Structural equation models of VMT growth in US urbanised areas

Reid Ewing
University of Utah, ewing@arch.utah.edu

Shima Hamidi
University of Utah

Frank Gallivan
ICF International

Arthur C. Nelson
University of Utah

James B. Grace
US Geological Survey, gracej@usgs.gov

Article

Urban Studies

Urban Studies
2014, Vol. 51(14) 3079–3096

DOI: 10.1177/0042098013516521
usj.sagepub.com
SAGE

Structural equation models of VMT growth in US urbanised areas

Reid Ewing
University of Utah, USA

Shima Hamidi
University of Utah, USA

Frank Gallivan
ICF International, USA

Arthur C Nelson
University of Utah, USA

James B Grace
US Geological Survey, USA

Abstract
Vehicle miles travelled (VMT) is a primary performance indicator for land use and transportation, bringing with it both positive and negative externalities. This study updates and refines previous work on VMT in urbanised areas, using recent data, additional metrics and structural equation modelling (SEM). In a cross-sectional model for 2010, population, income and freeway capacity are positively related to VMT, while gasoline prices, development density and transit service levels are negatively related. Findings of the cross-sectional model are generally confirmed in a more tightly controlled longitudinal study of changes in VMT between 2000 and 2010, the first model of its kind. The cross-sectional and longitudinal models together, plus the transportation literature generally, give us a basis for generalising across studies to arrive at elasticity values of VMT with respect to different urban variables.

Keywords
compact development, road use pricing, transportation investments, vehicle miles travelled

Received January 2013; accepted November 2013

Corresponding author:
Reid Ewing, Department of City and Metropolitan Planning, University of Utah, College of Architecture and Planning, 220 AAC, Salt Lake City, UT 84103, USA.
Email: ewing@arch.utah.edu

Introduction

The new federal surface transportation act, Moving Ahead for Progress in the 21st Century (MAP-21), passed by Congress and signed into law by the President in July 2012 advances several goals, including improving traffic safety, reducing traffic congestion, and 'minimizing transportation-related fuel consumption and air pollution' (Section 1201:134, p. 278). All of the above depend on vehicle miles travelled or VMT (Ewing and Dumbaugh, 2009; Ewing et al., 2002, 2008).

Growth of VMT brings both positive and negative externalities. On the positive side, it suggests economic growth and personal mobility. On the negative side, it is a contributor to traffic congestion, vehicle crashes, greenhouse gas emissions and other negative externalities of automobile use. VMT is undeniably a key indicator of transportation system performance.

This study updates and refines previous work, using recent data, additional metrics and structural equation modelling to explain VMT levels of urbanised areas and to test the effects of various policy and planning levers. The study concludes with best-estimate elasticities of VMT per capita with respect to these variables.

Literature review

This literature review covers four related topics, all affecting VMT. VMT is related to land use, highway capacity, the real price of fuel and transit access. These relations provide all the independent variables needed to explain VMT levels in different urbanised areas.

The literature on the first three topics is so extensive we will limit this review to meta-analyses. Unlike traditional research methods, meta-analyses use summary statistics from individual primary studies as the data points in a new analysis.

Built environment and VMT

In travel research, urban development patterns have come to be characterised by 'D' variables. The original 'three Ds', coined by Cervero and Kockelman (1997), are density, diversity and design. The Ds have multiplied since Cervero and Kockelman's original paper, with the addition of destination accessibility and distance to transit (Ewing and Cervero, 2001, 2010; Liu and Shen, 2011; Nasri and Zhang, 2012; Salon et al., 2012; Tracy et al., 2011). While not part of the environment, demographics are another D in travel studies, controlled as confounding influences.

Leck (2006) identified 40 published studies of the built environment and travel, and selected 17 that met minimum methodological and statistical criteria. While Leck's meta-analysis stopped short of estimating average effect sizes, it did evaluate the statistical significance of relationships between the built environment and travel, finding residential density, employment density and land use mix to be inversely related to VMT at the $p < 0.001$ significance level.

Ewing and Cervero (2010) uncovered more than 200 studies of the built environment and travel. Of these, 60 studies yielded usable outcome measures from which to compute weighted average elasticities in a meta-analysis. An elasticity is a measure of effect size equal to the percentage change in an outcome variable (such as VMT) with respect to a 1% increase in an explanatory variable (such as density). The D variable that is most strongly associated with VMT is destination accessibility. In fact, the -0.19 VMT elasticity is nearly as large as the elasticities of the first three D variables – density, diversity and design – combined.

Next-most strongly associated with VMT are design metrics expressed in terms of intersection density or street connectivity. The elasticities of these two street network

variables are identical, both −0.12. Both short blocks and frequent intersections shorten travel distances, apparently to about the same extent. Surprisingly, population density was found to be weakly associated with travel behaviour once these other variables are controlled. In an effort to explain the much higher elasticities reported in the literature, the paper notes: 'The relatively weak relationships between density and travel likely indicate that density is an intermediate variable that is often expressed by the other Ds (i.e., dense settings commonly have mixed uses, short blocks, and central locations, all of which shorten trips and encourage walking)' (Ewing and Cervero, 2010: 12).

Highway capacity and VMT

There are many scholarly studies of the VMT inducing effects of highway expansion (the 'build it and they will come' idea). We are aware of only one meta-analysis of this literature. Based on his review, Cervero (2002) concludes that '… the preponderance of research suggests that induced-demand effects are significant, with an appreciable share of added capacity being absorbed by increases in traffic, with a few notable exceptions'.

In the short-run a variety of sources contribute to increased traffic without any highway-induced development. These include changes in route, mode, time of travel and destination. In addition, there is the possibility of new trips that would not have occurred without the new infrastructure capacity. In the long run, increases in highway capacity may improve accessibility to developable lands and lower travel times to the point where residences and businesses are drawn to locate near the expanded highway capacity (Ewing, 2008). Cervero (2002) computes a long-run elasticity of VMT with respect to highway capacity of between 0.63 and 0.73.

