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Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas

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Abstract. Concerns over rising fuel prices and greenhouse-gas emissions have prompted research into the influences of built environments on travel, notably vehicle miles traveled (VMT). On the basis of data from 370 US urbanized areas and using structural equation modeling, population densities are shown to be strongly and positively associated with VMT per capita (direct effect elasticity = −0.604); however, this effect is moderated by the traffic-inducing effects of denser urban settings having denser road networks and better local-retail accessibility (indirect effect elasticity = 0.223, yielding a net effect elasticity = −0.381). Accessibility to basic employment has comparatively modest effects, as do size of urbanized area, and rail-transit supplies and usage. Nevertheless, urban planning and city design should be part of any strategic effort to shrink the environmental footprint of the urban transportation sector.

1 Introduction: the policy context

Heightened concerns over climate change, gasoline prices, and congestion have sparked research into the influences of urban form and land-use patterns on motorized travel, notably vehicle miles traveled (VMT). VMT per capita is widely viewed as the strongest single correlate of environmental degradation and resource consumption in the transport sector—as individuals log more and more miles in motorized vehicles, the amount of local pollution (eg particulate matter) and global pollution (eg greenhouse gas, or GHG, emissions) increases, as does the consumption of fossil fuels, open space, and other increasingly scarce resources.

Recent policy initiatives have further fueled interest in this subject. In California, where ground transportation is responsible for 38% of greenhouse gases, state legislators recently passed the Global Warming Solution Act (Assembly Bill 32, AB32) that calls for a 25% reduction in GHG emissions below the trend line by 2020, or to 1990 levels—in total, the elimination of 169 million tonnes of carbon dioxide and other GHGs. Cities and counties that fail to make a good-faith effort to achieve this target risk losing state transportation funding.

Controversy reigns over how climate-change targets might be met in states like California. Within the transport sector, one view holds that GHG-reduction targets can best be achieved through 'sustainable mobility': for example, the introduction of low-carbon fuels and new technologies that increase fuel efficiency so that Americans can continue driving their cars at will, albeit with far less GHG emissions. At the other end of the spectrum are those arguing for 'sustainable urbanism': for example, redesigning our cities and regions so there is less need to drive and, if one does, driving can be done over shorter distances and more efficiently (eg consolidate trips at one-stop mixed-use centers). Leading this conservation charge are new urbanists, environmentalists, and other advocates of smart growth who contend that a bane of modern-day living is excessive dependency on the private car. Creating more walkable, transit-friendly, urban landscapes, they contend, will not only reduce VMT and thereby curb GHGs, energy consumption, and local air pollution, but also provide for more housing and lifestyle choices.

Adapting from Mui et al (2007), GHG emission reductions in the transport sector will come from some combination of lowering the values of the three terms in equation (1):

$$\text{GHG emissions} = \underbrace{\underset{\text{fuel consumption}}{\left(\frac{\text{gallons}}{\text{mile}}\right)} \times \underset{\text{carbon content}}{\left(\frac{\text{carbon}}{\text{gallon}}\right)}}_{\substack{\text{sustainable}\\ \text{mobility}}} \times \underbrace{\underset{\text{activity}}{\left(\substack{\text{vehicle miles}\\ \text{traveled}}\right)}}_{\substack{\text{sustainable}\\ \text{urbanism}}} \qquad (1)$$

Presently, the science seems to favor the sustainable mobility course. The relationships of biofuels, plug-in hybrid cars, and other technological advances to GHG emissions are deterministic: for example, cellulosic ethanol derived from Midwest prairie grass (6 grams of CO_2-equivalent per mega joule, or 6 g CO_2-e/MJ) is 92% less carbon intensive than ethanol produced from Midwest corn (76 g CO_2-e/MJ) (Boies et al, 2008). The likely influences of future land-use patterns and urban form are far fuzzier. Skepticism is reflected in the initial decision of California's Air Resources Board (CARB), the state agency in charge of implementing AB 32, to assume that land-use changes, or VMT reductions, will contribute to less than 2% of the state's GHG-reduction targets (2 million of the 169 million tonnes). Politicians like certainty. The UN Framework Convention on Climate Change reports that worldwide, most GHG-reduction policies focus on technological fixes because they are far more politically acceptable (Frank et al, 2007).

Despite such skepticism, a number of climate-change forecasts place a strong emphasis on VMT reductions—whether through rearranging urban landscapes or regulating automobile use via price signals or government fiat. Projections by the Center for Climate Change, a nonprofit think tank based in Washington, DC, estimates that in the absence of substantial reductions in VMT per capita, all increases in fuel-efficient and low-carbon fuels will only slow, not reverse, the rise in per capita CO_2 emissions (Condon, 2008). A study of the Seattle, Washington, metropolitan area found that even with an 'aggressive technology' scenario, in which 75 miles per gallon were assumed along with cuts in GHG emissions per gallon of fuel of nearly half, per capita VMT would still need to fall nearly 20% to achieve 2050 emission targets (Frank et al, 2007).

2 Past research

Doubts about the potential GHG-reducing effects of sustainable urbanism are understandable in light of inconsistent research findings to date. In *Growing Cooler*, Ewing et al (2008) provide a fairly rosy prognosis of the climate-stabilization potential of smart growth. If 60% to 90% of new growth occurs in a compact form, the authors estimate that VMT will fall by 30% and cut US transportation CO_2 emissions by 7% to 10% by 2050, relative to a trend line of continued sprawl. This is similar to what might happen with a doubling of fuel prices in real dollar terms. In a study commissioned by the California Air Resources Board (CARB), Ewing and Nelson (2008) estimate that VMT reductions from compact development and transportation demand management could achieve 7% to 8% of California GHG-reduction targets—not the 2% estimated by CARB. In Minnesota, VMT reductions are slated to play a more prominent role, contributing to 14% of the state's GHG-reduction targets by 2025 (Boies et al, 2008). Such estimates are informed by the work of researchers like Bailey et al (2008), Chatman (2003), Dunphy and Fisher (1996), Holtzclaw (1994), and Holtzclaw et al (2002), who show respectable elasticities (on the order of -0.30) between urban densities and VMT. Density combined with rail transit investments, some suggest, could yield even greater dividends: Brown et al (2008), for instance, estimated that America's densest metropolitan areas and those with mature railway networks are the lowest carbon emitters per capita.

Past studies of built environments have been criticized for such statistical problems as self-selection and model-specification biases (Boarnet, 2004; Cao et al, 2007; Krizek, 2003). Several studies that have sought to control for endogeneity between residential density and VMT found such weak effects that the authors concluded that feasible changes in residential densities would not have any important effects on VMT, GHG, or fuel use (Bhat and Guo, 2007; Boarnet and Sarmiento, 1998; Golob and Brownstone, 2005). Several meta-analyses of the influences of density on VMT also suggest modest effects. Ewing and Cervero (2001, page 92) found VMT to be more strongly influenced by regional accessibility than by density: "This means that dense, mixed-use developments in the middle of nowhere may offer only modest regional travel benefits." The authors estimated the 'typical' elasticity between local density and VMT to be -0.05 (versus -0.20 for regional accessibility). In the handbook on "Traveler response to transportation system changes: land use and site design", Kuzmyak et al (2003) cite a mid-point elasticity of density and VMT with similarly low values: -0.05 to -0.10.

