Research-Based Article

Testing Newman and Kenworthy's Theory of Density and Automobile Dependence

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Reid Ewing[1], Shima Hamidi[2], Guang Tian[1], David Proffitt[1], Stefania Tonin[3], and Laura Fregolent[3]

Abstract

This study tests four hypotheses related to the much-cited work on density and automobile dependence by Newman and Kenworthy, using multivariate analysis and data for 157 large US urbanized areas. We find that density alone explains only a small fraction of the variation in vehicle miles traveled (VMT), and many confounders account for the differences in automobile dependence. We also find that it is not the localized density of individual neighborhoods that causes VMT to be lower in compact urbanized areas but rather the relative accessibility of neighborhoods to the rest of the region.

Keywords

auto dependence, VMT, density, sprawl index

Introduction

Peter Newman and Jeffrey Kenworthy, in their classic book *Cities and Automobile Dependence* and in subsequent publications, popularized the idea that per capita automobile usage drops off exponentially with rising population density. Their original curve, showing gasoline use per capita versus gross population density (GPD), is one of the iconic images of the urban planning field. At one extreme is Houston; at the other is Hong Kong. Data points lie so close to a negative exponential curve that it seems to represent a universal truth about cities.

Newman and Kenworthy's work has been widely adopted, with thousands of citations in professional and academic reports. A recent Google search on the terms "newman kenworthy density" turned up nearly thirty thousand hits, with references to Newman and Kenworthy's density curve appearing in books, planning policy guidelines, and other practice-oriented publications. For example, in their book *The Ecology of Place*, Beatley and Manning present population density as an important factor determining the sustainability of urban areas (Beatley and Manning 1997). On the policy front, the UK Commission for Integrated Transport's report *Planning for Sustainable Travel*, which updates UK policy makers on planning research, includes a lengthy section on the relationship between population density and automobile travel and refers directly to Newman and Kenworthy's "pioneering" studies (Hickman et al. 2009). Similarly, a United Nations Environmental Programme guide to carbon neutrality reproduces Newman and Kenworthy's population density/energy consumption graph directly in its report (Kirby 2008).

This study tests four hypotheses related to the work of Newman and Kenworthy using multivariate analysis and data for 157 large US urbanized areas. First, based on our sample, we find that there is much more scatter around a best-fit curve than their original work suggests, and that density explains only a small fraction of the variation in per capita vehicle miles traveled (VMT). Second, we find that density continues to be significant when control variables such as per capita income and average fuel price are added to a multiple regression model, but the significance and effect size of density drop sharply. The addition of control variables greatly improves the explanatory power of the model. Third, we find that a more complete metric than density, a compactness/sprawl index widely used in the planning literature and measured by four factors—density, mixed use, degree of centering, and street connectivity—has a stronger relationship to per capita VMT than GPD alone. However, the difference is not great, and it is the density component of this more complete metric that accounts almost entirely for the

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[1]City and Metropolitan Planning, University of Utah, Salt Lake City, UT, USA
[2]Institute of Urban Studies, University of Texas, Arlington, TX, USA
[3]Department of Design and Planning in Complex Environments, University Iuav, Venice, Veneto, Italy

Corresponding Author:
Reid Ewing, City and Metropolitan Planning, University of Utah, 375 South 1530 East, Salt Lake City, UT 84112, USA.
Email: ewing@arch.utah.edu

relationship to per capita VMT. Finally, we find that relationships between the built environment and VMT are different in aggregate (metropolitan-level) studies such as this one, as compared to disaggregate (household-level) studies that mostly populate the literature. In particular, the importance of density, as a built environmental measure, differs. We discuss why this may be the case.

Literature Review

There are rich literatures relating VMT to density, the built environment generally, highway capacity, the real price of fuel, and transit service. Peter Newman and Jeffrey Kenworthy were the first to explore the relationship between VMT (and proxies for it) and density. We will review their work. The literatures on the second through fourth topics (built environment, highway capacity, and fuel price) are 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. The last topic, the relationship between transit service and VMT, is the most recent addition to the literature, and that too will be explored.