Fuel prices and VMT

The meta-analytical literature on VMT growth with respect to the real price of fuel is sparse. The primary work in the area is Graham and Glaister's (2004) review of more than 50 studies measuring the fuel price elasticities for car trips and car kilometres within European Union countries. Looking at both short-term (less than 1 year) and long-term effects, the researchers found that the unweighted mean short-run elasticities for trips and kilometres across the studies were roughly equivalent at −0.16. Over time, however, the two measures diverged, with trips decreasing only slightly to −0.19, but kilometres dipping substantially to −0.31. A parallel study by Goodwin et al. (2004) summarising 69 studies from Europe and North America came to similar conclusions, with a mean short-term vehicle-km elasticity of −0.1 and a long-term elasticity of −0.29.

Meta studies of gasoline demand versus price are more numerous, and given that gasoline demand is a rough proxy for VMT, particularly in the short-run, this literature sheds light on the fuel price–VMT relationship. One meta-analytic study derived a long-run mean price elasticity of gasoline demand of −0.53 (Brons et al., 2006). Another meta-analysis of gasoline price elasticities based on hundreds of studies across the globe found a mean short-run elasticity of −0.23 and a mean long-run elasticity of −0.58 (Espey, 1998). This study concludes with this relevant thought: 'The finding of different elasticity estimates using data prior to 1974 and data after 1974 suggests the need for updated studies and for care to be taken in extrapolating into the future using elasticity estimates from the 1970s or even the 1980s'.

In an oft-cited recent study, which overcomes some of the methodological limitations of earlier studies, Small and Van Dender (2007) observed a low (under −0.10)

short-run price elasticity of gasoline demand. But importantly, they found gasoline's long-run price elasticity to be much higher, approximately −0.43. Also, they found that the elasticity of VMT with respect to fuel cost per mile (controlling for increased vehicle fuel efficiency) was roughly half the price elasticity of gasoline demand. This indicates that personal travel is so highly valued that people will buy more fuel-efficient vehicles rather than reduce their VMT when gasoline prices rise.

Transit service and VMT

Historically, research examining the role of public transit in reducing VMT and greenhouse gas (GHG) emissions has focused directly on mode shifts from driving to transit occurring as a result of transit investments. Such research typically shows only modest reductions in vehicle travel. However, a growing body of research suggests that cities with comprehensive transit facilities achieve more efficient use of their transportation systems that is not fully captured by mode shifts from driving to transit. This concept, commonly referred to as transit leverage or the land use multiplier effect, states that one mile travelled on transit corresponds with a disproportionately higher reduction in automobile travel. The multiplier is typically expressed as VMT reduced per passenger-mile of transit or as a multiplier of the mode shift effects of transit.

In other words, the influences of transit – including more compact and mixed land uses in station areas, a higher propensity by users to chain trips, reduced traffic congestion and a significantly higher rate of related non-motorised travel (walk and bike trips) – converge to reduce automobile travel and GHG emissions to a greater degree than simply the distance travelled via transit. Even those who live near transit but do not utilise it may drive less owing to the compact, mixed-use neighbourhoods and opportunities to walk and bike fostered by transit.

The mechanism by which transit leverages larger reductions in VMT is straightforward. Transit creates opportunities for transit-oriented development (TOD), 'compact, mixed-use development near transit facilities with high-quality walking environments' (Cervero et al., 2004: 11), which by definition combines all of the D variables. Being compact, mixed-use and walkable, such developments not only encourage transit use, but encourage walking, bicycling, short automobile trips and multi-purpose trip chaining (Ewing and Cervero, 2010).

However, researchers have yet to reach a consensus on the magnitude of the land use multiplier effect. Studies, which draw on data from different cities and use different methods, have produced estimates for the land use multiplier ranging from 1.29 to 9 (APTA, 2009; Lem et al., 2013). Estimates of the land use multiplier can even vary widely within a given study. This wide range of study results raises questions about the validity and reliability of the numbers.

Parallel analyses

The book *Growing Cooler* (Ewing et al., 2008) asked and attempted to answer the question: how does compact development affect VMT and associated greenhouse gas emissions that contribute to global warming? Using structural equation modelling and both cross-sectional and longitudinal data for 84 large US urbanised areas, Chapter 8 estimated elasticities of VMT with respect to population, real per capita income, population density, highway lane miles, transit revenue miles, transit passenger miles and the real price of fuel (see Table 1). Table 1 suggests, for example, that a 1% increase in highway lane miles will bring about a 0.55% increase in VMT.

Table 1. Elasticities of VMT with respect to urban variables (Ewing et al., 2008).

	Cross-sectional analysis	Longitudinal analysis	Best estimate
Population	0.97	0.874	0.95
Real per capita income	0.531	0.538	0.54
Population density	−0.213	−0.152	−0.30
Highway lane miles	0.463	0.684	0.55
Transit revenue miles	−0.075	−0.023	−0.06
Transit passenger miles	−0.068	−0.03	−0.06
Heavy-rail miles	−0.013	−0.021	−0.01
Light-rail miles	−0.003	−0.002	NA
Real fuel price	NA	−0.171	−0.17

More recently, Cervero and Murakami (2010) similarly used structural equation modelling, plus cross-sectional data from 370 US urbanised areas, to estimate elasticities of VMT per capita with respect to household income, population density, road density, rail density and other land use variables related to density and accessibility. Their results are presented in Table 2. They are generally consistent with the results of Ewing et al. (2008), though the elasticity of roadway density is smaller and the elasticity of population density is larger.

Table 2. Elasticities of VMT per capita with respect to urban variables (Cervero and Murakami, 2010).

	Estimate
Household income	0.21
Population density	−0.38
Roadway density	0.42
Rail density	−0.003
Urbanised area	0.02
% Commuting by auto	0.60

Update and refinement

This study updates the analyses of Ewing et al. (2008) and Cervero and Murakami (2010). Relationships are estimated through 2010, whereas the earlier analyses ran only through 2005 and 2003, respectively. Our initial sample includes all urbanised areas in the USA. Some were lost to the sample for lack of complete data sets, for lack to transit service or for lack of freeway capacity. The final sample of 315 urbanised areas represents 82% of the nation's urban population and 65% of the nation's total population.