Two factors, it should be noted, account for different assessments of the role which built environments might play in driving down VMT. One is whether density is treated as a single, all-encompassing predictor or as a proxy for other built-environment variables; Golob and Brownstone (2005) and Bhat and Guo (2007), for instance, express the built environment based on population density alone. In the recent works of Ewing et al (2008), Ewing and Nelson (2008), and Marshall (2008), density serves as a stand-in for smart growth, soaking up the influences of three other 'Ds': diversity (of land uses), designs (which are pedestrian friendly), and destination accessibility. At the extreme, very dense neighborhoods in Manhattan are also land-use diverse, highly walkable (eg short block faces), and very accessible to other destinations (courtesy of public transit, which itself can only be sustained by density). Recent analyses, such as the one by Ewing and Nelson (2008), rely on the meta-analysis results of Ewing and Cervero (2001) wherein the additive elasticity between VMT and the 4 Ds was set at around -0.3. An even bigger factor that appears to account for different estimates is the assumed share of future housing stock that is new or redevelopment. In *Growing Cooler*, Ewing et al (2008) assume that the share will reach two thirds by 2050, extrapolating from the estimates of Nelson (2006) that "more than half of all development on the ground in 2025 will not have existed in 2000." In its calculations, CARB applies a more modest figure of 30%—more in line with the observations of Downs (2004) about the rigidity of land-use changes in contemporary America.

The present study offers additional insight into the question of how much urban form and, in particular, urban densities, influence VMT. Our analysis is nationwide in scope, using data from 370 urbanized areas in the United States, making the findings more generalizable, we believe, than many past studies focused on a single metropolitan area. Others who have turned to cross-sectional national-level data to address this topic include Glaeser and Kahn (2008), who quantify transportation carbon emissions of sixty-six large metropolitan areas using the 2001 National Household Travel Survey (NHTS). A drawback of the use of urbanized or metropolitan areas as data observations, however, is the possibility of aggregation biases. In our study, whereas the dependent variable, VMT per capita, is measured for urbanized areas at large, some of the key built-environment predictors—notably, accessibility to jobs and to retail activities—are calculated at a fairly fine-grained resolution, measured by averaging values for all 500 m grid cells within each urbanized area. In addition, we turn to structural equation modeling (SEM) to build and estimate a path model that accounts for possible two-way relationships among variables, thus statistically controlling for possible endogeneity problems. Although the analysis is cross-sectional, which limits the ability to draw cause–effect inferences, we believe that the robustness of the dataset, combined with the successful estimation of a structural equation model, yield results of policy relevance. The paper ends with a discussion of what our research findings imply for climate-change and energy-conservation policies.

3 Research approach and data

Initially, we attempted to model the influences of temporal changes in various measures of built environment on VMT per capita during the 1993–2003 period. However, data-incompatibility problems prompted us to focus on cross-sectional relationships for 2003. For example, VMT data obtained from *Highway Statistics*, published annually by the Federal Highway Administration (FHWA), are available for 400 urbanized areas in 2003; however, in 391 cases geographical boundaries were different in 1993. The 400 urbanized areas with fully reported VMT data were matched with the 2000 Census and other data sources. However, geographical inconsistencies across sources forced us to drop 30 cases, resulting in a database with 370 urbanized area observations, shown in figure 1. Given that VMT estimates were derived from local traffic counts, the FHWA dataset is not perfect. Still, it provides, we believe, the most reliable VMT data for US urbanized areas that is available. The VMT dataset, moreover, is not thought to be systematically biased in one direction or another across the 370 urbanized areas and thus, we believe, is sufficient for statistical modeling purposes.

As discussed above, our key research question was whether built-environment variables, notably density and destination accessibility, significantly influence VMT per capita, controlling for other predictors, and if so, what is the relative magnitude of influences. Density and destination accessibility are two of the '4 Ds' that influence

Figure 1. Geographic boundaries of 370 US urbanized areas, 2000 (source: US Census 2000).

travel behavior (Cervero and Kockelman, 1997; DKS Associates, 2007). Our analysis examines the influences of population as well as employment densities. As noted above, the verdict on the impacts of density on travel are quite mixed. In our analysis, Destination accessibility represents relative access of households to jobs as well as to retail activities. Past research, as summarized by Ewing and Cervero (2001), generally shows destination accessibility to be a far stronger predictor of travel behavior than is density. Because of both data limitations and the aggregate nature of our data, we were unable to measure the other two 'Ds' of the built environment directly: diversity (or land-use mix) and design (generally expressed in terms of walkability measures). Our research does, however, include proxies of these two additional Ds: destination accessibility, wherein high values generally reflect diverse, or mixed-use, environments; and road density, wherein high values denote high road coverage and thus relatively good connectivity for pedestrians and cyclists.

Given the complex nature of relationships between built environments, travel, and other factors, we turned to structural equation modeling (SEM) to construct and estimate a predictive model. As a modeling tool, SEM has gained acceptance in a range of fields, including education, psychology, public health, and transportation (Golob, 2001; Zhu et al, 2006). The technique involves simultaneously measuring the covariance structure of multiple variables along designated paths so as to establish associative relationships. SEM is particularly useful for teasing out complex multivariate data structures and, in particular, for tracing through the relative direct and indirect effects of variables on each other. Maximum likelihood estimation (MLE) allows both one-way and two-way relationships between variables to be modeled. In the case of two-way relationships (ie nonrecursive structures), potential endogeneity biasing effects are statistically corrected through the use of MLE.

An initial step in conducting SEM is to postulate causal (or, more loosely, associative) relationships, typically expressed as a path diagram. As an exploratory technique, SEM allows the researcher to add or drop variables and paths, and to change the directionality of paths, based on changes in statistical fit, overall model performance, and judgment (presumably informed by a priori theory). The analyst faces a trade-off between presenting a complete model which captures every possible relationship but is, as a result, potentially complex and difficult to decipher, and a simpler, parsimonious structure which is more interpretable and captures the essence of relationships (yet potentially omits nuanced, indirect effects). We tested a large number of possible path combinations which logically explain relationships between built environments, transportation supply, regional accessibility, socioeconomic factors, and transportation demand. Traditional utility theories of travel demand (Ben-Akiva and Lerman, 1985; McFadden, 1976) guided our selection of variables albeit, given the macroscale of our analysis, the predictor variables were far more aggregate than is found in most choice models (McFadden and Reid, 1975). The job-accessibility score of an urbanized area, for instance, captured the performance characteristics (eg travel time) of its regional transportation network. After several iterations, we settled on a model with reasonably good statistical fits, which was theoretically interpretable and, within the data constraints we faced, informed our core research question.