Density and VMT

Newman and Kenworthy's *Cities and Automobile Dependence* (1989a) is one of the most influential planning books of all time. In it and related papers (Newman and Kenworthy 1989b; Newman and Kenworthy 2006; Newman and Kenworthy 2011a, 2011b; Newman 2014), the authors suggest that in world cities (actually metropolitan areas), per capita fuel use is inversely related to GPD (see Figure 1). The relationship follows an exponential function.

More recently, Kenworthy et al. (1999) and Newman (2014) reproduced this graph for a greatly expanded set of world cities (see Figure 2). Data points again lie very close to a best-fit curve.

Newman and Kenworthy's work has been criticized for stating the obvious (that car use per capita and density will always be hyperbolic since population is in the denominator of one and numerator of the other) and for ignoring other variables that affect fuel use (population size and income, for example) (Dujardin et al. 2012; Gordon and Richardson 1989; Perumal and Timmons 2015). Their analyses were bivariate rather than multivariate (Dujardin et al. 2012). Other criticisms include the possible incomparability of the different countries studied. Perumal and Timmons (2015) argue that compared to the US cities, Hong Kong has very high population density and very low automobile usage, yet the differences between Hong Kong and Houston likely go far beyond density.

They (actually Kenworthy and Laube 1999) have subsequently shown that car use itself (in per capita vehicle kilometers traveled) is inversely related to density (in persons per hectare). In the same article, they also looked at other simple correlations (see Figures 3 through 5).

In their most recent work, *The End of Automobile Dependence: How Cities Are Moving beyond Car-Based Planning* (Newman and Kenworthy 2015), Newman and Kenworthy retreat ever so slightly from their previous focus on density as the solution to automobile dependence. They have a section titled "Is Increasing Density Enough to End Automobile Dependence?" which hints at a broader perspective. However, this section adds only one variable to the sustainability equation: transit service, and even this variable is tied to density. To quote, "In response to the question of whether increased density alone is enough, we say that public transit improvements are also needed–but the two go together, they are totally intertwined" (174). They then proceed to "debunk" ten supposed "myths" about density, completing their case for density as a "sustainability multiplier" (174–87). In terms of statistics, they assert that for their sample of fifty-eight cities (actually metropolitan areas), urban density alone accounts for 84 percent of the variance in car use per person.

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 (1997), are density, diversity, and design. The Ds have multiplied since then, with the addition of destination accessibility and distance to transit (Ewing and Cervero 2001, 2010). While not part of the environment, demographics are another D in travel studies, controlled as confounding influences.

A recent meta-analysis uncovered more than two hundred studies of the built environment and travel (Ewing and Cervero 2010). Of these, sixty-two 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 per capita) with respect to a 1 percent increase in an explanatory variable (such as density). In this analysis, 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.

The variables 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 fairly similar. Both short blocks and frequent intersections shorten travel distances, apparently to about the same extent. Surprisingly, population density is weakly associated with travel behavior once these other variables are 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

