Combined Effects of Compact Development, Transportation Investments, and Road User Pricing on Vehicle Miles Traveled in Urbanized Areas

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Vehicle miles traveled (VMT) is the primary determinant of traffic congestion, vehicle crashes, greenhouse gas emissions, and other effects of transportation. Two previous studies have sought to explain VMT levels in urbanized areas. This study updates and expands on previous work with more recent data, additional metrics, and structural equation modeling (SEM) to explain VMT levels in 315 urbanized areas. According to SEM, population, income, and gasoline prices are primary exogenous drivers of VMT. Development density is a primary endogenous driver. Urbanized areas with more freeway capacity are significantly less dense and have significantly higher VMT per capita. 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. The indirect effect of transit on VMT through land use, the so-called land use multiplier, is more than three times greater than the direct effect through transit ridership.

U.S. transportation policy has changed little since the 1950s, when gas was 20 cents a gallon and President Eisenhower launched the Interstate Highway System. Today, the world is very different. Americans are stuck with costly commutes and congestion. Roads and bridges are poorly maintained. The climate is threatened by rising greenhouse gas (GHG) emissions. The nation needs a transportation system that is ready for the rapidly changing economy of the 21st century.

The new federal surface transportation act, Moving Ahead for Progress in the 21st Century, 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.” All of the above depend on vehicle miles traveled (VMT).

This study updates and expands on previous work, using more recent data, additional metrics, and structural equation modeling to explain VMT levels of urbanized areas and to test the effects of various policy and planning levers. It concludes with best-estimate elasticities of VMT per capita with respect to these levers.

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LITERATURE REVIEW

There is a rich literature relating VMT to land use, highway capacity, the real price of fuel, and transit access. The literature on the first three topics is so extensive this review will be limited 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 characterized by D variables. The original three Ds, coined by Cervero and Kockelman, are density, diversity, and design (*1*). The Ds have multiplied since Cervero and Kockelman’s original article, with the addition of destination accessibility and distance to transit (*2, 3*). While not part of the environment, demographics are another D in travel studies, controlled as confounding influences.

A recent meta-analysis uncovered more than 200 studies of the built environment and travel (*3*). Of these, 60 studies yielded usable outcome measures from which to compute weighted average elasticities. 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 relation to intersection density or street connectivity. The elasticities of these two street network variables are fairly similar. 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 behavior once these other variables were controlled. In an effort to explain the much higher elasticities reported in the literature, the article 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)” (*3*).

Highway Capacity and VMT

On the basis of the meta-analysis of the VMT-inducing effects of highway expansion, Cervero 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" (*4*).

In the short run a variety of sources contribute to increased traffic without any change in development patterns. 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 at which residences and businesses are drawn to locate near the expanded highway capacity (*5*). Cervero computes a long-run elasticity of VMT with respect to highway capacity of between 0.63 and 0.73 (*4*).

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 review of more than 50 studies measuring the fuel price elasticities for car trips and car kilometers in European Union countries (*6*). 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 kilometers 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 kilometers dipping substantially to –0.31. A parallel study by Goodwin et al. summarizing 69 studies from Europe and North America came to similar conclusions, with a mean short-term vehicle kilometer elasticity of –0.1 and a long-term elasticity of –0.29 (*7*).

Metastudies 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 (*8*). 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 (*9*). 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 observed a low (under –0.10) short-run price elasticity of gasoline demand (*10*). But 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.

Transit Service and VMT

Historically, research examining the role of public transit in reducing VMT and GHG emissions has focused 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, which 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 1 mi traveled on transit corresponds to 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 nonmotorized travel (walk and bike trips)—converge to reduce automobile travel and GHG emissions to a greater degree than simply the distance traveled via transit. Even those who live near transit but do not use it may drive less as a result of the compact, mixed-use neighborhoods and opportunities to walk and bike fostered by transit. Figure 1 illustrates how the land use multiplier relates