Figure 2 presents the finalized path diagram for the SEM results presented in this paper. The criss-crossing of arrows suggests a complex set of relationships, which no doubt characterizes this topic. However, the diagram actually captures the influences of just a handful of dimensions that bear on travel. The key policy, or dependent, variable of interest—daily vehicle miles of travel per capita (VMT/Cap)—lies at the top of the diagram, with predictor variables directly feeding into it via path arrows, or indirectly through other predictors and intermediate steps. The key predictor variables of interest, those related to the built environment, are represented by density and accessibility variables (shown at the bottom of the diagram). Other variables in the model served mainly as statistical controls, reflecting factors like transportation supply (eg Roadden—road density), travel choices (eg Autocom%—automobile commute shares), and sociodemographic factors (eg HHinc—median household income). Although we originally attempted to estimate nonrecursive relationships, recursive estimates (without two-way arrows between variables) yielded the best, most interpretable results.

Table 1 defines the variable names shown in the path diagram of figure 2, along with data sources, the geographical scale of measurement, and descriptive statistics. Two geographical scales were used for computing variables. Values for the most-aggregate variables were drawn from each urbanized area as a whole (eg for VMT/Cap and HHinc variables). For the destination-accessibility variables (Basicjobacc and Locretacc)

Table 1. Variable descriptions, sources, and statistics for 370 US urbanized areas.

Variable name	Variable description	Data source and computations	Descriptive statistics	
			mean	standard deviation
Travel variables				
VMT/Cap	Vehicle miles of travel per capita, 2003; daily vehicle miles per person	FHWA, *Highway Statistics* 2003, Section V, Table HM71 & HM72	23.36	6.16
Autocom%	Percent of commute trips by private automobile; mean estimate, 2000	CTPP, Part 3, 2000 Census; computed and averaged over 500 m grid cells from GIS raster files	91.40	3.68
Railpaxmi/Cap	Rail passenger miles per capita, for 2003	APTA, *Public Transportation Fact Book*, 53th Edition, FHWA, *Highway Statistics* 2003	9.13	57.43
Transportation-supply variables				
Roadden	Roadway infrastructure density, 2003; directional miles of roadway per square mile of urbanized land area	FHWA, *Highway Statistics* 2003	8.35	2.95
Railden	Urban passenger rail infrastructure density, 2003; one-way directional fixed-guideway track miles per 10 000 square miles of urbanized land area	APTA, Public Transportation Fact Book, 53th Edition; FHWA, *Highway Statistics* 2003	214.21	1 315.90
Built-environment variables				
Popden	Population density, 2003; persons per square mile, in thousands	FHWA, *Highway Statistics* 2003	1 718.59	878.94
Basicjobden	Basic employment density, 2003; mean number of basic (export-industry) jobs per square mile	Department of Commerce, *County Business Patterns Zip Code Series* (*CBP-Z*); FHWA, *Highway Statistics* 2003; basic jobs were distributed to job centers with 5000 or more workers	413.07	247.78
Locretden	Local-serving retail employment density, 2003; mean number of local-serving (retail, service, and trade) jobs per square mile—a proxy for intensity of retail/shopping activities	Department of Commerce, *County Business Patterns Zip Code Series* (*CBP-Z*); FHWA, *Highway Statistics* 2003; local-serving jobs were distributed to retail clusters with 1000 or more retail jobs and assigned to urbanized areas	137.77	76.72

Table 1 (continued).

Variable name	Variable description	Data source and computations	Descriptive statistics	
			mean	standard deviation
Built-environment variables (continued)				
Basicjobacc	Basic-employment accessibility index, mean estimate, 2003; mean number of basic-industry jobs within 30 minutes travel time on highway networks across 500 m grid cells of urbanized area, weighted by number of households in grid cells	Department of Commerce, *County Business Patterns Zip Code Series* (*CBP-Z*); Bureau of Census, 2000 Census, STF-1A; Bureau of Transportation Statistics, NHPN version 2004.06: GIS shape files in *National Transportation Atlas Database 2006*; computed as weighted average of 500 m grid cells from GIS raster files	139.03	643.20
Locretacc	Local retail accessibility index, mean estimate, 2003; proxy for accessibility to retail activities, computed as mean number of local retail/service/trade jobs within 30 minutes travel time on highway networks across 500 m grid cells of urbanized area, weighted by number of households in grid cells	Department of Commerce, *County Business Patterns Zip Code Series* (*CBP-Z*); Bureau of Census, 2000 Census, STF-1A; Bureau of Transportation Statistics, NHPN version 2004.06: GIS shape files in *National Transportation Atlas Database 2006*; computed as weighted average of 500 m grid cells from GIS raster files	40.37	97.09
Urbanized area control variables				
Urbanarea	Urbanized area, in square miles, 2003	FHWA, *Highway Statistics* 2003; Bureau of Census, 2000 Census, GIS shape files	240.77	431.75
HHinc	Household income, median, 2000, in 1000 US$	Bureau of Census, 2000, STF 1A	44.16	10.51
Interactive variables				
Autocom%_s	Percent of commute trips by private automobile in South Region of USA, mean estimate, 2000; averaged across 500 m grid cells of urbanized area, weighted by number of households in grid cells	CTPP, Part 3, 2000 Census; computed as weighted average of 500 m grid cells from GIS raster files, to convert metropolitan-scale data to urbanized areas	13.01	31.62
Urbanarea_n	Urbanized area, in square miles, 2003, in Northeast Region of USA	FHWA, *Highway Statistics* 2003; Bureau of Census, 2000 Census, GIS shape files	48.14	302.45
Locretacc_n	Local retail accessibility index in Northeast Region of USA, mean estimate, 2003; proxy for accessibility to retail activities, averaged over 500 m grid cells of urbanized area, weighted by number of households in grid cells	Department of Commerce, *County Business Patterns Zip Code Series* (*CBP-Z*); Bureau of Census, 2000 Census, STF-1A; Bureau of Transportation Statistics, NHPN version 2004.06; GIS shape files in *National Transportation Atlas Database 2006*	7.72	59.26

Note: FHWA—Federal Highway Administration; APTA—American Public Transit Association; CTPP—Census Transportation Planning Package; CBP—County Business Patterns; GIS—geographic information systems; STF—Summary Tape File; NHPN—National Highway Program Network.