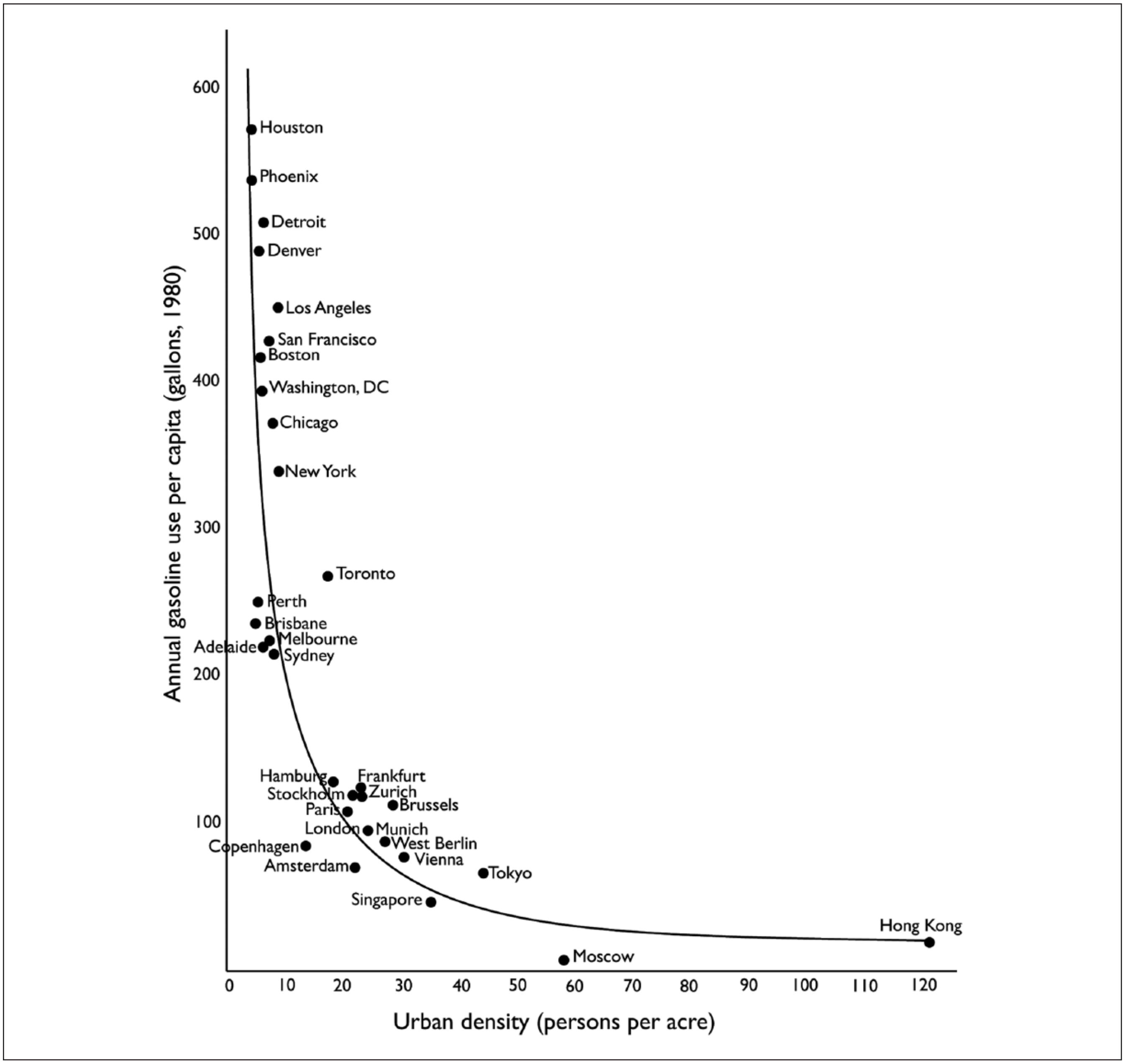

Figure 1. Gasoline use per capita versus population density, 1980.
Source: Newman and Kenworthy (1989a), 128.

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)" (12).

The studies referenced above use disaggregate data (household-level data) to explore relationships between the built environment around households (the Ds) and household travel outcomes. There is a whole different literature that tests for relationships using aggregate data. The two literatures have developed somewhat independently. These aggregate studies posit relationships between urban form, often measured by "sprawl indices," and average travel outcomes for large areas such as counties, metropolitan areas, or urbanized areas. Because of omitted variables, aggregation bias, the ecological fallacy, and geographic scale, these studies could logically provide different results.

The built environment in the urban form studies is also represented by D variables, but with different names given to the different Ds. Development density remains as density, but land use diversity is described as land use mix, and street network design is described as street connectivity. The other two Ds, most importantly, destination accessibility, do not factor into sprawl indices. And, of course, the