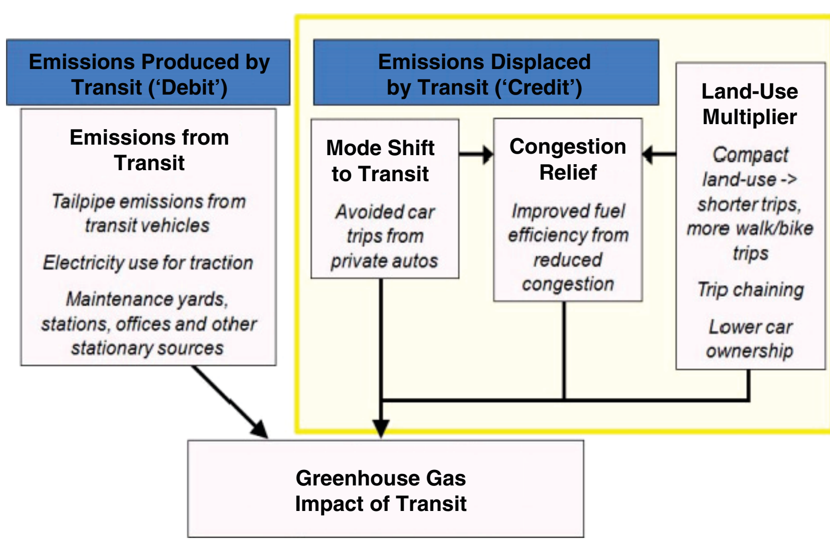

FIGURE 1 Overview of APTA approach to estimating GHG effects of public transit (*11*).

TABLE 1 Summary of Land Use Multiplier Studies (*11*)

Study	Cities	Land Use Multiplier	Methodological Issues
Pushkarev and Zupan (*13*)	U.S. metropolitan areas with at least 2 million population	4	Correlation only; does not show causal relationship of transit.
Newman and Kenworthy (*14*)	32 global cities	5 to 7	Correlation only; does not show causal relationship of transit.
Holtzclaw (*15*)	Matched pairs in the San Francisco Bay, California, Area	1.4 to 9	Correlation only; does not show causal relationship of transit.
Neff (*16*)	U.S. urbanized areas	5.4 to 7.5	Assumes fixed travel time budgets.
Bailey et al. (*17*)	Entire United States	1.9	Accounts only for land use effects caused by transit. The structural equations modeling used had relatively low explanatory power; may not be applicable to subnational scales.
New York MTA (*18*)	MTA Service Territory	1.29 to 6.34	Wide variation in results depending upon parameters selected.
Los Angeles Metro (*19*)	Los Angeles County, California	5.3	Time series regression showed no effect; regional analysis comparing counties in greater Los Angeles produced the indicated multiplier.

NOTE: MTA = Metropolitan Transportation Authority.

to the other ways in which transit produces and displaces GHG emissions.

The mechanism by which transit leverages larger reductions in VMT is straightforward. Transit creates opportunities for transit-oriented development, “compact, mixed-use development near transit facilities with high-quality walking environments,” which by definition combines all of the D variables (*12*).

However, researchers have yet to reach a consensus on the magnitude of the land use multiplier effect. Table 1 summarizes these studies, which draw on data from different cities and use different methods and which have produced estimates for the land use multiplier ranging from 1.29 to 9. Estimates of the land use multiplier can vary widely even within a given study.

More recently, a 2012 study conducted by Los Angeles, California, Metro used two separate approaches to estimate a land use multiplier for transit systems in Los Angeles County: a time-series regression analysis of changes in land use around transit stations between 1990 and 2010 and a regional analysis that compared travel patterns between Los Angeles County and other counties in the greater Los Angeles area. Only the regional analysis comparing Los Angeles County with adjacent counties produced measurable results, estimating a land use multiplier of 5.3. The study concluded that the time series analysis did not produce measurable results because the indirect effects of transit on VMT are too long term to be captured by a longitudinal model with only a 20-year time span. This suggests that, in the absence of in-depth data and sophisticated modeling techniques, cross-sectional regional analyses may be best for analyzing the indirect effects of transit on VMT.

Parallel Analyses

The book *Growing Cooler* asked and attempted to answer the question, how does compact development affect VMT and associated GHG emissions that contribute to global warming (*20*)? With structural equation modeling and cross-sectional and longitudinal data for 84 large U.S. urbanized 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 2). Table 2 suggests, for example, that a 1% increase in highway lane miles will bring about a 0.55% increase in VMT.

More recently, Cervero and Murakami similarly used structural equation modeling, plus cross-sectional data from 370 U.S. urbanized 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 (*21*). Their results are presented in Table 3. They are generally consistent with the results of Ewing et al. (*20*) although the elasticity of roadway density is smaller and the elasticity of population density is larger.