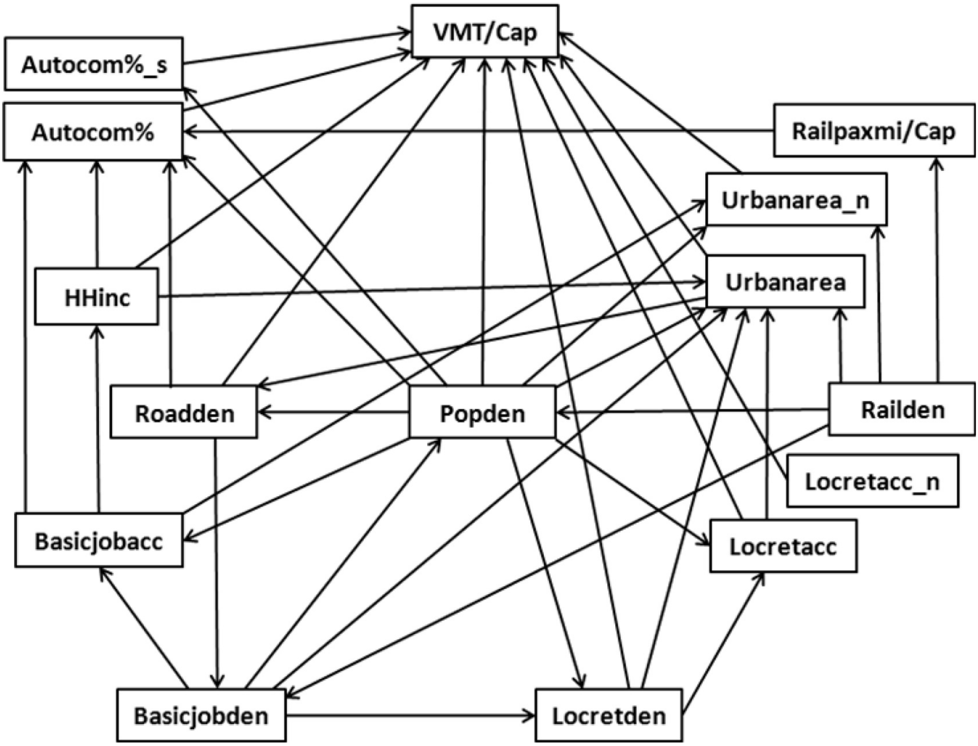


Figure 2. Path diagram of factors influencing vehicle miles traveled (VMT) per capita among 370 US urbanized areas, 2003 (see table 1 for description of the variables shown).

as well as automobile commute shares (Autocom%), values were first calculated for each 500 m grid cell within an urbanized area; resulting values were then summed over all grid cells in the urbanized area, and this value was then divided by the number of grid cells weighted by number of households in each cell, yielding an 'average'. Thus accessibility to basic jobs and local retail activities was measured at a relatively fine-grained resolution; however, the value reported for each urbanized area represents an arithmetic average.

The path diagram in figure 2, it should be noted, contains several interaction terms. These terms captured unique effects of predictor variables for certain region of the USA. For example, Locretacc_n expresses the influences of local-serving retail accessibility in the 151 urbanized areas of the nine states that make up the northeast region of the country. Inclusion of this variable improved the model fit by capturing unique influences of local-serving retail on VMT relative to other parts of the USA. No other unique relationships between local-serving retail and VMT were found, and thus no other region-specific interaction terms are shown in the model. Such regional interaction terms allowed us to capture key variables that influence VMT per capita differences across the nation, thus accounting for fixed effects (eg cultural, historical, geopolitical factors).

Also, as they are key variables in our analysis, the computations of the two destination-accessibility variables—Basicjobacc and Locretacc—deserve further explanation. Destination accessibility reflects the ability to reach destinations, increasing as a function of spatial proximity and transportation mobility. Our index is based on an isochronic measure, representing the cumulative count of activities (ie jobs) that can be reached within a given travel time over a transportation network (in our case, within

30 minutes travel time on the highway network of an urbanized area under free-flow conditions) (Cervero, 2005; Levinson and Krizek, 2005; Wachs and Kumagai, 1973). We again emphasize that ours is a fairly fine-grained measure, computed for each 500 m grid cell within an urbanized area, with the mean of all grid cells representing the 'average' measure of accessibility for an urbanized level (weighted by the number of households in each grid cell). Mathematically, the mean basic-job accessibility value for each urbanized area in 2003 was computed as:

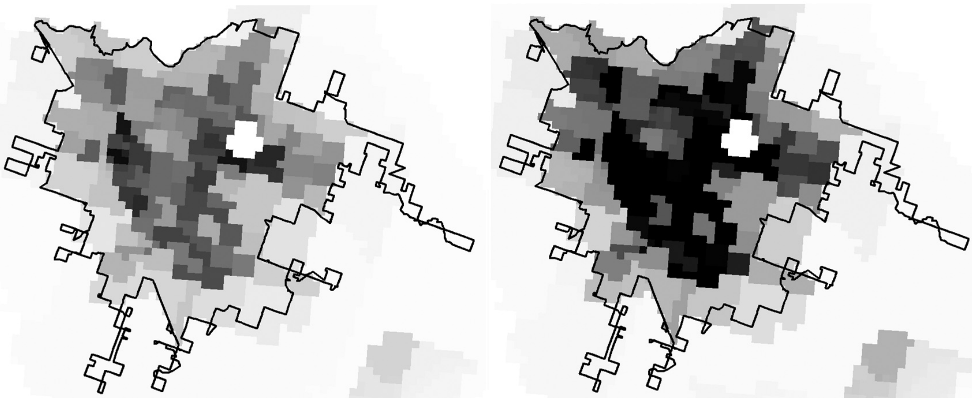
$$\mathsf{Basicjobacc}_k = \frac{1}{N_k} \sum_{i=1}^{N_k} \left(h_i \sum_j W_{ij} b_j \right) , \qquad (2)$$

where

i is 500 m grid cell i ($i = 1$ to N_k);
j is job center j in the US ($j = 1$ to 4446);
k is urbanized area k ($k = 1$ to 370);
N_k is the number of 500 m grid cells in urbanized area k;
h_i is household density (number of households in 500 m grid cell i, in year 2000);
b_j is number of basic-job workers in job center j, in year 2003;
W_{ij} equals 1 if $c_{ij} < c_{ij}^*$ and 0 otherwise;
c_{ij} is travel time between centroid of grid i and j;
c_{ij}^* is the predetermined highway network commuting time from i to j within which basic jobs are cumulatively counted (30 minutes).

Local-retail accessibility (Locretacc) was similarly computed, with the term for basic-job workers in equation (2) replaced by the count of local-retail workers in job centers.

Figure 3 maps basic-job and local retail accessibility levels within 30-minute highway network travel times for 500 m grid cells which were computed for one of the urbanized areas—Fresno, California; darker shades reflect higher accessibility levels. The values recorded for this one urbanized area were averaged over all the 500 m grid cells, to derive a metric on basic-job and local-retail accessibility for the 'typical' household in the region.



(a) (b)

Figure 3. (a) Basic-job accessibility and (b) local-retail accessibility for 30-minute travel-time isochrones, plotted for 500 m grid cells—Fresno, California, 2000.

4 Empirical results and interpretations

The path model shown in figure 1 was estimated using the AMOS 7.0 software package (SPSS Inc.). Initially, two structural equation models (SEMs) were estimated: one expressing the variables in table 1 using a logarithmic scale and the other expressing them in linear (nonlogarithmic) form. Since the two models produced similar goodness-of-fit statistics and significant levels for key predictors, we opted to present the logarithmic model results. An advantage of a log-linear model is that parameter estimates represent elasticities, reflecting the relative sensitivity (percentage change) of VMT per capita to a 1% increase in each predictor variable—holding other factors constant.

Table 2 presents the SEM results. The rows of the table show independent variables which directly influence VMT/Cap, as well as those that influence the dependent variable indirectly via other predictors. Interaction variables which capture the unique influences of several predictors in particular regions of the country are also shown. Coefficients on direct paths and indirect paths are shown as well, along with total (direct + indirect) coefficients.