This analysis refines earlier analyses in two respects. First, it distinguishes between freeways and other main highways and streets on the assumption that the two types of roadway capacity may have different effects on VMT. Whereas freeway capacity may increase VMT by inducing traffic and sprawl, arterial and collector mileage may have less induced effect and may allow more direct routing of traffic in a more complete grid. It also distinguishes between heavy-rail and light-rail mileage, which could have different effects on the built environment and VMT. Also, the new analysis replaces a single transit service measure, transit revenue miles per capita, with two measures, one representing service coverage and the other service frequency. Service coverage is roughly measured in terms of route miles of service divided by urbanised area in square miles. Average service frequency is roughly measured in terms of revenue miles of service divided by route miles of service. These are distinct service dimensions, essentially uncorrelated.

Methodology

Research design

In this study, a cross-sectional model is estimated to capture the long-run relationships between transportation and land use at a point in time, 2010. Each urbanised area has had decades to arrive at quasi-equilibrium among land use patterns, road capacity, transit capacity and VMT. This quasi-equilibrium is captured via structural equation modelling (SEM).

A longitudinal (time step) model is also estimated. This is done as a check on our cross-sectional model, and also to capture the short-term effects of changes in land use, highway, transit and fuel price variables on VMT. The vast majority of studies of travel and the built environment are cross-sectional in nature. The Transportation Research Board report, *Does the Built Environment Influence Physical Activity? Examining the Evidence* (TRB, 2009), calls for longitudinal studies that use data for the same places over time to predict behaviour. These are rare because longitudinal data are rare. '… [M]ost of the studies conducted to date have been cross-sectional. Longitudinal study designs using time-series data are also needed to investigate causal relationships between the built environment and physical activity.' The same need exists in studies of VMT.

Method of analysis

SEM is a statistical technique for evaluating complex hypotheses involving multiple, interacting variables (Grace, 2006). The estimation of SEM models involves solving a set of equations. There is an equation for each 'response' or 'endogenous' variable in the system. They are affected by other variables, and may also affect other variables. Variables that are solely predictors of other variables are termed 'influences' or 'exogenous' variables. They may be correlated with one another but are determined outside the system.

Typically, solution procedures for SEM models focus on observed versus model-implied correlations in the data. The unstandardised correlations or co-variances are the raw material for the analyses. Models are automatically compared to a 'saturated' model (one that allows all variables to intercorrelate), and this comparison allows the analysis to discover missing pathways and, thereby, reject inconsistent models.

Data

Growing Cooler used data from the TTI Urban Mobility data base to estimate VMT models. For this study, data were instead gathered from several different primary sources. This is due to three critical shortcomings of the current TTI data base, which contains 2010 data and was released in 2011:

- Small sample size: The 2010 TTI data base contains data for 101 large urbanised areas. This relatively small sample limits the statistical power of the analysis and the ability to discern significant relationships. It also makes it difficult to generalise results to smaller urbanised areas.
- No land use variables: Previous versions of the TTI data base contained one land use variable, the gross density of each urbanised area, but this measure has been dropped from more recent versions. The lack of land use variables makes it impossible to use the current TTI data alone to examine the indirect effects of transit on VMT.
- Discrepancies with official data bases: The current TTI data base contains estimates of transit passenger miles that differ from the official figures in the National Transit Database. The reason

> is unclear, but these discrepancies lead us to question whether the TTI data base is appropriate for use in this study.

We gathered data from several primary sources for our cross-sectional and longitudinal analyses. For the sake of consistency, the boundaries used to compute explanatory variables had to be the same as the boundaries used to estimate our dependent variable, VMT per capita from FHWA *Highway Statistics*.

The *Highway Statistics* definition of urbanised area is different than the census definition. According to FHWA, 'the boundaries of the area shall encompass the entire urbanised area as designated by the U.S. Bureau of the Census plus that adjacent geographical area as agreed upon by local officials in cooperation with the State'. Cervero and Murakami (2010) used the census boundaries for their analysis and deleted urbanised areas from the sample if the census and FHWA boundaries were hugely different. We chose not to make such approximations or lose many cases, and therefore set out to find FHWA-adjusted boundaries for urbanised areas in a geospatial shapefile format, which we could then use to conduct spatial analyses in GIS (see Figure 1).

FHWA advised us to contact individual state DOT offices for their shapefiles, which we did. This sometimes required several calls to find the right office. In this way, we were able to obtain shapefiles for all 50 states and 443 urbanised areas. We then combined the individual state files into one national shapefile by using the 'merge' function in GIS. Many of the urbanised areas cross state boundaries and in this case we had more than one polygon for each urbanised area. So, we used the 'dissolve' function in GIS to integrate those polygons into one for each urbanised area.

After cleaning the data, we did several spatial joins in GIS to capture data from other sources. For example, we used the 'centroid' function to join 2010 census tracts to FHWA-adjusted urbanised areas. We then aggregated values of per capita income for census tracts to obtain urbanised area weighted averages (weighted by population).

Variables

The variables in our models are defined in Tables 3 and 4. The variables fall into three general classes:

- Our outcome variables, VMT per capita in 2010 in the cross-sectional analysis, percentage change in VMT between 2000 and 2010 in the longitudinal model.
- Exogenous explanatory variables. The exogenous variables, population and per capita income, are determined by regional competitiveness. The real fuel price is determined by federal and state tax policies and regional location relative to ports of entry and refining capacity. Variables representing highway capacity and rail system capacity were also treated as exogenous, as they are the result of long-lived policy decisions to invest in highways or transit. Analogous changes in these variables are used in the longitudinal analysis.
- Endogenous explanatory variables. The endogenous variables are a function of exogenous variables and are, in addition, related to one another. They depend on real estate market forces and regional and policy decisions: whether to increase transit revenue service, whether to zone for higher densities. Analogous changes in these variables are used in the longitudinal analysis.