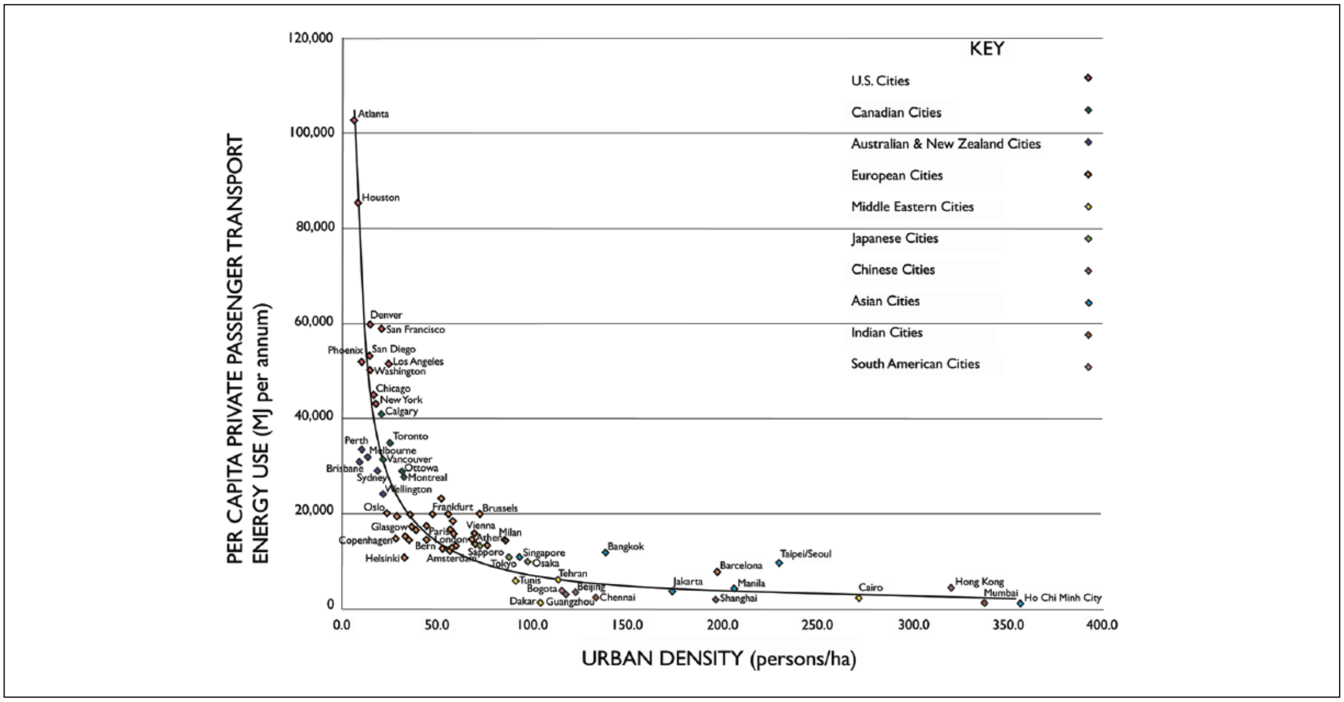

Figure 2. Per capita private passenger transport energy use and urban density in global cities.
Source: Newman (2014).

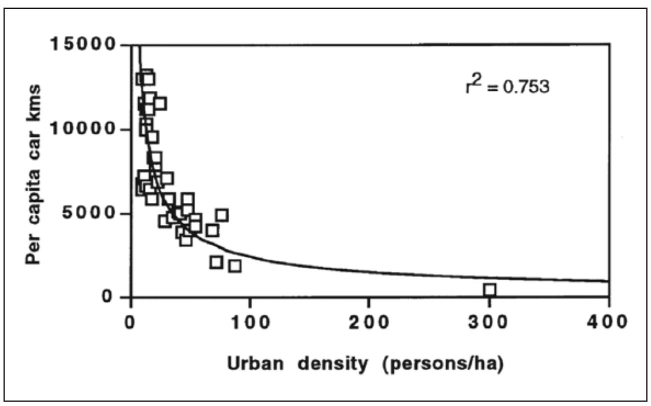

Figure 3. Urban density versus car use in developed and developing cities, 1990.
Source: Kenworthy and Laube (1999).