The bottom of table 2 shows the summary statistics of the model. Multiple measures of fit are typically used in interpreting SEM output. In addition to χ^2, Kline (1998)

Table 2. Structural equation model, log–log estimation: model summary dependent variable: VMT/Cap.

Independent variables	Direct coefficient	indirect coefficient	Total coefficient
Direct			
Popden	−0.604	0.233	−0.381
Roadden	0.419	−0.005	0.415
Autocom%	0.602	0.000	0.602
HHinc	0.260	−0.052	0.209
Locretden	0.097	0.024	0.121
Locretacc	0.079	0.013	0.091
Urbanarea	0.036	−0.019	0.017
Interaction			
Locretacc_n	−0.140	0.000	−0.140
Urbanarea_n	0.121	0.000	0.121
Autocom%_s	0.027	0.000	0.027
Indirect			
Basicjobden	–	−0.075	−0.075
Basicjobacc	–	0.018	0.018
Railpaxmi/Cap	–	−0.002	−0.002
Railden	–	−0.003	−0.003
Summary statistics			
N	370		
χ^2	263.038		
Degrees of freedom (df)	56		
χ^2/df	4.697		
CFI (> 0.900)	0.969		
NFI (> 0.950)	0.961		
NNFI (> 0.900)	0.942		
RMSEA (≈ 0.05)	0.100		

Note: CFI—comparative fit index; NFI—normed fit index; NNFI—nonnormed fit index; RMSEA—root mean square error of approximation.

and Fan et al (1999) recommend the use of the goodness-of-fit measures shown below, with their corresponding cutoff values shown in parentheses:
comparative fit index: CFI (> 0.90),
normed fit index: NFI (> 0.95),
nonnormed fit index: NNFI (or the Tucker-Lewis Index: TLI) (> 0.90),
root mean square error of approximation: RMSEA (~ 0.05).
Our model satisfied the first three criteria and approximated the fourth. Additionally, all path coefficients were statistically significant at the 0.05 probability level, as detailed in table 3.

Figure 4 plots the elasticities of seven independent variables which directly affect VMT/Cap, along with three interaction variables. The strongest predictors are population densities, automobile commuting modal shares, and roadway density, followed by household income. The direct effects of population density are quite high, yielding an elasticity estimate well above that found in most previous studies (Ewing and Cervero, 2001). High automobile-commuting shares are, as expected, also strongly associated with high VMT/Cap, with the highest elasticity in the southern region of the USA (elasticity $= 0.602 + 0.027 = 0.629$). This is consistent with recent findings of Glaeser and Kahn (2008) that per capita emissions are largest in southern metropolitan areas. From figure 4, high provisions of road infrastructure are also associated with high VMT/Cap, as is the control variable, household income.

Figure 4 also shows that the direct influences of local retail density and accessibility on VMT/Cap are fairly modest, as is the effect of urban area size. High densities and access to retail, service, and trade activities are seen to have an inducement effect on motorized travel, consistent with the arguments of Crane (1996) that high accessibility lowers transportation costs, thus spawning more travel. High retail densities,

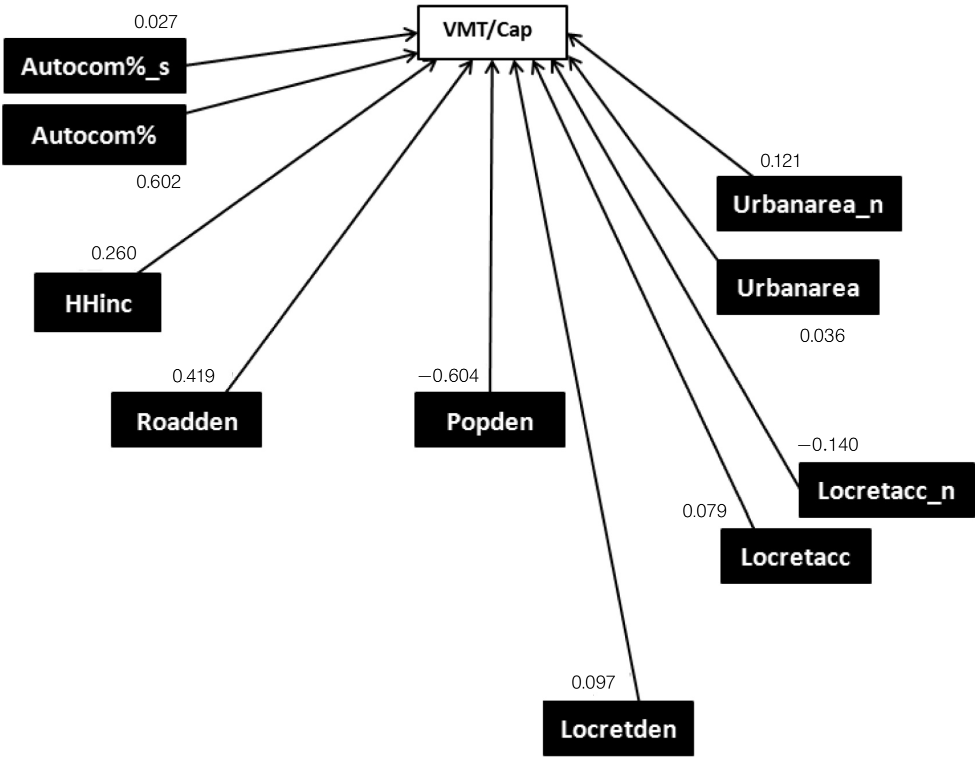


Figure 4. Structural equation model: direct effects.

we note, reflect the clustering of retail activities in shopping centers and indoor malls (owing in part to how this variable was measured—1000 or more retail-service jobs assigned to retail clusters). High accessibility to and densities of major retail shopping centers likely induce travel not only by spurring shopping (particularly large-volume purchases) but also due to factors like site designs (eg plentiful free parking) which promote access by private car. The northeast region, we note, represents an exception, with a net elasticity of −0.061 (0.079 – 0.140). This could reflect the presence of more walkable neighborhoods with traditional retail districts in many northeastern cities than are found in other parts of the USA. The other key non-residential land-use variables in the dataset—basic-job density and accessibility—had no statistically significant direct effects on VMT/Cap, operating instead indirectly through other variables.

Urban railway supply and ridership were hypothesized to be significant negative correlates of VMT/Cap. Tables 2 and 3 reveal that the relationships were in fact very

Table 3. Structural equation modeling path estimations (elasticities).