In the cross-sectional analysis, all variables were transformed by taking natural logarithms. The use of logarithms has two

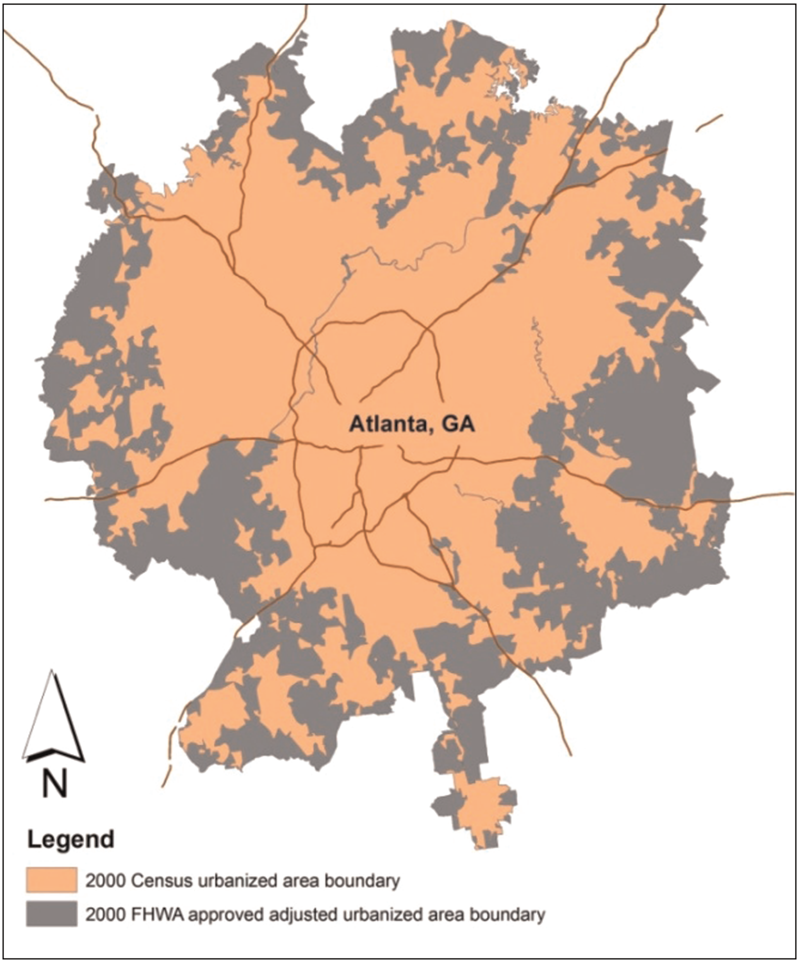

Figure 1. 2000 Census and FHWA-adjusted urbanised areas boundaries for Atlanta.

advantages. First, it makes relationships among our variables more nearly linear and reduces the influence of outliers (such as New York and Los Angeles). Second, it allows us to interpret parameter estimates as elasticities, which summarise relationships in an understandable and transferable form.

In the longitudinal analysis, all variables are represented by percentage changes over the decade of 2000 to 2010. These variables allow us to directly estimate elasticities, as elasticities are percentage changes in dependent variables with respect to percentages changes in independent variables.

Models

Our SEM models were estimated with the software package Amos (version 7.0, SPSS 2007) and maximum likelihood procedures. The path diagrams in Figures 2 and 3 are copied directly from Amos. Causal pathways are represented by uni-directional straight arrows. Correlations are represented by

Table 3. Variables included in the cross-sectional model (2010).

Variable	Definition	Source	Mean	Standard deviation
Dependent variable				
Vmt	Natural log of daily VMT per capita	FHWA Highway Statistics	3.09	0.25
Exogenous variables				
pop	Natural log of population (in thousands)	US Census	12.45	1.16
inc	Natural log of income per capita	American Community Survey	10.13	0.19
fuel	Natural log of average metropolitan fuel price	Oil Price Information Service	1.03	0.06
flm	Natural log of freeway lane miles per 1000 population	FHWA Highway Statistics	−0.46	0.53
olm	Natural log of other lane miles per 1000 population	FHWA Highway Statistics NAVTEQ	0.91	0.32
hrt	Directional route miles of heavy-rail lines per 100,000 population[a]	National Transit Database	0.04	0.23
lrt	Directional route miles of light-rail lines per 100,000 population[a]	National Transit Database	0.09	0.33
Endogenous variables				
popden	Natural log of gross population density	US Census	7.33	0.44
rtden	Natural log of transit route density per square mile	National Transit Database	0.67	0.82
tfreq	Natural log of transit service frequency	National Transit Database	8.51	0.59
tpm	Natural log of annual transit passenger miles per capita	National Transit Database	3.76	1.12

Note:
[a] 1 was added to values so that urbanised areas with no rail mileage would have a zero value when log transformed.

Table 4. Variables included in the longitudinal model (2000 to 2010).

Variable	Definition	Source	Mean	Standard deviation
Dependent variable				
chgvmt	Percentage change in daily VMT between 2000 and 2010	FHWA Highway Statistics	27.0	24.1
Exogenous variables				
chgpop	Percentage change in population	US Census	23.9	22.2
chginc	Percentage change in income per capita	US Census, American Community Survey	−1.6	5.9
chgfuel	Percentage change in metropolitan average fuel price	Oil Price Information Service	46.1	4.6
chgflm	Percentage change in freeway lane miles	FHWA Highway Statistics	51.5	116.4
chgocm	Percentage change in other centreline miles	FHWA Highway Statistics	30.6	29.2
Endogenous variables				
chgden	Percentage change in gross population density	US Census	−6.7	26.8
chgtrm	Percentage change in annual transit revenue miles	National Transit Database	37.2	67.2

curved bi-directional arrows (to simplify the already complex causal diagrams, some correlations are omitted). By convention, circles represent error terms in the model, of which there is one for each endogenous (response) variable.

