passenger load in a conventional bus in 2006, which is 9.22 according to Rubin et al (2010).

For the land use variables, we use population and employment information aggregated by census tract for Seattle and by TAZ for Virginia, Baltimore, and DC. The sizes of these census tracts and TAZs are roughly equal in the case study areas. In particular, we measure residential density, employment density, entropy, average block size, and distance from city center (central business district/CBD) to represent built environment characteristics. Entropy indicates the extent of mixed land development (e.g., houses, shops, restaurants, offices) and is computed with the following equation:

$$\text{Entropy} = -\sum_{j} \frac{P_j * \ln(P_j)}{\ln(J)} \qquad (1)$$

where Pj is the proportion of land use in the jth land use category and J is the number of different land use type classes in the area. This entropy measures ranges from 0 (homogeneous land use such as housing-only divisions often found in rural and suburban areas) to 1 (most diverse and equally mixed land use, sometimes found in city centers). Four (i.e., $J = 4$) land use types are considered: residential, service, retail, and other. Since per capita VMT often has a skewed distribution, we use the naturally logged per capita VMT as the travel behavior variable for all cases. Table 1 summarizes all built environment factors used in our analysis and their hypothesized effects on VMT.

Table 1: Built environment factors.

Measure	Definition	Hypothesized impact on VMT
Residential density	Population/Area size	Negative*
Employment density	Employment/Area size	Negative
Land use mix (entropy)	Mixture of residential, retail employment, service employment, and other employment land use types	Negative
Block size	Average block size within census tract and TAZ	Positive**
Distance from CBD	Straight line from CBD	Positive

* "Negative" herein means higher residential density leads to lower VMT per person, which is desirable.

** "Positive" herein means larger block sizes leads to higher VMT per person, which is undesirable.

Table 2 presents the descriptive statistics for major variables in all four case study areas. In general, the characteristics of travelers are similar in the four case studies. Seattle and DC residents have slightly higher average income (standard deviation of income is not computed because income is reported in categories in all four cases). Residents in the Virginia case have slightly larger family sizes, more vehicles, and older residents. All samples contain slightly more females than males (0.5 would indicate a 50-50 split). The built environment characteristics are quite different in these cases. DC has the highest residential and employment density, while Virginia has the lowest density (much lower than the other three case study areas probably due to much smaller city sizes). The differences in other land use factors are also significant. These descriptive statistics are encouraging because cases with similar travelers but different built environment features are ideal for this study.

3.2 Multilevel Bayesian Regression Model Specification

The Bayesian multilevel model can be considered as an extension of regression models that produce different coefficients by subject groups (Hong et al. 2011; Shen et al. 2011). Subjects in the same level/group are likely to be similar to each other in terms of their observable characteristics. For example, persons living in the same census tract can share similar characteristics (e.g., attitudes) that are not included in statistical models. By adding group indicators, one can resolve this auto-correlation problem. However, including all group indicators will cause collinearity problems. In the multilevel model developed for this research, we estimate a group-level model and a person-level model simultaneously. This approach requires the si-

Table 2: Descriptive statistics.

	Seattle		Virginia		DC		Baltimore	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household income	\$ 70,000-80,000		\$60,000-64,999		\$75,000-99,999		\$60,000-74,999	
Household size	2.56	1.24	2.70	1.25	2.53	1.27	2.58	1.28
Worker 1	0.36	0.48	0.33	0.47	0.36	0.48	0.34	0.47
Worker 2	0.44	0.5	0.43	0.49	0.51	0.5	0.5	0.5
# of vehicles	2.13	1.07	2.50	1.16	1.98	1.06	2.12	1.09
Age	50.13	15.06	53.87	15.70	47.56	15.76	48.79	15.78
Gender	0.46	0.5	0.47	0.50	0.48	0.5	0.47	0.5
Residential density (persons/sq. mi.)	4017	4382	1950	1783	7015	8610	5309	5846
Employment density (jobs/sq. mi.)	2014	8395	766	1049	3990	13128	2623	9597
Entropy (no unit)	0.32	0.14	0.60	0.16	0.41	0.22	0.47	0.21
Average block size (mile)	0.08	0.14	0.15	0.17	0.14	0.31	0.10	0.15
Distance from CBD (mile)	15.32	10.20	18.15	12.16	15.40	12.87	13.71	8.72

multaneous estimation of group-level indicators (i.e., varying intercepts and slopes for different groups) from group-level predictors and person-level indicators (i.e., VMT) from person-level variables.