UPDATE AND EXPANSION

This study updates and expands the Ewing et al. (*20*) and Cervero and Murakami (*21*) analyses. It updates in the sense that relationships are estimated through 2010, while the earlier analyses ran only through 2005 and 2003, respectively.

The study expands in two ways. First, this analysis 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. While freeway capacity may increase VMT by inducing traffic and sprawl, arterial and collector mileage may have a less

TABLE 2 Elasticities of VMT with Respect to Urban Variables (*20*)

Variable	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

NOTE: NA = not available.

TABLE 3 Elasticities of VMT per Capita in Relation to Urban Variables (*21*)

Variable	Estimate
Household income	0.21
Population density	−0.38
Roadway density	0.42
Rail density	−0.003
Urbanized area	0.02
Percentage commuting by auto	0.60

induced effect and may allow more direct routing of traffic in a more complete grid. The study 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 regard to route miles of service divided by urbanized area in square miles. Average service frequency is roughly measured in regard to revenue miles of service divided by route miles of service. These service dimensions are distinct, essentially uncorrelated. Another transit variable is also added to the model, average fare revenue per passenger mile. It represents a separate dimension of transit service that might be expected to affect transit passenger miles and VMT.

Second, the new analysis expands the sample of urbanized areas, from 84 urbanized areas for Ewing et al. (*20*) and 370 urbanized areas for Cervero and Murakami (*21*) to 443 areas in this study. The initial sample includes all urbanized areas in the United States. Some were lost to the sample for lack of transit service, for lack of freeway capacity, or for lack of complete data sets. The final sample of 271 urbanized areas represents 80% of the nation's urban population and 62% of the nation's total population.

This analysis differs from that of Ewing et al. in other respects. In *Growing Cooler*, VMT was measured as the sum of VMT on freeways plus VMT on arterials, as estimated by the Texas Transportation Institute (TTI). In this analysis, VMT is measured as the total for all classes of roadways in urbanized areas, as reported in FHWA's *Highway Statistics.* The measure of VMT is broader, and when compared with TTI's estimates for the same period, is plausibly larger for nearly all urbanized areas, as it should be.

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 urbanized 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 modeling (SEM).

Method of Analysis

SEM is a statistical technique for evaluating complex hypotheses involving multiple, interacting variables (*22*). 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 called "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 unstandardized correlations or covariances are the raw material for the analyses. Models are automatically compared with a saturated model (one that allows all variables to intercorrelate), and this comparison allows the analysis to discover missing pathways and, by that means, reject inconsistent models.

Data

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

- Small sample size. The 2010 TTI database contains data for 101 large urbanized 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 generalize results to smaller urbanized areas.
- No land use variables. Previous versions of the TTI database contained one land use variable, the gross density of each urbanized 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 databases. The TTI database 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 one to question whether the TTI database is appropriate for use in this study.

Data were gathered from several primary sources for this cross-sectional analysis. For the sake of consistency, the boundaries used to compute explanatory variables had to be the same as the boundaries used to estimate the dependent variable, VMT per capita from FHWA's *Highway Statistics.*

The *Highway Statistics* definition of urbanized area is different from the census definition. According to FHWA, "the boundaries of the area shall encompass the entire urbanized 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 used the census boundaries for their analysis and deleted urbanized areas from the sample if the census and FHWA boundaries were hugely different (*21*). The choice made for this research was not to make such approximations or lose many cases and therefore to set out to find FHWA adjusted boundaries for urbanized areas in a geospatial shapefile format, which could then be used to conduct spatial analyses in GIS (see Figure 2).

FHWA advised that individual state department of transportation offices be contacted for their shapefiles, which was done. Sometimes several calls were required to find the right office. In this way, it was possible to obtain shapefiles for all 50 states and 443 urbanized areas. The individual state files were then combined into one national shapefile by using the "merge" function in GIS. Many of the urbanized