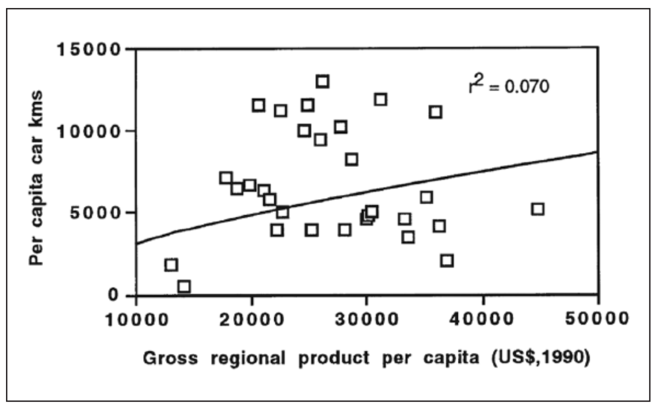

Figure 4. Gross regional product per capita versus car use per capita in developed cities, 1990.
Source: Kenworthy and Laube (1999).

geographic scale is all different. In the disaggregate studies, it is the neighborhood built environment that is represented by the Ds. In the aggregate studies, it is the extent of sprawl in the county, metropolitan area, or urbanized area as a whole that is measured.

Early attempts to measure the extent of urban sprawl focused on density (Pendall 1999; Fulton et al. 2001; Lopez and Hynes 2003; Anthony 2004; Lang 2003; Pendall and Carruthers 2003). Density was the primary indicator of sprawl in the early studies likely because it is easy to measure, and captures one important dimension of sprawl. The most notable feature of early studies was the failure to define sprawl in all its complexity.

Most scholars now agree that sprawl is a multidimensional phenomenon that is best quantified by a combination of measures (Galster et al. 2001; Ewing, Pendall, and Chen 2002; Cutsinger et al. 2005; Frenkel and Ashkenazi 2008; Jaeger et al. 2010; Mubareka et al. 2011; Torrens 2008). The most widely used compactness/sprawl metrics are those of Ewing, Pendall, and Chen (2002), updated in Ewing and Hamidi (2014a). Compactness indices have now been developed for metropolitan areas (Hamidi et al. 2015), census urbanized areas (Hamidi and Ewing 2014), and metropolitan counties (Ewing, Hamidi, and Grace 2016; Ewing et al. 2014b).

The approach used in these studies is the same. First, using principal components analysis (PCA), they estimate factor

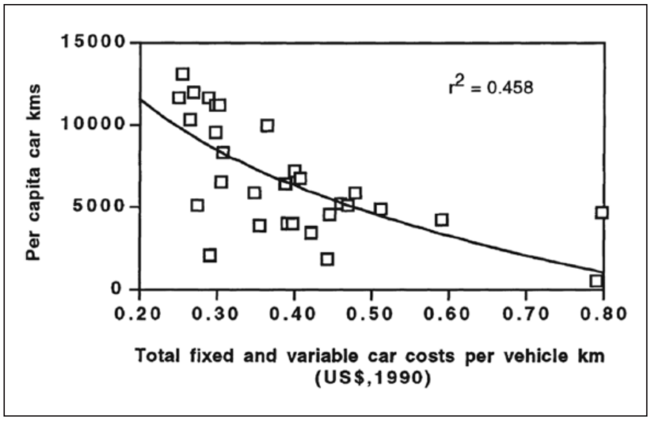

Figure 5. Cost of cars versus car use in developed cities, 1990.
Source: Kenworthy and Laube (1999).

scores for four dimensions of urban form: development density, land use mix, activity centering, and street connectivity. They then sum the four scores, regress the result on the natural logarithm of population, and use the standardized residuals to compute overall compactness/sprawl indices for the areas in their sample. The indices are standardized with a mean of 100 and a standard deviation of 25. The resulting indices are independent of population. Thus, the degree of sprawl for any given metropolitan or urbanized area is judged relative of other areas of the same size. It makes little sense to compare the degree of sprawl in the New York City urbanized area, with a population of more than eighteen million, to places such as the Ithaca, NY, urbanized area, with a population of just over fifty thousand.