In addition to considering the aforementioned five built-environment variables, we also control for many socioeconomic and demographic factors. Previous studies have found that the inclusion of sufficient socioeconomic and demographic variables can help control for the residential self-selection effect (e.g., NAS 2009). The final model specification is as follows:

$$y_i \sim N\left(\alpha_{j[i]} + \beta_{SES}^{\top} X_{iSES}, \sigma_y^2\right), \text{for } i = 1, \ldots, n \qquad (2)$$

Where:

$$\alpha_j \sim N\left(\gamma + \gamma_{BE}^{\top} X_{jBE}, \sigma_\alpha^2\right), \text{for } j = 1, \ldots, J \qquad (3)$$

y_i represents naturally logged VMT for person i. X_{SES} and X_{BE} indicate various socioeconomic factors and built environment measures respectively. j is the group indicator. Varying intercept α_j is estimated from group level predictors (e.g., built environment variables at the TAZ and census tract levels) and assumed to be normally and independently distributed. Since we employ the Bayesian estimation approach, we need to assign prior distributions for all model coefficients. Non-informative prior distributions for β, γ and uniform prior distributions for σ_y, σ_α are assigned. The posterior distribution density function therefore is:

$$P(\alpha, \beta_{SES}^{\top}, \gamma_{BE}^{\top}, \sigma_y, \sigma_\alpha | y, X_{SES}, X_{BE}) \propto$$
$$\prod_{j=1}^{J} \prod_{i=1}^{n_j} N(y_{ij} | \alpha_j + \beta_{SES}^{\top} X_{ijSES}\, \sigma_y^2) \prod_{j=1}^{J} N(\alpha_j | \gamma + \gamma_{BE}^{\top} X_{jBE}, \sigma_\alpha^2 \qquad (4)$$

The Bayesian approach does not require the direct estimation of the mean and standard deviation of model coefficients. Instead, the posterior distribution for each model coefficient (which is a random variable) is estimated. One can easily compute distribution parameters such as mean and standard deviation from the posterior distribution. It is also possible to apply the posterior distributions to conduct policy analysis.

4 Results

Tables 3a and 3b summarize model estimation results in all four cases and presents empirical evidence of the impact of urban form on VMT per person. All models include the same control covariates and built environment measures except for the inclusion of distance to bus stop in the Seattle case and the exclusion of education levels in the Baltimore and DC cases because of limited data. One of the benefits of the Bayesian estimation approach is that we can directly simulate posterior distributions of model coefficients rather than employing the asymptotic distribution assumption. Therefore, we compute the 95 percent and 90 percent confidence intervals for each coefficient estimate. If 0 does not fall in the 95 percent (90 percent) confidence interval for a coefficient estimate, the coefficient is statistically significant at the 95 percent (90 percent) level. Conventional regression models produce a single R^2 to indicate the model goodness of fit. With the multilevel methods, we need to measure two different R^2s at the group and person levels, respectively. Gelman and Pardoe (2006) developed R^2 for Bayesian multilevel models at different levels as follows:

$$\Theta_k = u_k^T + \epsilon_k, \text{for } k = 1, \dots, K \tag{5}$$

$$R^2 = 1 - \frac{E(V_{k=1}^{K} \epsilon_k)}{E(V_{k=1}^{K} \Theta_k)} \tag{6}$$

where u_k^T is the batch of linear predictors, ϵ_k is the errors from distribution of mean 0 and standard deviation δ, Θ_k refers to individual data points, and E stands for the posterior distribution mean. The overall model explanatory power is good but not great. Adding variables such as commuting trip distance and built environmental factors at destinations will increase the model goodness of fit, but such information is not available in our datasets.