Most of the causal paths shown in the path diagrams are statistically significant (have non-zero values). The exceptions are a few paths that are theoretically significant, though not statistically significant.

The main goodness-of-fit measure used to choose among models was the chi-square statistic. Probability statements about an SEM model are reversed from those associated with null hypotheses. Probability values (p-values) used in statistics are measures of the degree to which the data are unexpected, given the hypothesis being tested. In null hypothesis testing, a finding of a p-value <0.05 indicates that we can reject the null hypothesis because the data are very unlikely to come from a random process. In SEM, we seek a model with a small chi-square and large p-value (>0.05) because that indicates that the data are not unlikely given that model (that is, the data are consistent with the model).

Cross-sectional results

The VMT model in Figure 2 has a chi-square of 26.5 with 22 model degrees of freedom and a p-value of 0.23. The low chi-square relative to model degrees of freedom and a high (>0.05) p-value are indicators of good model fit.

The regression coefficients in Table 5 give the predicted effects of individual variables, all other things equal. These are the direct effects of one variable on another. They do not account for the indirect effects through other endogenous variables. Also of interest are the total effects of different variables on VMT per capita, accounting for both direct and indirect pathways (see Table 6).

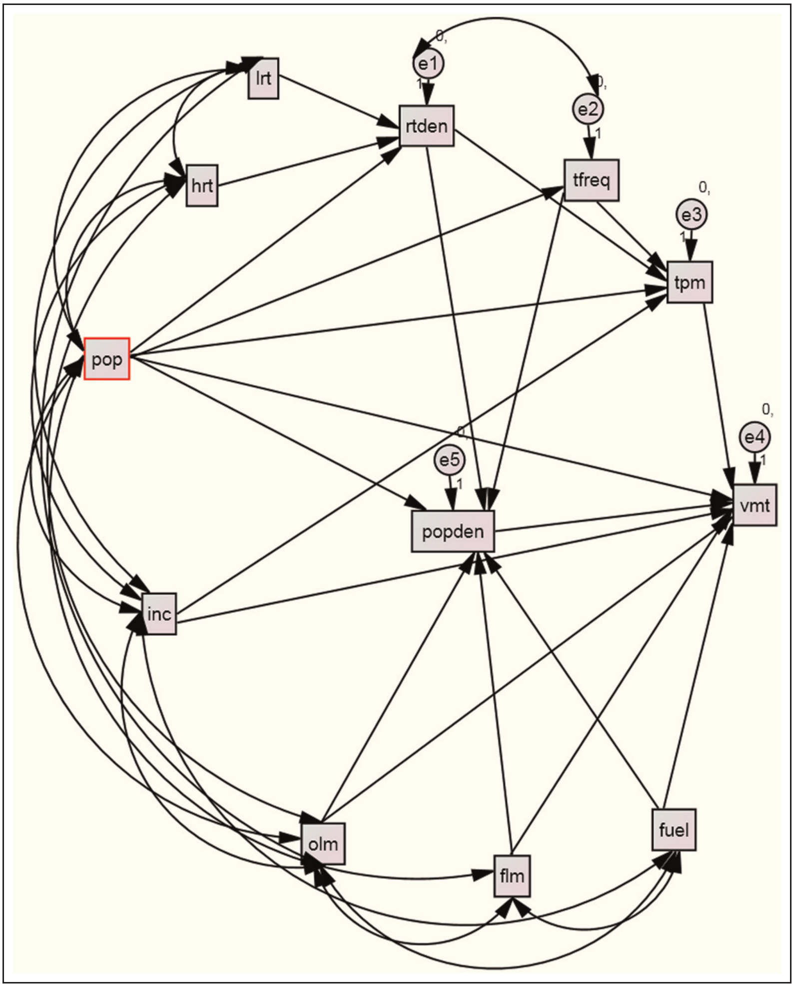

Figure 2. Causal path diagram explaining VMT per capita for urbanised areas.

Population growth is a driver of VMT growth. As urbanised areas grow, destinations tend to become farther apart (for example, the suburbs are farther from the CBD). Therefore, the direct effect of population size on VMT per capita is positive and significant because of the simple fact of their size. At the same time, as urbanised areas grow, they become denser and shift away from a singular focus on road capacity to meet travel demands toward a balance of roads and transit. Therefore, the indirect effect of population on VMT per capita is negative.

Another exogenous driver of VMT growth is income. As per capita income rises, people travel more by private vehicle, reflecting the general wealth of the community. The direct effect of per capita income on VMT per capita is positive and highly significant. Income has an indirect effect as well, through transit passenger miles per capita. Surprisingly, the effect of income on transit use is positive, hence the indirect

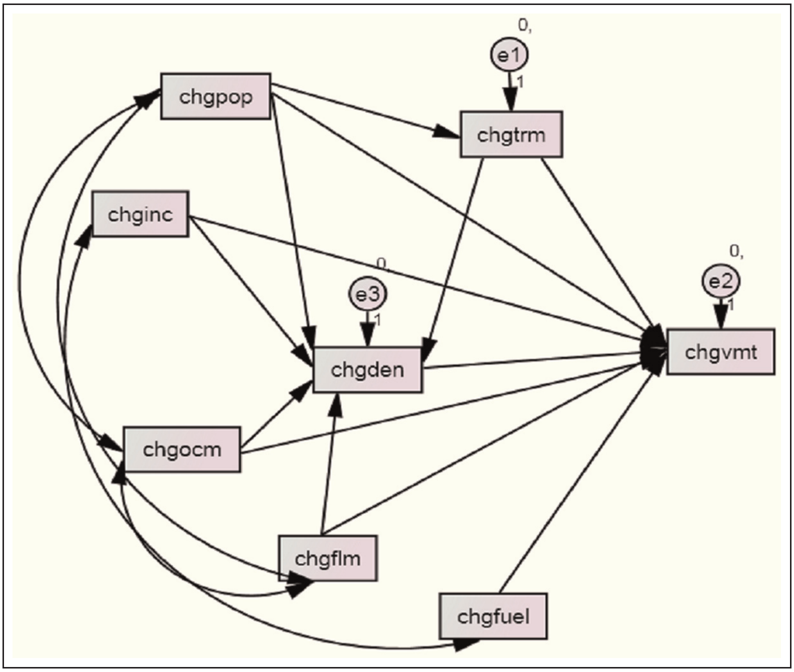

Figure 3. Causal path diagram explaining change in VMT for urbanised areas.

effect on VMT is negative. Wealthier communities may provide more transit service, and higher income residents in large regions such as New York may use transit to commute in from the suburbs.