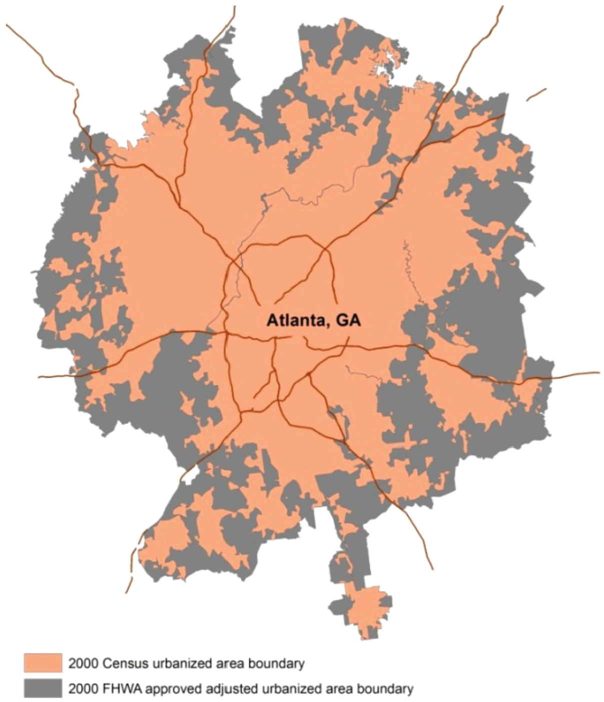

FIGURE 2 Year 2000 census and FHWA adjusted urbanized area boundaries for Atlanta, Georgia.

areas cross state boundaries, and in this case there was more than one polygon for each urbanized area. So, the "dissolve" function in GIS was used to integrate those polygons into one for each urbanized area.

After the data were cleaned, several spatial joins were done in GIS to capture data from other sources. For example, the "centroid" function was used to join 2010 census tracts to FHWA adjusted urbanized areas. Values of per capita income for census tracts were then aggregated to obtain urbanized area weighted averages (weighted by population).

Variables

The variables in the models are defined in Table 4. The variables fall into three general classes:

- Independent variable. VMT per capita is the dependent variable.
- 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.
- 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, and whether to recover more of the transit costs from the farebox.

All variables were transformed by taking natural logarithms. The use of logarithms has two advantages. First, it makes relationships between the variables more nearly linear and reduces the influence of outliers (such as New York and Los Angeles). Second, it allows one to interpret parameter estimates as elasticities, which summarize relationships in an understandable and transferable form.

Model

The SEM model was estimated with the software package Amos (Version 7.0, SPSS 2007) and maximum likelihood procedures.

TABLE 4 Variables Included in Urbanized Area Model

Variable	Definition	Source	Mean	Standard Deviation
Dependent Variable				
vmt	Natural log of daily VMT per capita	FHWA Highway Statistics	3.09	0.26
Exogenous Variables				
pop	Natural log of population (in thousands)	U.S. Census	12.57	1.16
inc	Natural log of income per capita	American Community Survey	10.14	0.19
fuel	Natural log of average fuel price metropolitan average fuel price	Oil Price Information Service	1.03	0.06
flm	Natural log of freeway lane miles per 1,000 population	FHWA Highway Statistics	−0.46	0.50
olm	Natural log of other lane miles per 1,000 population	FHWA Highway Statistics NAVTEQ	0.88	0.31
hrt	Directional route miles of heavy-rail lines per 100,000 population[a]	National Transit Database	0.05	0.24
lrt	Directional route miles of light-rail lines per 100,000 population[a]	National Transit Database	0.10	0.35
Endogenous Variables				
popden	Natural log of gross population density	U.S. Census	7.37	0.43
rtden	Natural log of average transit service density[a] (route miles per square mile)	National Transit Database	0.74	0.80
tfreq	Natural log of average transit service frequency (revenue miles per route mile)	National Transit Database	8.55	0.60
fare	Natural log of average fare (average fare revenue per passenger mile)	National Transit Database	−1.66	0.60
tpm	Natural log of annual transit passenger miles per capita	National Transit Database	3.91	1.05