The selected socio-economic and demographic variables have statistically significant influences on per-person VMT in all cases. As people age, they tend to drive more, probably due to the increase of their work and family-related travel needs. However, the effect of age is non-linear, indicating that older people will eventually drive less after they reach certain ages. More highly educated people drive more (post-graduate education is the reference case). Education level is an important determinant of job placement. It seems from our findings that jobs requiring high levels of education tend to require more spatially dispersed business activities. It is also possible that highly educated people are more likely to engage in more spatially dispersed social and recreational activities. In terms of gender effects, males travel more than females. Individuals from larger households tend to drive less. This is expected, since household travel demand can be spread among more household members. Persons in households with one or more workers drive more than households with no worker, which is also expected. The relationship between per-person VMT in households with two or more workers and per-person VMT in households with just one worker is different across the four cases. On one hand, if two or more workers live together, their commut-

Table 3a: Results for multilevel models for Seattle and Virginia.

	Seattle						Virginia					
Variable	Mean	SD	95% interval		90% interval		Mean	SD	95% interval		90% interval	
Intercept	3.065	0.046	2.977	3.153	2.989	3.142	2.756	0.045	2.663	2.844	2.678	2.830
Age	1.221	0.137	0.935	1.487	0.992	1.434	0.935	0.153	0.638	1.255	0.699	1.188
Age_sq	-1.313	0.142	-1.590	- 1.022	-1.537	-1.080	-1.042	0.156	-1.362	-0.749	-1.296	-0.800
Education (high sch.)	-0.184	0.040	-0.263	-0.105	-0.247	-0.116	-0.141	0.041	-0.221	-0.058	-0.207	-0.072
Education (college)	-0.012	0.030	-0.066	0.047	-0.058	0.039	0.007	0.034	-0.059	0.075	-0.047	0.064
Gender	0.151	0.023	0.107	0.196	0.113	0.190	0.213	0.025	0.164	0.263	0.172	0.254
Household size	-0.230	0.029	-0.288	-0.173	-0.277	-0.182	-0.224	0.032	-0.291	-0.165	-0.278	-0.174
Number of vehicles	0.346	0.030	0.287	0.403	0.296	0.394	0.255	0.030	0.195	0.316	0.206	0.306
Household income	0.158	0.029	0.097	0.217	0.111	0.207	0.203	0.030	0.142	0.260	0.154	0.253
Worker 1	0.240	0.042	0.156	0.316	0.170	0.305	0.015	0.039	-0.059	0.097	-0.050	0.082
Worker 2+	0.294	0.045	0.208	0.381	0.220	0.367	0.088	0.042	0.006	0.167	0.016	0.158
Distance to bus stop	0.036	0.032	-0.026	0.098	-0.017	0.088						
Residential density	**-0.308**	**0.035**	**-0.375**	**-0.236**	**-0.364**	**-0.252**	**-0.262**	**0.060**	**-0.380**	**-0.149**	**-0.361**	**-0.163**
Employment density	**-0.071**	**0.039**	**-0.146**	**0.005**	**-0.135**	**-0.010**	**0.034**	**0.093**	**-0.150**	**0.215**	**-0.116**	**0.191**
Entropy	**-0.149**	**0.033**	**-0.211**	**-0.086**	**-0.202**	**-0.095**	**-0.003**	**0.049**	**-0.100**	**0.094**	**-0.087**	**0.076**
Average block size	**0.153**	**0.040**	**0.073**	**0.239**	**0.087**	**0.221**	**0.220**	**0.051**	**0.119**	**0.317**	**0.140**	**0.305**
Distance from CBD	**0.331**	**0.037**	**0.257**	**0.402**	**0.271**	**0.391**	**-0.043**	**0.043**	**-0.128**	**0.039**	**-0.112**	**0.027**
sigma.a	0.196	0.019	0.157	0.234	0.164	0.226	0.169	0.022	0.129	0.216	0.134	0.207
sigma.y	0.948	0.009	0.930	0.965	0.933	0.961	1.063	0.009	1.046	1.080	1.049	1.078
R^2 (person level)	0.238						0.112					
R^2 (group level)	0.768						0.585					