To		From	Coefficient	*p*-value
VMT/Cap	<	Autocom%	0.602	0.025
VMT/Cap	<	Autocom%_s	0.027	0.000
VMT/Cap	<	HHinc	0.260	0.000
VMT/Cap	<	Locretden	0.097	0.000
VMT/Cap	<	Locretacc_n	−0.140	0.000
VMT/Cap	<	Popden	−0.604	0.000
VMT/Cap	<	Roadden	0.419	0.000
VMT/Cap	<	Urbanarea	0.036	0.036
VMT/Cap	<	Urbanarea_n	0.121	0.000
VMT/Cap	<	Locretacc	0.790	0.000
Autocom%_s	<	Popden	−0.931	0.000
Autocom%	<	HHinc	−0.070	0.000
Autocom%	<	Popden	−0.039	0.000
Autocom%	<	Railpaxmi/Cap	−0.004	0.000
Autocom%	<	Roadden	0.029	0.000
Autocom%	<	Basicjobacc	0.007	0.000
Railpaxmi/Cap	<	Railden	0.707	0.000
Urbanarea_n	<	Popden	−0.152	0.001
Urbanarea_n	<	Railden	0.091	0.000
Urbanarea_n	<	basicjobacc	−0.056	0.000
Urbanarea	<	basicjobden	0.233	0.036
Urbanarea	<	HHinc	−0.579	0.000
Urbanarea	<	Locretden	−0.394	0.002
Urbanarea	<	Popden	−0.970	0.000
Urbanarea	<	Railden	0.073	0.000
Urbanarea	<	Locretacc	0.749	0.000
Roadden	<	Popden	0.422	0.000
Roadden	<	Urbanarea	−0.047	0.006
HHinc	<	Basicjobacc	0.099	0.000
Popden	<	Basicjobacc	0.466	0.000
Popden	<	Railden	0.024	0.000
Locretacc	<	Locretden	0.340	0.047
Locretacc	<	Popden	0.977	0.000
Locretden	<	Basicjobden	0.722	0.000
Locretden	<	Popden	0.230	0.000
Basicjobacc	<	Basicjobden	0.605	0.000
Basicjobacc	<	Popden	0.810	0.000
Basicjobden	<	Railden	0.057	0.000
Basicjobden	<	Roadden	0.303	0.005

weak and indirect. Other researchers have found stronger effects. Bailey et al (2008) found that public transit in the USA influenced VMT directly as well as secondarily through land-use effects. Availability of a rail station within ¾ mile and a bus stop within ¼ mile of one's residence was associated with fewer miles driven. The authors estimate that, without any public transit services, American households would drive 102.2 more miles per year, adding 37 million metric tonnes of carbon dioxide emissions. Brown et al (2008) also found an association: among the 100 largest US metropolitan areas, New York, and San Francisco rank first and second in passenger miles of rail transit usage per capita, and fourth and twentieth in carbon footprint per capita, respectively. Since transit and land-use relationships unfold over time, in the case of our analysis, we suspect that the absence of reliable longitudinal data limited our ability to capture large significant relationships between railway track mileage and VMT/Cap.

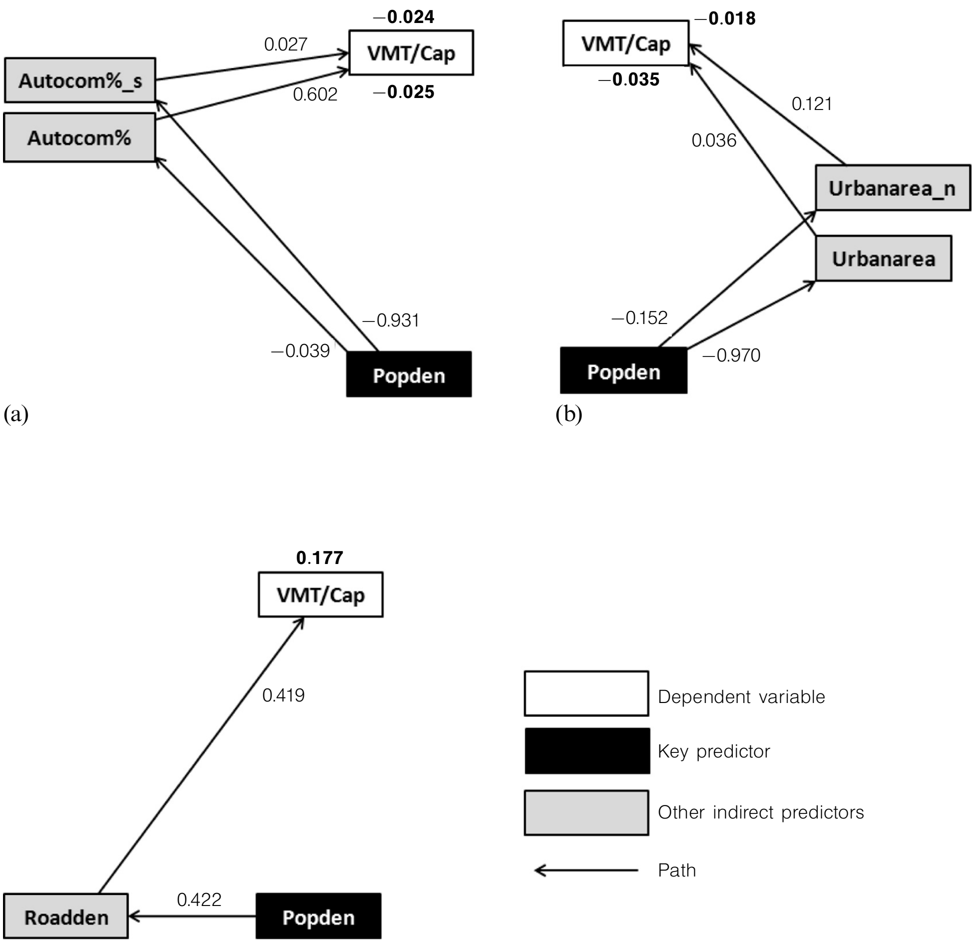
In the remainder of this section we discuss the results shown in tables 2 and 3 in greater detail, focusing on the direct and indirect effects of built-environment variables. Diagrams which trace the cumulative effects of indirect paths on VMT/Cap are used to estimate 'net' elasticities.

4.1 Direct and indirect effects of population density

The direct elasticity between population density and VMT/Cap among the 370 urbanized areas is fairly high: all else being equal, a 1% increase in population density is associated with a 0.6% decline in VMT/Cap. However, this significant negative direct effect is offset by positive indirect effects, yielding a net, or total, elasticity of -0.381.

The positive indirect effects of population density on VMT/Cap are revealed by the paths shown in figures 5 and 6. Figure 5(a) shows that high population density lowers VMT/Cap through its association with lower auto-commuting shares [with composite indirect elasticities of -0.039×0.602 (or 0.024) and -0.931×0.027 (or -0.025)]. [See Asher (1981) for discussions on the path-analysis method of decomposing elasticities into direct and indirect components.] Figure 5(b) shows that the tendency of urbanized areas with high population densities to consume less land area (holding other factors constant) further lowers VMT/Cap (slightly more in the northeast region), though again the composite indirect effect is quite modest.