Controlling for other influences, areas with more freeway capacity are significantly less dense and have significantly higher VMT per capita. Areas with more highway capacity in arterials, collectors and local streets are also significantly less dense (which affects VMT per capita indirectly) but the direct effect of other highway capacity on VMT per capita is not significant. From the standpoint of induced traffic, other roadways are more benign than freeways.

Transit has an effect opposite to that of highways. Areas with more service coverage and more service frequency have higher development densities, which leads to lower VMT per capita. They also have more transit passenger miles per capita, which leads to lower VMT per capita. The causal path through transit passenger miles constitutes the direct effect of transit on VMT. The causal path through development density constitutes the indirect or land use effect of transit on VMT.

The two rail variables, HRT and LRT directional route miles per capita, are positively associated with route coverage, and through that variable, increase transit passenger miles per capita and reduce VMT per capita. Surprisingly, neither HRT route mileage nor LRT route mileage has a direct effect on the development density of urbanised areas. One possible explanation for the failure of rail to raise densities is the oft-cited potential of rail extensions into the suburbs to cause sprawl, as long-distance commuters park and then ride into the city.

The real fuel price is negatively associated with VMT per capita, both directly and indirectly through an effect on development

Table 5. Path coefficient estimates (regression coefficients) and associated statistics for direct effects in the 2010 cross-sectional model (see Figure 2).

			coeff	S.E.	C.R.	P
tfreq	←	pop	0.235	0.025	9.234	<0.001
rtden	←	lrt	0.495	0.131	3.787	<0.001
rtden	←	hrt	0.355	0.187	1.900	0.057
rtden	←	pop	−0.103	0.042	−2.463	0.014
popden	←	olm	−0.552	0.047	−11.748	<0.001
popden	←	rtden	0.197	0.017	11.528	<0.001
tpm	←	pop	0.141	0.041	3.440	<0.001
tpm	←	tfreq	0.796	0.077	10.406	<0.001
popden	←	tfreq	0.187	0.023	8.035	<0.001
tpm	←	rtden	0.839	0.049	17.124	<0.001
popden	←	flm	−0.108	0.020	−5.383	<0.001
tpm	←	inc	0.902	0.208	4.345	<0.001
popden	←	pop	0.066	0.011	5.849	<0.001
popden	←	fuel	0.733	0.236	3.111	0.002
vmt	←	fuel	−0.448	0.238	−1.883	0.060
vmt	←	den	−0.238	0.043	−5.577	<0.001
vmt	←	olm	0.040	0.051	0.784	0.433
vmt	←	flm	0.133	0.021	6.412	<0.001
vmt	←	inc	0.304	0.062	4.889	<0.001
vmt	←	tpm	−0.016	0.011	−1.427	0.154
vmt	←	pop	0.078	0.012	6.635	<0.001

Table 6. Direct, indirect, and total effects of variables on VMT per capita in the 2010 cross-sectional model (see Figure 2).

	direct	indirect	total
pop	0.078	−0.025	0.052
inc	0.304	−0.015	0.289
fuel	−0.448	−0.175	−0.623
hrt	0	−0.021	−0.021
lrt	0	−0.03	−0.03
flm	0.133	0.026	0.159
olm	0.04	0.131	0.172
den	−0.238	0	−0.238
rtden	0	−0.06	−0.06
tfreq	0	−0.057	−0.057
tpm	−0.016	0	−0.016

densities. The direct price elasticity, around −0.45, is what one would expect from the literature (the long-run elasticity being much greater than the short-run elasticity). There are persistent regional variations in real fuel prices and these appear to affect both urban form and VMT per capita.

Urbanised area density is negatively related to VMT per capita. The elasticity, −0.24, suggests that every 1% rise in density is associated with a 0.24% decline in VMT per capita. With density serving as a proxy for all the D variables (density, diversity, design and destination accessibility), the elasticity looks reasonable.

Longitudinal results

The VMT model in Figure 3 has a chi-square of 6.5 with 11 model degrees of freedom and a p-value of 0.84. The low chi-square relative to model degrees of freedom and a high (>0.05) p-value are indicators of excellent model fit.

The regression coefficients in Table 7 give the predicted effects of individual variables,

Table 7. Path coefficient estimates (regression coefficients) and associated statistics for direct effects in the 2000–2010 longitudinal model (see Figure 3).

			coeff.	S.E.	C.R.	*P*
chgtrm	←	chgpop	0.303	0.206	1.475	0.14
chgden	←	chginc	−0.53	0.256	−2.069	0.039
chgden	←	chgocm	−0.685	0.081	−8.435	<0.001
chgden	←	chgflm	−0.022	0.013	−1.698	0.089
chgden	←	chgpop	0.454	0.105	4.334	<0.001
chgden	←	chgtrm	0.013	0.024	0.535	0.593
chgvmt	←	chgfuel	−0.078	0.22	−0.355	0.723
chgvmt	←	chgden	−0.085	0.045	−1.896	0.058
chgvmt	←	chgpop	0.555	0.071	7.848	<0.001
chgvmt	←	chgocm	0.19	0.061	3.129	0.002
chgvmt	←	chgflm	0.018	0.009	2.111	0.035
chgvmt	←	chginc	0.118	0.173	0.683	0.495
chgvmt	←	chgtrm	−0.01	0.015	−0.681	0.496

Table 8. Direct, indirect, and total effects of variables on percentage change in VMT in the 2000–2010 longitudinal model (see Figure 2).