ing distances may become longer on average since they need to consider multiple work places in residential location choices. On the other hand, multi-worker households enjoy greater carpool opportunities and transit use flexibilities. Vehicle ownership and high income both encourage people to drive more. Public transit accessibility does not statistically influence per-person VMT in the Seattle case.

Built environment measures significantly influence per-person VMT in our case studies. All four models show that *residential density* has a statistically significant negative impact on VMT. This is consistent with previous findings. *Employment density* is statistically negatively correlated with VMT only in the Seattle and Baltimore cases. *Entropy* or level of mixed development has a statistically significant negative impact on VMT in all but the Virginia case. These results indicate that people living in more compact/mixed-development neighborhoods tend to drive less. *Average block size* has a positive relationship with VMT. In general, a smaller block size indicates better street connectivity and walkability. *Distance from CBD* is also positively associated with VMT in all cases except the Virginia case, which shows that people living further away from the CBD tend to drive more.

Since all continuous variables have been standardized with mean and two standard deviations, and the VMT variable is naturally lagged, it is not very straightforward to interpret the coefficient estimates. For instance, the coefficient for residential density is –0.308 in the Seattle case. This implies that if the residential density increases from the sample mean (4017 persons/square mile) to two standard deviations above the sample mean (12,781 persons/square mile), VMT per person would decrease by 26.5 percent, i.e., [exp(–0.308*0) – exp(–0.308*1)]/ exp(–0.308*0). We have developed Table 4 and Figure 1 to better interpret the model coefficients and enable easy comparison across the four cases.

Table 4 shows the percentage of change in VMT per person in response to a one-standard-deviation increase of builtenvironment variable values from their respective sample means. Again, we use the residential density in the Seattle case as an example. The mean residential density in Seattle is 4017 persons per square mile. An increase in residential density by one standard deviation from the mean represents a 109 percent density increase from the mean. This residential density increase is predicted by the Bayesian multilevel model to reduce VMT per person by 14.27 percent, i.e., [exp(–0.308*0) – exp(–0.308*0.5)]/ exp(–0.308*0). In general, the impact of residential density increase on VMT reduction is much more significant than the impact of employment density increase. The DC case with the best existing transit services and highest existing density is the urban area where compact (higher den-

Table 3b: Results for multilevel models for Baltimore and DC.