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

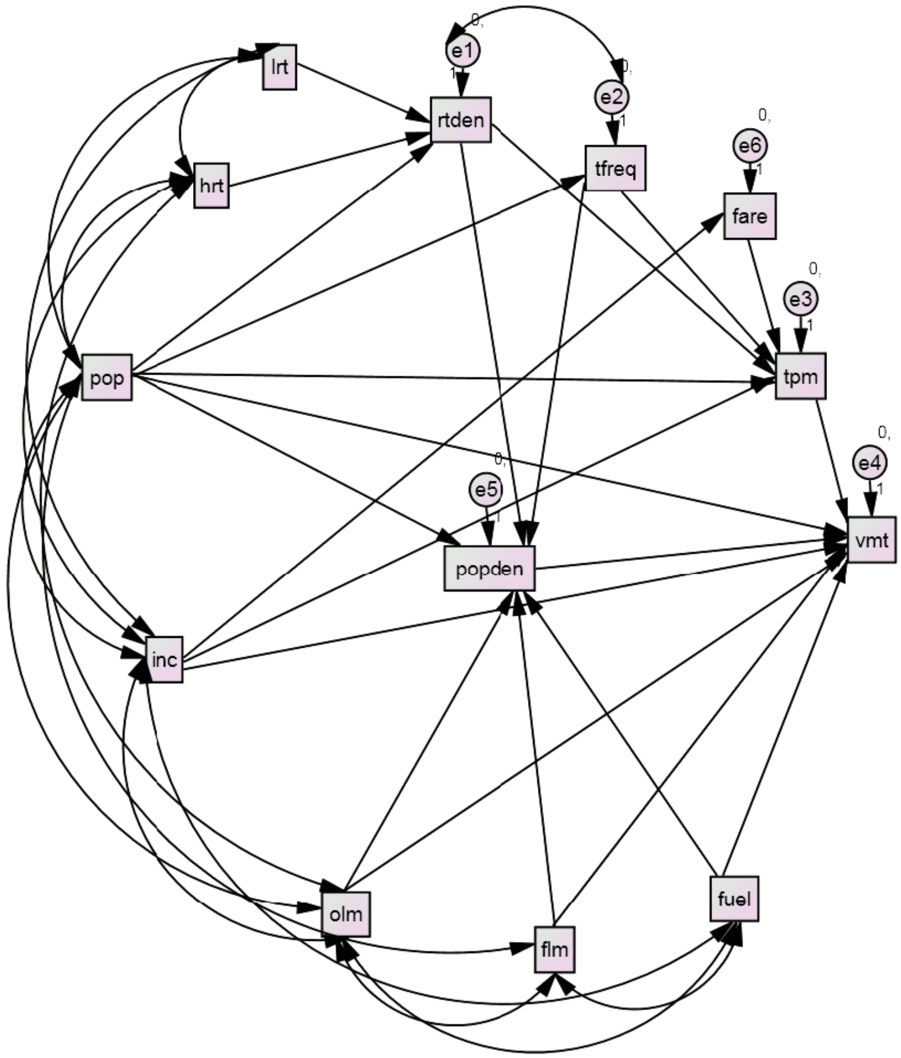

FIGURE 3 Causal path diagram explaining VMT per capita for urbanized areas.

The path diagram in Figure 3 is copied directly from Amos. Causal pathways are represented by unidirectional straight arrows. Correlations are represented by curved bidirectional arrows (to simplify the already complex causal diagram, 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 diagram are statistically significant (have non-zero values). The exceptions are a few paths that are theoretically significant, although not statistically significant.

The main goodness-of-fit measure used to choose between 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 <.05 indicates that the null hypothesis can be rejected because the data are very unlikely to come from a random process. In SEM, a model with a small chi-square and large p-value (>.05) is sought because that value indicates that the data are not unlikely given that model (i.e., the data are consistent with the model).

RESULTS

The VMT model in Figure 3 has a chi-square of 26.5 with 22 model degrees of freedom and a p-value of .23. The low chi-square relative to model degrees of freedom and a high (>.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 being 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 direct and indirect pathways (see Table 6).

Population growth is a driver of VMT growth. As urbanized areas grow, destinations tend to become farther apart (e.g., the suburbs are farther from the central business district). Therefore, the direct effect of population size on VMT per capita is positive and significant. At the same time, as urbanized 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.

Another exogenous driver of VMT growth is income. As per capita income rises, people travel more by private vehicle, reflect-

TABLE 5 Path Coefficient Estimates (Regression Coefficients) and Associated Statistics for Direct Effects in 2010 VMT per Capita Model