	Direct effect	Indirect effect	Total effect
chgpop	0.555	−0.042	0.513
chgtrm	−0.01	−0.001	−0.011
chgflm	0.018	0.002	0.02
chgocm	0.19	0.058	0.249
chginc	0.118	0.045	0.163
chgfuel	−0.078	0	−0.078
chgden	−0.085	0	−0.085

all other things equal. These are the direct effects of one variable on another. They do not account for the indirect effects through other endogenous variables. Also of interest are the total effects of different variables on the percentage change in VMT, accounting for both direct and indirect pathways (see Table 8).

Consistent with the cross-sectional model, population and income growth are exogenous drivers of VMT growth. Controlling for these influences, areas with more freeway expansion become less dense and have more VMT growth. Even more so, areas experiencing expansion of arterials, collectors and local streets become less dense and have more VMT growth. The larger effect of lower-order roads relative to freeways is an unexpected finding, and contrasts with our cross-sectional results.

The transit variable, percentage change in transit revenue miles, is not significant in the longitudinal model. Apparently transit effects take longer to manifest themselves than the 10-year time step of our longitudinal study. Percentage changes in real gasoline prices are also not significant. There was a very significant rise in gasoline prices over the decade, but not much variation in the rise from place to place. Variation from place to place is required for statistically significance effects.

Finally, changes in density are significantly related to changes in VMT, with the expected negative sign. The elasticity of VMT growth with respect of density growth, −0.085, is smaller than the elasticity of VMT per capita with respect of density, −0.238. There may be a lag in the effect of density on VMT.

Best-estimate elasticity values

The cross-sectional and longitudinal models together, plus the earlier results of Ewing

Table 9. Best-estimate elasticity values.

	Ewing et al. (2008)	Cervero and Murakami (2010)	Cross-sectional	Longitudinal	Best-estimate
pop	0.95	–	–	0.55	0.75
inc	0.54	0.21	0.29	0.12	0.30
flm	–	–	0.13	0.18	0.15
olm	0.55	0.42	0.04	0.19	0.20
trm	−0.06	–	−0.016	−0.01	−0.03
fuel	−0.17	–	−0.45	−0.08	−0.20
den	−0.30	−0.38	−0.24	−0.08	−0.25

et al. (2008) and Cervero and Murakami (2010), plus the transportation literature generally, give us a basis for generalising across studies to arrive at elasticity values of VMT with respect to different urban variables (see Table 9). The research designs, variable definitions and sample sizes are so different that a formal meta-analysis seems inappropriate. Instead, we have simply reached an intuitive compromise near the average values.

Discussion and conclusion

As debates about air quality, energy and climate policy have heated up, increased attention has been paid to the roles of urban form and transit infrastructure in addressing these policy challenges. The vigour that has accompanied research in the area, however, has sometimes given rise to warnings against overexuberance. While acknowledging that land development patterns likely have an influence on travel, a special Transportation Research Board panel recently signaled that it did not have as much ‘verifiable scientific evidence’ as it would have liked to support its conclusions (TRB, 2009: 131), conclusions that have been criticised by some as unnecessarily conservative (Ewing et al., 2011).

From both cross-sectional and longitudinal models, this study shows that population and income are primary, exogenous drivers of VMT. Development density is a primary, endogenous driver. Urbanised areas with more freeway capacity are significantly less dense and have significantly higher VMT per capita. In the cross-sectional analysis for 2010, areas with more transit service coverage and service frequency have higher development densities and per capita transit use, which leads to lower VMT per capita. Surprisingly, route miles of heavy rail and light rail are not significant drivers of density and VMT, after controlling for transit service coverage and service frequency. The implication is that the specific transit technology employed is less important than the level of service.

Findings of the cross-sectional model are generally confirmed in a more tightly controlled longitudinal study of changes in VMT between 2000 and 2010 versus changes in explanatory variables. However, the effect of transit service ceases to be statistically significant when other variables are controlled in the longitudinal study.

The analyses presented in this paper advance the state of research in some significant ways. By using data from 315 different urbanised areas, the analysis provides a nationally comprehensive assessment, covering two-thirds of the US population. The use of structural equation modelling (SEM) facilitates observation of multiple interactions among ‘independent’ variables, providing a way of capturing many synergistic effects that are occurring on the ground.

Moreover, rather than focusing on just one factor that affects travel demand, the analysis provides a holistic approach that integrates all of the major groups of influences: demographics, development patterns, system capacities and transportation costs (see Bartholomew, 2009).

Naturally, the analyses have their limitations. They do not account for residential self-selection, that is, the tendency of people to locate in places that support their travel preferences. Residential self-selection has generally been found to attenuate the effects of the built environment on travel (Cao et al., 2009). Still, self-selection effects appear smaller than built environmental effects, and may even enhance built environmental effects in certain cases (Chatman, 2009; Ewing and Cervero, 2010; Lund et al., 2006). Moreover, such effects seem much more likely to affect the choice of neighbourhood within an urbanised area than the choice of urbanised area, the geographic scale of this study. Regional factors such as job availability and climate seem likely to dominate the choice of urbanised area.

Another limitation of this study is the absence of congestion measures in our models, congestion being a factor that could suppress automobile travel and VMT. The main reason for excluding congestion measures is lack of available data. Congestion data are proprietary. INRIX, the supplier of congestion data to the Texas Transportation Institute (TTI) for its Annual Mobility Report, only supplies data for 101 of the 315 urbanised areas in our sample. We did, however, test the theory that congestion suppresses VMT for the 101 urbanised areas. The variable was not significant, and entered with the reverse sign to that suggested by theory.

Limitations notwithstanding, the integrated approach used here has led to several important findings: freeway expansions seem to have stronger induced-demand effects than arterial expansions; increases in development densities and fuel costs are, in fact, associated with reduced driving, and in some cases the association is stronger than previously measured. Transit service coverage and service frequency have direct and indirect effects on VMT, the latter much larger in magnitude than the former. These observations provide a platform for understanding of how different policy options might work on the ground.