	Baltimore						DC					
Variable	Mean	SD	95% interval		90% interval		Mean	SD	95% interval		90% interval	
Intercept	2.285	0.050	2.180	2.381	2.204	2.365	2.192	0.038	2.116	2.265	2.130	2.251
Age	1.459	0.150	1.176	1.740	1.216	1.704	1.631	0.113	1.415	1.855	1.447	1.824
Age_sq	-1.521	0.156	-1.830	-1.213	-1.774	-1.269	-1.576	0.116	-1.808	-1.362	-1.770	-1.387
Gender	0.242	0.028	0.187	0.301	0.195	0.291	0.198	0.021	0.158	0.242	0.165	0.233
Household size	-0.472	0.035	-0.543	-0.402	-0.531	-0.413	-0.325	0.027	-0.375	-0.272	-0.368	-0.281
Number of vehicles	0.365	0.038	0.292	0.438	0.303	0.428	0.581	0.029	0.524	0.638	0.534	0.629
Household income	0.381	0.036	0.310	0.455	0.320	0.440	0.184	0.025	0.133	0.235	0.142	0.225
Worker 1	0.343	0.053	0.236	0.450	0.253	0.427	0.159	0.039	0.083	0.238	0.095	0.226
Worker 2	0.395	0.059	0.280	0.507	0.296	0.489	0.129	0.043	0.045	0.215	0.060	0.201
Residential density	**-0.344**	**0.047**	**-0.438**	**-0.250**	**-0.422**	**-0.268**	**-0.444**	**0.030**	**-0.503**	**-0.387**	**-0.496**	**-0.396**
Employment density	**-0.085**	**0.049**	**-0.181**	**0.008**	**-0.165**	**-0.002**	**-0.010**	**0.036**	**-0.079**	**0.058**	**-0.069**	**0.051**
Entropy	**-0.074**	**0.038**	**-0.148**	**0.001**	**-0.134**	**-0.012**	**-0.195**	**0.031**	**-0.257**	**-0.138**	**-0.248**	**-0.146**
Average block size	**0.089**	**0.048**	**-0.004**	**0.180**	**0.010**	**0.167**	**0.021**	**0.029**	**-0.037**	**0.077**	**-0.027**	**0.068**
Distance from CBD	**0.264**	**0.048**	**0.168**	**0.355**	**0.184**	**0.341**	**0.456**	**0.032**	**0.398**	**0.518**	**0.404**	**0.509**
sigma.a	0.256	0.026	0.201	0.308	0.212	0.296	0.282	0.016	0.252	0.313	0.256	0.307
sigma.y	1.098	0.011	1.078	1.120	1.081	1.116	1.174	0.007	1.159	1.188	1.161	1.185
R^2 (person level)	0.264						0.278					
R^2 (group level)	0.596						0.685					

sity), mixed-use (higher entropy), and in-fill (lower distance to the CBD) land use is the most effective in reducing VMT of all four cases.