The remaining indirect effects shown in figures 5(c) and 6 are positive, offsetting the negative association of population on VMT/Cap. Figure 5(c) shows that areas with higher population densities tend to also have higher road-infrastructure densities, a factor which induces travel. This estimated indirect effect is quite high: $+0.177$ (0.422×0.419). While dense urban areas do not generally build new road capacity any faster than less dense ones (Carruthers and Ulfarsson, 2008), historically, transportation infrastructure investments have been targeted at the nation's densest, largest urbanized areas. Figure 6(a) shows the other significant positive and offsetting indirect effect: via the influences of population density on local retail accessibility and urbanized area size. Dense urban sets tend to enjoy relatively high retail accessibility which, as discussed above, correlates with high VMT/Cap. This positive indirect effect $(0.977 \times 0.079 = 0.077)$ is supplemented by a positive association between retail accessibility and urban-area size, which tends to increase VMT/Cap further $(0.977 \times 0.749 \times 0.036 = 0.026)$. The other positive indirect effects shown in figure 6 are fairly moderate in size, reflecting the influences of basic-job accessibility [operating through urbanized area size (for an indirect effect of $0.810 \times -0.056 \times 0.121 = -0.005$) and household income (indirect effect of $0.810 \times 0.099 \times 0.260 = 0.021$), for a net effect of 0.016] and local-retail density (operating through a host of intermediaries that produce a net indirect effect of 0.027).



(a) (b) (c)

Figure 5. Indirect effects of population density on VMT/Cap, via (a) automobile commuting, (b) urbanized area, and (c) road-infrastructure density.

The net overall indirect influences of the intermediate factors shown in figures 5 and 6 equal 0.221 (−0.024 −0.025 −0.035 −0.018 +0.177 +0.103 +0.016 +0.027). In sum, the strong negative elasticity between population density and VMT/Cap of −0.604 is offset by the moderate positive association between population density and three factors that increase VMT/Cap—road density, urbanized area size, and retail accessibility—yielding a total net elasticity of −0.381. That is, weighing intermediate effects, a doubling of population densities is associated with a 38% decline in VMT/Cap, holding other factors constant. This net effect, we note, is close to the simple product-moment correlation between population density and VMT/Cap of −0.417. The reconstitution of a simple correlation coefficient by the sum of direct and indirect path coefficients suggests a fairly well-specified model that captures the predominant influences of the policy variable, in our case 'population density', on the dependent variable VMT/Cap (Asher, 1981).

4.2 Indirect effects of basic-job density

The SEM results in tables 2 and 3 showed that basic-job density and accessibility influence VMT/Cap indirectly. Figure 7 traces several of the indirect paths of basic-job accessibility.

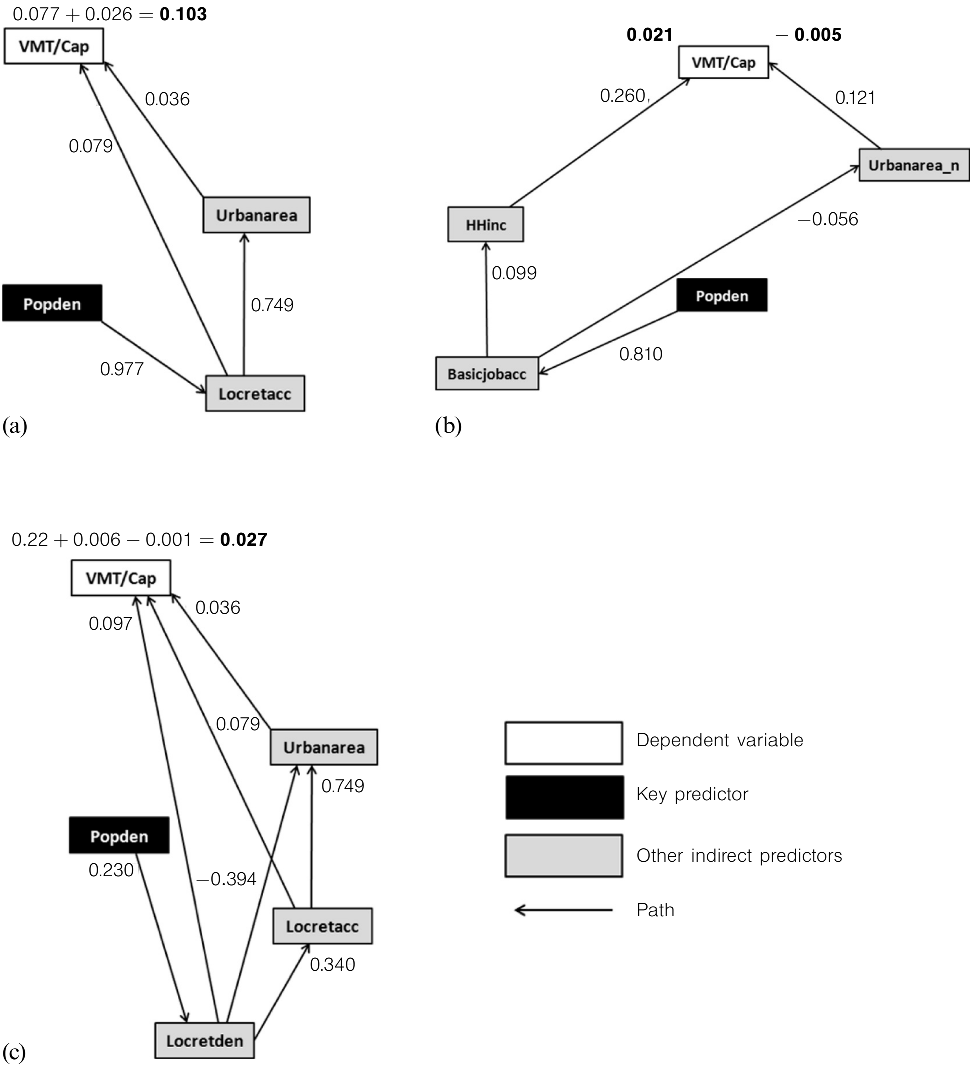


Figure 6. Indirect effects of population density on VMT/Cap, via (a) local retail-accessibility, (b) basic-job accessibility, and (c) local-retail density.

The strongest indirect effect is shown in figure 7(a). Consistent with traditional urban location theory (Lowry, 1968), basic employment prompts the formation of households, with the resulting higher densities associated with lower VMT/Cap. Settings with higher population densities tend to be less sprawled, which further drives down VMT/Cap. The net indirect influence of basic-job density operating through these two intermediate variables is -0.290 $[(0.466 \times -0.604) + (0.466 \times -0.970 \times 0.036) + (0.233 \times 0.036)]$. Figure 7(b) reveals a more complex set of intermediate steps between basic-job density and VMT/Cap, operating through local-retail accessibility and density as well as urbanized area size, yielding a positive indirect effect of 0.086. The effects of basic-job density on basic-job accessibility and other intermediaries, shown in figure 7(c), are fairly small. Overall, the intermediate positive influence of basic-job density on population density and its corresponding negative impacts on VMT/Cap [figure 7(a)] exceed the positive indirect effects shown in figures 7(b) and 7(c), producing a net negative indirect effect of -0.075.