Both the individual factors and overall index are then validated against transportation outcomes and other quality-of-life measures. These compactness/sprawl indices have been widely used in health and other research. The indices have been related to traffic fatalities (Ewing, Pendall, and Chen 2003; Ewing and Hamidi 2015; Ewing, Hamidi, and Grace 2016a), physical inactivity, obesity, heart disease, cancer prevalence (Berrigan et al. 2014; Cho et al. 2006; Doyle et al. 2006; Ewing, Pendall, and Chen 2003; Ewing et al. 2014b; Fan and Song 2009; Griffin et al. 2012; Joshu et al. 2008; Kelly-Schwartz et al. 2004; Kim et al. 2006; Kostova 2011; Lee, Ewing, and Sesso 2009; Plantinga and Bernell 2007), air pollution (Ewing, Pendall, and Chen 2002; Schweitzer and Zhou 2010; Stone 2008), extreme heat events (Stone, Hess, and Frumkin 2010), residential energy use (Ewing and Rong 2008), social capital (Nguyen 2010), emergency response times (Trowbridge, Gurka, and O'Connor 2009), teenage driving (Trowbridge and McDonald 2008), private-vehicle commute distances and times (Ewing, Pendall, and Chen 2003; Hamidi et al. 2015; Hamidi and Ewing 2014; Holcombe and Williams 2012; Zolnik 2011), housing plus transportation costs (Hamidi and Ewing 2015), and economic and social upward mobility (Ewing et al. 2016). While most studies have linked sprawl to negative outcomes, there have been exceptions (see, in particular, Holcombe and Williams 2012).

In a recent study using updated indices, the elasticity of VMT with respect of a county compactness index was estimated to be −0.78 (Ewing, Hamidi, and Grace 2016). This elasticity is considerably higher (in absolute magnitude) than the elasticity of VMT with respect to density alone.

Highway Capacity and VMT

Based on a meta-analysis of the VMT inducing effects of highway expansion, Cervero (2002) concludes, "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 fifty studies measuring the fuel price elasticities for car trips and car kilometers 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 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, Dargay, and Hanly (2004) summarizing sixty-nine studies from Europe and North America came to similar conclusions, with a mean short-term vehicle-kilometer elasticity of −0.10 and a long-term elasticity of −0.29.

Meta-analysis 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). The second 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. In addition, 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 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 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 to a greater degree than simply the distance traveled via transit. Even those who live near transit but do not utilize it may drive less because of the compact, mixed-use neighborhoods 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" (TCRP Report 102), which by definition combines all of the D variables. 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. Estimates of the land use multiplier can even vary widely within a given study. A recent study pegged the multiplier at about 3.0 (Ewing and Hamidi 2014b).

Table 1. Elasticities of Vehicle Miles Traveled with Respect to Urban Variables.

	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

Source: Ewing et al. (2008).

Table 2. Elasticities of Per Capita Vehicle Miles Traveled with Respect to Urban Variables.

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

Source: Cervero and Murakami (2010).

Multivariate Analyses

Unlike the studies described above, which focus on one correlate of VMT at a time, another class of studies seeks to estimate elasticities of VMT with respect to relevant variables in a multivariate context. This article does as well.

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 modeling and both cross-sectional and longitudinal data for eighty-four large US 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 1). Table 1 suggests, for example, that a 1 percent increase in density will bring about a 0.3 percent drop in VMT.

More recently, Cervero and Murakami (2010) similarly used structural equation modeling, plus cross-sectional data from 370 US urbanized areas, to estimate elasticities of per capita VMT 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

Table 3. Direct, Indirect, and Total Effects of Variables on Per Capita Vehicle Miles Traveled in the Cross-Sectional Model for 2010.

	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
popden	−0.238	0	−0.238
rtden	0	−0.06	−0.06
tfreq	0	−0.057	−0.057
tpm	−0.016	0	−0.016

Source: Ewing et al. (2014a).

density is larger. A 1 percent increase in density would be expected to bring about a 0.38 reduction in per capita VMT.

Most recently, Ewing et al. (2014a) used structural equation modeling and cross-sectional data for 315 urbanized areas to estimate refined elasticities of per capita VMT with respect to population, household income, population density, freeway and arterial lane miles per 1,000 population, transit passenger miles per capita, average fuel price, and other variables. Their results are presented in Table 3. Their results are generally consistent with the earlier estimates. A 1 percent increase in density would be expected to bring about a −0.238 percent decline in per capita VMT.