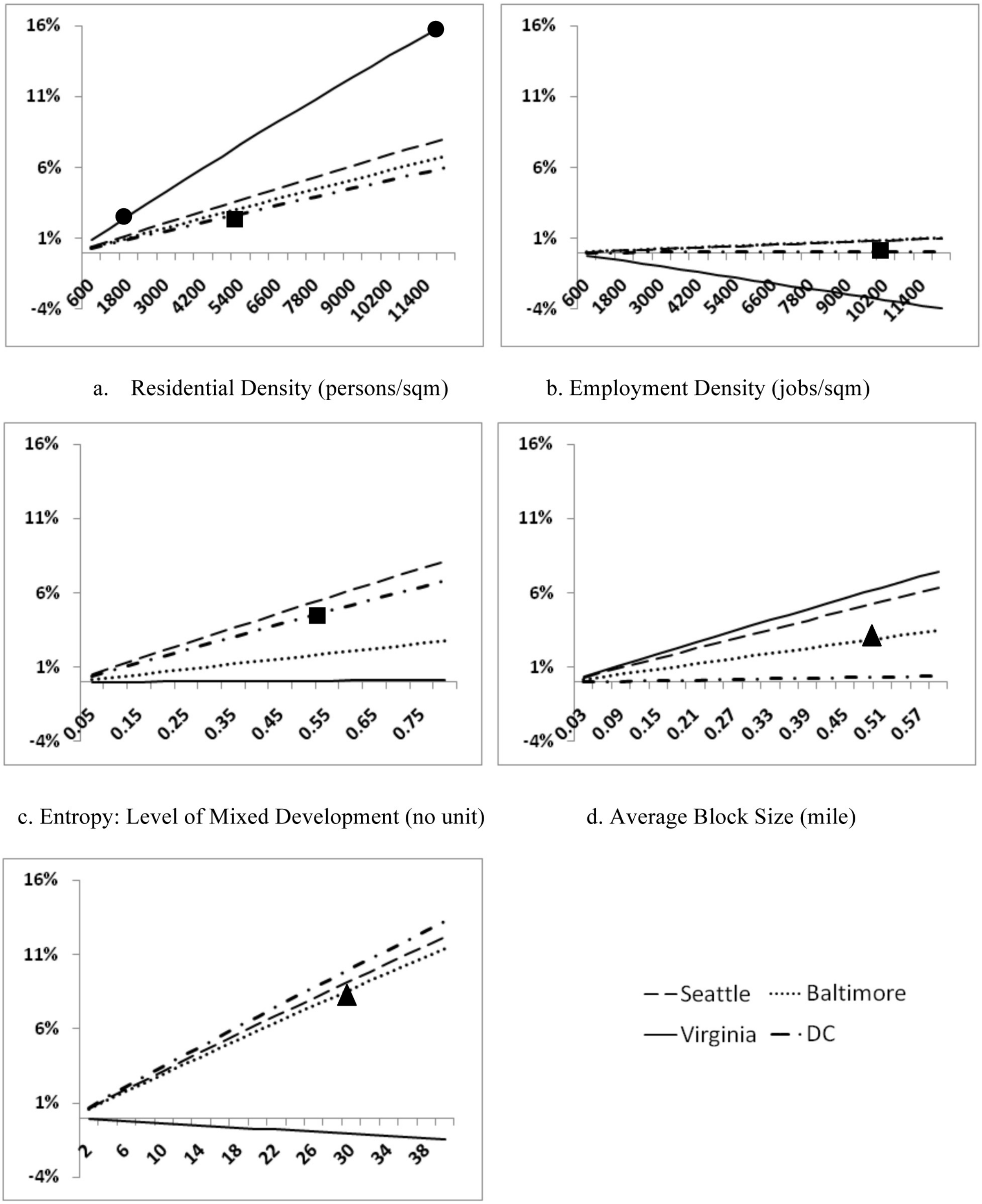
The impact of built environment on VMT is very different in the Virginia case from that of all three other cases. Notably, in the Virginia case, which happens to be the case with much smaller urban areas than the other three cases, mixed land development is much less effective. This is probably because in smaller urban areas, even those living in neighborhoods with well mixed land development may still need to travel far to reach work and non-work destinations. In other words, mixed development areas are less likely to be self-sufficient in smaller urban areas. Centralized development (reducing distance from the CBD) is also the least effective in the Virginia case, which may be explained by semi-rural areas near the fringes of the Virginian cities where residents already travel less than their urban center counterparts. Reducing the average block size turns out to be the most effective in the Virginia case with the largest existing average block size.

The impact of land use changes on VMT depends on both current built environment characteristics and proposed land use change. This is illustrated in Figure 1, which shows the impact of a 20 percent land use change (a. increased residential density; b. increased employment density; c. increased level of mixed-use development; d. reduced average block size; and e. reduced distance to the CBD) from various existing built environment statuses on VMT reduction in all four case study areas. In each of the five graphs, the horizontal axis represents various current built-environment patterns (from 0 to two standard deviations above the mean values). The vertical axis denotes the percentage reduction in VMT per person that corresponds to the 20 percent land use change. For instance, from the residential density graph (see the two round dots in Figure 1a), we can observe that for Virginia (solid line), a 20 percent increase of residential density in an area with an existing density of 11,400 persons/sqm (right-hand side of the horizontal axis) can produce about a 16 percent reduction in per-person VMT. The same 20 percent increase in residential density in an area with an existing density of 1,950 persons/sqm (average density in the Virginia case) will only produce about a 3 percent reduction in VMT. While findings from Figure 1 are largely similar to those from Table 4, the 20 percent land use changes in Figure 1 are much more attainable than the much larger land use changes in Table 4. Similar graphs can be plotted for any percentage change in land use patterns, not just 20 percent.