In considering our results, we recognise that our implementation of structural equation modelling makes a number of assumptions (Kline, 2012), the most important being model adequacy. Included in the assumptions of any SE model are logical causal assumptions that must be defended based on scientific knowledge or reasoning, as well as testable implications evaluated using statistical criteria. Linear relations (between logged variables) were assumed in our application. Testable implications depend on model–data consistency, which the results indicate was achieved in this study. While model adequacy ensures unbiased path coefficients, standard errors and probability statements also depend on normal independent errors. Diagnostics suggest no major problems with error assumptions. Finally, our ability to generalise outside the sample depends on additional assumptions about extrapolability.

Funding

This research was funded by a HUD Sustainable Communities Grant and by the Transit Cooperative Research Program

References

Bartholomew K (2009) Cities and accessibility: The potential for carbon reductions and the need for national leadership. *Fordham Urban Law Journal* 36(2): 159–209.

Brons M, Nijkamp P, Pels E, et al. (2006) *A Meta-analysis of the Price Elasticity of Gasoline Demand. A System of Equations Approach*. Amsterdam: Tinbergen Institute Discussion Paper.

Cao X, Mokhtarian PL and Handy SL (2009) Examining the impacts of residential self-selection on travel behaviour: A focus on empirical findings. *Transport Reviews* 29(3): 359–395.

Cervero R (2002) Induced travel demand: Research design, empirical evidence, and normative policies. *Journal of Planning Literature* 17(1): 3–20.

Cervero R and Kockelman K (1997) Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research D* 2(3): 199–219.

Cervero R and Murakami J (2010) Effects of built environments on vehicle miles traveled: Evidence from 370 US urbanized areas. *Environment and Planning A* 42: 400–418.

Cervero R, et al. (2004) *Transit-Oriented Development in the United States: Experiences, Challenges, and Prospects*. TCRP Report 102, Transportation Research Board.

Chatman DG (2009) Residential self-selection, the built environment, and nonwork travel: Evidence using new data and methods. *Environment and Planning A* 41(5): 1072–1089.

Espey M (1998) Gasoline demand revisited: An international meta-analysis of elasticities. *Energy Economics* 20: 273–295.

Ewing R (2008) Highway induced development: Results for metropolitan areas. *Transportation Research Record* 2067: 101–109.

Ewing R and Cervero R (2001) Travel and the built environment. *Transportation Research Record* 1780: 87–114.

Ewing R and Cervero R (2010) Travel and the built environment: A meta-analysis. *Journal of the American Planning Association* 76(3): 265–294.

Ewing R and Dumbaugh E (2009) The built environment and traffic safety: A review of empirical evidence. *Journal of Planning Literature* 23(4): 347–367.

Ewing R and Rong F (2008) Impact of urban form on U.S. residential energy use. *Housing Policy Debate* 19: 1–30.

Ewing R, Bartholomew K, Winkelman S, et al. (2008) *Growing Cooler: The Evidence on Urban Development and Climate Change*. Washington, DC: Urban Land Institute.

Ewing R, Pendall R and Chen D (2002) *Measuring Sprawl and Its Impacts*. Washington, DC: Smart Growth America.

Ewing R, Nelson AC, Bartholomew K, et al. (2011) Response to Special Report 298 – Driving and the built environment: The effects of compact development on motorized travel, energy use and CO_2 emissions. *Journal of Urbanism* 4(1): 1–5.

Goodwin P, Dargey J and Hanly M (2004) Elasticities of road traffic and fuel consumption with respect to price and income: A review. *Transport Reviews* 24(3): 275–292.

Grace JB (2006) *Structural Equation Modeling and Natural Systems*. Cambridge: Cambridge University Press.

Graham DJ and Glaister S (2004) Road traffic demand elasticity estimates: A review. *Transport Reviews* 24(3): 261–274.

Harford JD (2006) Congestion, pollution, and benefit-to-cost ratios of U.S. public transit systems. *Transportation Research Part D: Transport and Environment* 11(1): 45–58.

Kline RB (2012) Assumptions in structural equation modeling. In: Hoyle RH (ed.) *Handbook of Structural Equation Modeling*. New York: Guilford Press, pp. 111–125.

Leck E (2006) The impact of urban form on travel behavior: A meta-analysis. *Berkeley Planning Journal* 19: 37–58.

Lem LL, Chami R and Moylan E (2013) The public transportation and land use multiplier: Greenhouse gas reduction potential and associated costs in the Los Angeles Southern California Metropolitan Region. In:*Transportation Research Board 92nd Annual Meeting*. (No. 13–2088).

Liu C and Shen Q (2011) An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers Environment and Urban Systems* 35(5): 347–357.

Lund HM, Willson R and Cervero R (2006) A re-evaluation of travel behavior in California TODs. *Journal of Architectural and Planning Research* 23(3): 247–263.

Nasri A and Zhang L (2012) Impact of metropolitan-level built environment on travel behavior. *Transportation Research Record* 2323: 75–79.

Salon D, Boarnet MG, Handy S, et al. (2012). How do local actions affect VMT? A critical review of the empirical evidence. *Transportation Research Part D: Transport and Environment* 17(7): 495–508.

Small KA and Van Dender K (2007) Fuel efficiency and motor vehicle travel: The declining rebound effect. *Economic Journal* 28(1): 25–51.

Tracy AJ, Su P, Sadek AW, et al. (2011) Assessing the impact of the built environment on travel behavior: A case study of Buffalo, New York. *Transportation* 38(4): 663–678.

Transportation Research Board (TRB) (2009) *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO_2 Emissions*. Special Report 298. Washington, DC: National Research Council.

Victoria Transport Policy Institute (2007) *Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior*. Available at: www.vtpi.org/tdm/tdm11.htm (accessed 17 August 2010).