Relationship			Coeff.	SE	C.R.	*p*
tfreq	<—	pop	0.235	0.028	8.382	<.001
rtden	<—	lrt	0.495	0.125	3.973	<.001
rtden	<—	hrt	0.406	0.178	2.274	.023
rtden	<—	pop	–0.146	0.043	–3.387	<.001
fare	<—	inc	0.448	0.192	2.331	.02
popden	<—	olm	–0.544	0.052	–10.457	<.001
popden	<—	rtden	0.203	0.019	10.516	<.001
tpm	<—	pop	0.149	0.043	3.469	<.001
tpm	<—	tfreq	0.735	0.08	9.229	<.001
popden	<—	tfreq	0.192	0.025	7.695	<.001
tpm	<—	rtden	0.81	0.054	15.134	<.001
popden	<—	flm	–0.126	0.023	–5.538	<.001
popden	<—	pop	0.068	0.012	5.699	<.001
popden	<—	fuel	0.678	0.245	2.763	.006
tpm	<—	fare	–0.156	0.062	–2.496	.013
tpm	<—	inc	1.012	0.225	4.494	<.001
vmt	<—	fuel	–0.5	0.24	–2.085	.037
vmt	<—	popden	–0.252	0.044	–5.679	<.001
vmt	<—	olm	0.008	0.055	0.152	.879
vmt	<—	flm	0.148	0.023	6.43	<.001
vmt	<—	inc	0.305	0.066	4.638	<.001
vmt	<—	tpm	–0.015	0.012	–1.253	.21
vmt	<—	pop	0.081	0.012	6.813	<.001

NOTE: See Figure 3. Coeff. = coefficient; SE = standard error; C.R. = critical ratio.

ing 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; therefore the indirect 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.

TABLE 6 Direct, Indirect, and Total Effects of Variables on VMT per Capita in Cross-Sectional Model for 2010

Variable	Direct Effects	Indirect Effects	Total Effects
pop	0.081	–0.024	0.057
popden	–0.252	0	–0.252
inc	0.305	–0.015	0.291
hrt	0	–0.026	–0.026
lrt	0	–0.032	–0.032
tfreq	0	–0.06	–0.06
rtden	0	–0.064	–0.064
fare	0	0.002	0.002
tpm	–0.015	0	–0.015
olm	0.008	0.137	0.145
flm	0.148	0.032	0.18
fuel	–0.5	–0.171	–0.671

NOTE: See Figure 3.

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 latter divided by the former is the land use multiplier.

Transit fare levels (average fare level per passenger mile) have an additional effect on transit passenger miles, whose elasticity value is –0.156. The value is just less than the old rule of thumb that every 10% increase in fare leads to a 3% drop in ridership and conversely that every 10% cut in fare leads to a 3% rise in ridership.

The two rail variables, heavy rapid transit (HRT) and light rail transit (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 urbanized 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 directly and indirectly through an effect on development densities. The direct price elasticity, about –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 urban form and VMT per capita.

Urbanized area density is negatively related to VMT per capita. The elasticity, –0.24, suggests that every 1% rise in density is associated with a .25% decline in VMT per capita. With density serving as a proxy for all D variables (density, diversity, design, and destination accessibility), the elasticity looks reasonable.

The size of transit's land use multiplier is also of interest. The two transit variables, which as noted previously are uncorrelated, have remarkably similar relationships to VMT. As shown in Table 7,

TABLE 7 Transit's Land Use Multipliers

Transit Variable	Value
Service Coverage	
Direct effect	–0.0122
Indirect effect	–0.0512
LU multiplier	4.21
Service Frequency	
Direct effect	–0.0110
Indirect effect	–0.0484
LU multiplier	4.39

NOTE: LU = land use.

the land use multipliers are in the range of 4.21 to 4.39 for the two transit variables.

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 vigor 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 TRB panel recently signaled that it did not have as much "verifiable scientific evidence" as it would have liked to support its conclusions (*23*), conclusions that have been criticized by some as overly conservative (*24*).

The analysis presented in this paper does not, of course, address all of the cautions and criticisms. It does, however, advance the state of research in some significant ways. By using data from 271 different urbanized areas, the analysis provides a nationally comprehensive assessment, covering 62% of the U.S. population. Moreover, rather than focusing on just one factor that affects travel demand, the analysis provides a holistic approach that integrates all major groups of influences: demographics, development patterns, system capacities, and transportation costs (*25*).

Naturally, the analysis has its limitations, suggesting several possible future investigations. Adding a longitudinal analysis is an obvious place to focus future research. That goal might be facilitated by the development of a richer and longer-term database. Another improvement would be the introduction of multilevel modeling capacities into the SEM framework to account for the fact that changes in conditions over time are occurring in each urban area, as well as between urban areas.

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, and increases in development densities and fuel costs are, in fact, associated with reduced driving, and in some cases the association is stronger than previously estimated. 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 how different policy options might work on the ground.

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