For government agencies and the decision makers who routinely decide whether to approve and/or financially support land use development projects or plans to reduce VMT, results such as those in Figure 1 can be very useful. For instance, a proposed local land use plan may lead to 20 percent increases in residential density, employment density, and mixed-use entropy in a specific subarea of the DC region with the following existing built environment characteristics: 2000 residents, residential density of 5400 persons/sqm, employment density of 10,200 jobs/sqm, and mixed-use entropy of 0.55. By applying model coefficients (see squared dots in Figures 1a, 1b, and 1c), we can estimate the reduction in VMT per person in that subarea to be 7.58 percent (2.75% + 0.08% + 4.76%). Despite the reduction in VMT per person, total VMT will still increase by 10.91 percent due to the influx of 20 percent more residents. In some other cases, two land use plans may be compared with one another. For instance, Plan A may produce an average block size of 0.51 mile and distance to CBD of 30 miles in Baltimore, while Plan B that includes smaller blocks and more infill developments reduces both measures by 20 percent. Our results show that Plan B can reduce VMT per person by 11.66 percent (2.98% + 8.68%; see triangular dots

Table 4: Interpretation of built environment variable coefficient estimates.

	Seattle		Virginia		Baltimore		DC	
	Base %Change	%VMT Change	Base %Change	%VMT Change	Base %Change	%VMT Change	Base %Change	%VMT Change
Residential density	4017 109%	-14.27%	1950 91%	-12.28%	5309 110%	-15.80%	7015 123%	-19.91%
Employment density	2014 417%	-3.49%	765 137%	1.71%	2623 366%	-4.16%	3990 329%	-0.50%
Entropy	0.32 44%	-7.18%	0.60 27%	-0.15%	0.47 45%	-3.63%	0.41 0.54%	-9.29%
Average block size	0.08 175%	7.95%	0.15 113%	11.63%	0.10 150%	4.55%	0.14 221%	1.06%
Distance from CBD	15.32 67%	18.00%	18.15 67%	-2.13%	13.71 64%	14.11%	15.4 84%	25.61%



a. Residential Density (persons/sqm)

b. Employment Density (jobs/sqm)

c. Entropy: Level of Mixed Development (no unit)

d. Average Block Size (mile)

e. Distance to CBD (mile)

Figure 1: VMT reduction with 20 percent change in built environment measures.

in Figures 1d and 1e).

Figure 2 below shows the estimated posterior distributions of all five built environment factors for each case study area (from left to right: residential density, employment density, entropy, block size, and distance to CBD). This further demonstrates the feasibility of the Bayesian multilevel modeling approach. All model coefficients used for the above analysis are derived from these simulated posterior distributions.