Hypotheses

This study reanalyzes Newman and Kenworthy's view of the relationship between the built environment and VMT using the data of Ewing et al. (2014a). We will test four hypotheses based on Newman and Kenworthy's work:

Hypothesis 1: That GPD (density in persons per square mile) bears a simple, smooth inverse relationship to per capita VMT for urbanized areas in the United States. The alternate hypothesis is that the relationship is not nearly so tightly fit when these two variables are measured independently and, in fact, has a high degree of scatter around a best-fit curve.

Hypothesis 2: That, when confounding variables are controlled, the relationship between GPD and per capita VMT continues to be strong and negative. The alternate hypothesis is that the relationship between GPD and per capita VMT is weakened to the point where it is no longer statistically significant when confounding variables are controlled.

Hypothesis 3: That a more complete measure of urban compactness/sprawl than GPD bears a similar inverse relationship to per capita VMT. The alternate hypothesis is that a more complete measure of compactness/sprawl, which accounts for more aspects of land use and street design, actually has a stronger relationship to per capita VMT than does GPD.

Hypothesis 4: That the relationship between density and per capita VMT is the same for urban form studies using aggregate (metropolitan level) data, such as Newman and Kenworthy's, and the more numerous travel behavior studies using disaggregate (household level) data. The alternate hypothesis is that density takes on disproportionate importance in aggregate studies that fail to account for all D variables and measure the built environment at the large scale of the metropolitan area rather than the small scale of the neighborhood.

Methodology

Research Design

In this study, cross-sectional models for built environment and VMT were 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.

Method of Analysis

Unlike the earlier study by Ewing et al. (2014a), which used structural equation modeling to explain the relationship between the built environment and VMT, this study uses ordinary least squares (OLS) regression, which is consistent with Newman and Kenworthy's approach. Density and (later) compactness are treated as exogenous influences on per capita VMT. In this manner, we are able to tease out the relative influence of density and compactness on per capita VMT, controlling for other correlates of VMT.

We also used PCA to create compactness indices for the 157 large Federal Highway Administration (FHWA) urbanized areas in our sample. We followed the same procedures as Hamidi and Ewing (2014) but applied them to FHWA-approved urbanized areas rather than census-designated urbanized areas.

Data

We gathered data from several primary sources for our 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 our dependent variable, per capita VMT from FHWA's *Highway Statistics*.

The *Highway Statistics* definition of urbanized area is different from the census definition. According to the 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

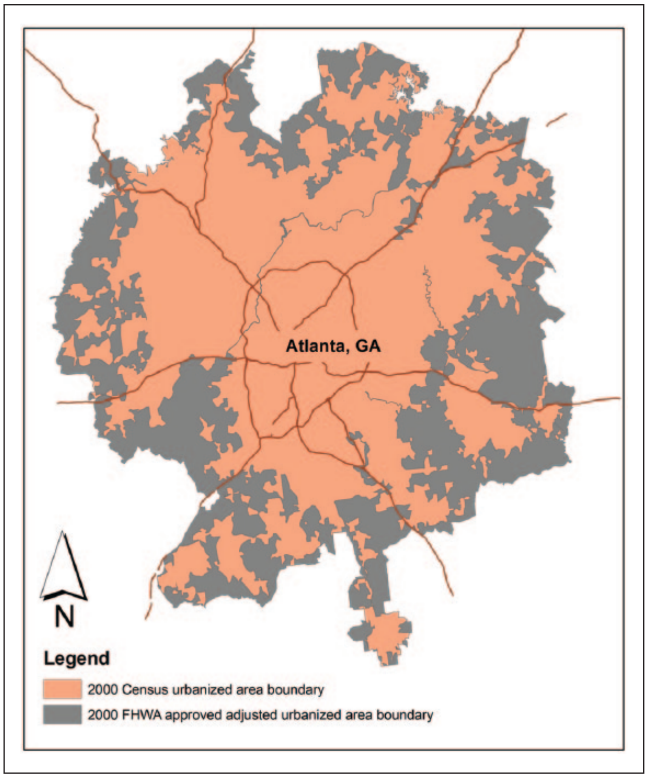

Figure 6. Year 2000 census and Federal Highway Administration (FHWA)-adjusted urbanized areas boundaries for Atlanta (one of the most sprawling urbanized area in the United States).