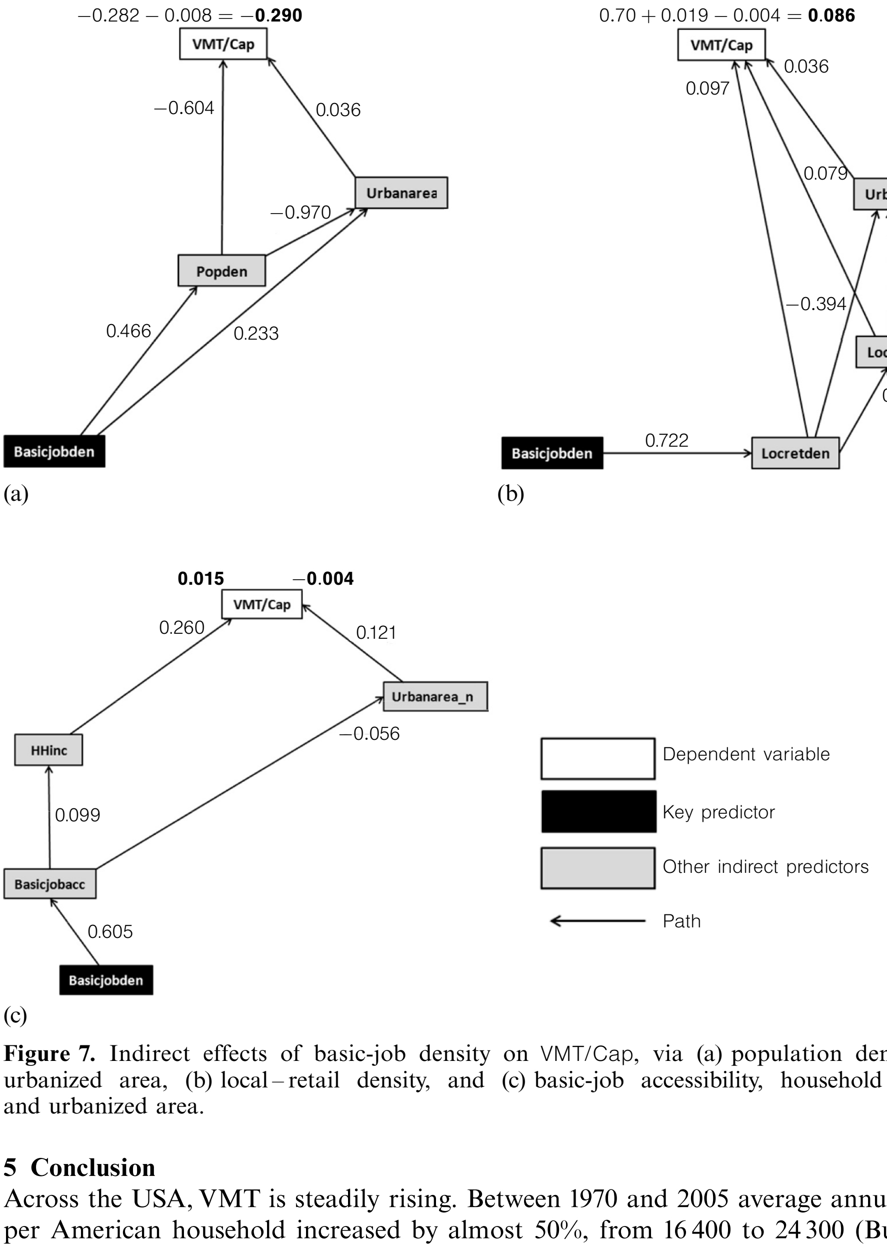


Figure 7. Indirect effects of basic-job density on VMT/Cap, via (a) population density and urbanized area, (b) local – retail density, and (c) basic-job accessibility, household income, and urbanized area.

5 Conclusion

Across the USA, VMT is steadily rising. Between 1970 and 2005 average annual VMT per American household increased by almost 50%, from 16 400 to 24 300 (Bureau of Transportation Statistics, 2007, table 1-32). With rising VMT, increased GHG emissions are inevitable given the prevalence of internal combustion engines as a means of propulsion. Indeed, carbon emissions from highway transport in major metropolitan areas are estimated to have increased by 8.6% from 2000 to 2005—faster than VMT growth (Brown et al, 2008).

A debate has ensued over the potential role of the built environment, and particularly of compact growth, in stabilizing global climates. Our research, drawn from the experiences of 370 US urbanized areas in 2003, reveals that higher population densities are strongly associated with reduced VMT/Cap. The high direct elasticity of −0.604, however, is offset by the travel-inducing effects of denser roadway infrastructure and higher access to retail shopping and the services typically found in dense urban settings. Our best estimate of the net elasticity of population density and VMT/Cap is −0.381. Although we sought to measure destination accessibility directly in our models, we believe that, for the most part, population density functioned as a surrogate, at least in part, of the other Ds of the built environment: namely, designs that are pedestrian friendly and diverse land uses.

The positive association of population density and road density, and the countervailing influence this has on VMT, could be called the 'Los Angeles effect'. The city of Los Angeles averages the highest overall population density in the USA, matched by a thicket of criss-crossing freeways and major arteries that form a dense road network (Eiden, 2005). The city also averages the highest level of vehicular travel per capita, and the worst traffic congestion in the USA, according to the Texas Transportation Institute (Schrank and Lomax, 2007). Eiden (2005, pages 7–8) calls this dysfunctional combination of high population and road densities the "worst of all worlds" and concludes that "because traffic congestion increases exponentially with car density and city size, so do the externalities associated with car travel". In Los Angeles, population densities are generally too high for a car-dependent city, yet they are not organized along linear corridors, such as is found in transit-friendly cities like Stockholm and Curitiba (Cervero, 1998), to draw sufficient travelers to public transit. Such population densities are too high for cars, and too poorly organized for transit—they are, by and large, dysfunctional densities.

Our research findings are consistent with those of other researchers who claim that urban planning and city design should be part of the solution in stabilizing global climates. Although in our study we found a moderately strong negative elasticity between population density and VMT/Cap, we also found that the positive association between neighborhood density and roadway provisions, as well as retail accessibility, moderated these effects. By extension, this suggests that the largest VMT reductions would come from creating compact communities which have below-average roadway provisions, more pedestrian/cycling infrastructure, and in-neighborhood retail activities which invite nonmotorized travel.

Our findings lend further credence to the accumulating body of evidence that the built environment should not be written off, and in some settings could very well play a pivotal role in lowering VMT, GHGs, and petroleum consumption. Pricing, city design, and urban management work on the demand side of the transportation sector's energy/carbon equation. Biofuels, plug-in hybrids, and technological advancements can provide supply-side fixes. To skew public policy excessively in one direction risks falling far short of climate-stabilization and energy-conservation targets. City design, along with other demand-side strategies such as carbon and congestion pricing, should supplement supply-side strategies as much as possible. Fortunately, the two sets of strategies are often complementary. Higher motoring prices, for example, promote compact development, a built form suitable for fleets of lightweight, low-emissions vehicles. A strategic and balanced policy of sustainable mobility and sustainable urbanism, we believe, offers the best hope of shrinking the urban transportation sector's environmental footprint in coming years.

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