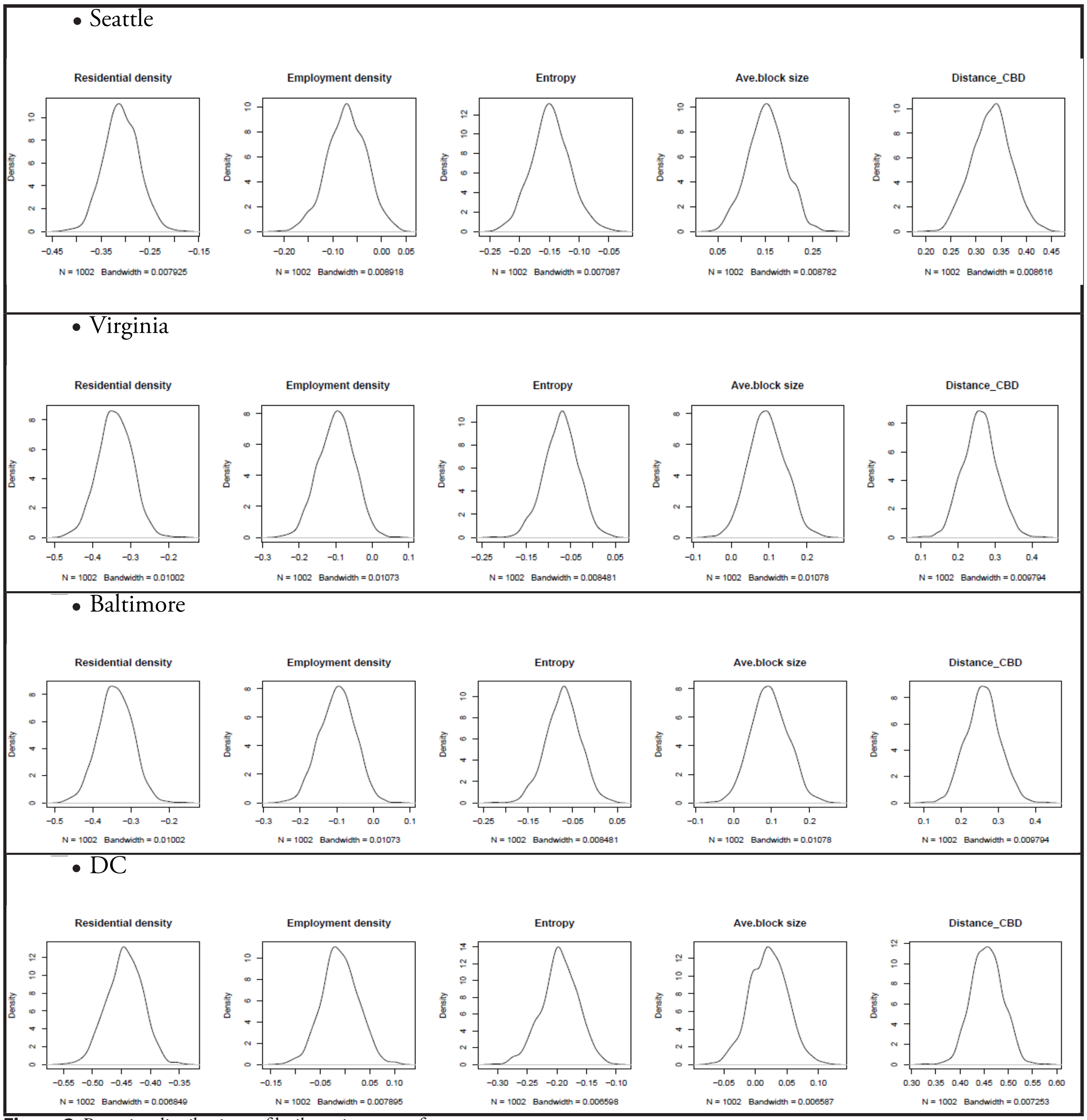


Figure 2: Posterior distributions of built environment factors.

5 Conclusions

This research develops Bayesian multilevel regression models to compare the different impacts of built environment factors on VMT in five US urban areas grouped into four cases. These models allow analysts and decision makers to estimate the VMT reduction effects of various proposed built environment changes (e.g., higher residential/employment density, mixed-use developments, smaller block sizes, and compact infill developments) and alternative land use plans given existing land use characteristics.

Our findings show that encouraging more compact, mixed-use, infill developments and smaller city blocks with various planning and policy tools can be effective in reducing VMT per person, and therefore, in addressing traffic congestion, energy consumption, and environmental quality issues. The effectiveness of these land use policies differs both across case study areas and within the same case study area. We have identified several factors that potentially influence the connection between built environment shifts and VMT changes, including urban area size, existing built environment status, transit service coverage and quality, and land use decision-making processes. Certain land use policies such as increasing employment density without promoting mixed-use developments and increasing residential density in areas with low existing residential density may not reduce VMT at all. Our comparative analysis also shows that mixed-use and urban infill developments in smaller urban areas are much less effective than those in larger urban areas.

Using four case study areas, it is difficult to accurately and quantitatively attribute the different impacts of built environment variables on VMT to various influencing factors. It is, however, feasible to conduct similar case studies in additional US cities for a meta-analysis that could potentially shed light on important policy debates—e.g., the relative effectiveness of compact, mixed-use, infill, and small-street-block developments under local-level versus regional-level land use decision making—in large urban areas versus small to medium urban areas, in one region of the US versus another region, and/or given various existing land use patterns.

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