(2010) used the census boundaries for their analysis and deleted urbanized 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 urbanized areas in a geospatial shapefile format, which we could then use to conduct spatial analyses in GIS (see Figure 6).

We obtained shapefiles for all fifty states and 443 urbanized areas and then combined the individual state files into one national shapefile by using the "merge" function in GIS. Many of the urbanized areas cross state boundaries, and in this case we had more than one polygon for each urbanized area. So, we used the "dissolve" function in GIS to integrate those polygons into one for each urbanized 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 urbanized areas. We then aggregated values of per capita income for census tracts to obtain urbanized area weighted averages (weighted by population).

Consistent with Hamidi and Ewing (2014), we limited our sample to large urbanized areas with populations of two hundred thousand or more for which all variables in Table 4 could be estimated. Of the 173 urbanized areas with populations of two hundred thousand or more, some cases were lost for lack of compactness metrics, others for lack of transit data, and still others for lack of fuel price data. The rationale for limiting our sample to larger urban areas is that small areas are different qualitatively than large areas. We wanted a more homogenous sample. In small areas, land uses are necessarily reasonably proximate to each other. Hence good accessibility, which defines compactness, is guaranteed. It is spurious to compare congestion in a large area like Los Angeles (population 12.6 million, where trips are long and congestion is intolerable) to congestion in a small area like Porterville, CA (population seventy-nine thousand, where trips are necessarily short and congestion is nonexistent).

Small urbanized areas would be expected to have significantly lower per capita VMT than larger urbanized areas. The Newman and Kenworthy samples consist of the largest world cities, and we are testing to see if the same dynamics apply to a set of more typical cities. Our final sample consists of 157 urbanized areas.

Variables

The variables in our models are defined in Table 4. They are as follows:

- Our dependent variable: per capita VMT;
- Our independent variables: The independent variables of primary interest are GPD and the aforementioned compactness index. Control variables include population size, per capita income, and metropolitan average fuel price. Variables representing highway capacity and transit capacity were also treated as exogenous, as they are the result of long-lived policy decisions to invest in highways or transit.

All variables were transformed by taking natural logarithms. The use of logarithms has two 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 summarize relationships in an understandable and transferable form.

Results

Compactness Indices

The factor loadings from the PCA are shown in Table 5. Five variables load on a density factor, two variables on a mixed use factor, four variables on a centering factor, and four variables on a street factor. Using the factor loadings, factor scores were computed for each of the 157 urbanized areas in our sample. Factor scores were then standardized on scale with a mean of 100 and a standard deviation of 25 (see Hamidi and Ewing 2014). This produced a single density factor, mixed use factor, centering factor, and street factor for each of the urbanized areas. The four were summed and

Table 4. Variables Included in the Urbanized Area Model.

Variable	Definition	Source	Mean	Standard Deviation
Dependent variable				
vmt	Natural log of daily VMT per capita	FHWA Highway Statistics	3.15	0.23
Independent variables				
pop	Natural log of population (in thousands)	US Census	6.40	0.96
inc	Natural log of income per capita (in thousands)	American Community Survey	3.27	0.19
fuel	Natural log of average fuel price metropolitan average fuel price	Oil Price Information Service	1.02	0.06
flm	Natural log of freeway lane miles per 1,000 population	FHWA Highway Statistics	−0.49	0.42
olm	Natural log of other lane miles per 1,000 population	FHWA Highway Statistics NAVTEQ	0.85	0.28
rtden	Natural log of transit route density per square mile	National Transit Database	0.60	0.75
tfreq	Natural log of transit service frequency	National Transit Database	8.68	0.55
popden	Natural log of gross population density	US Census	7.44	0.43
compact	Natural log of compactness index	Multiple sources—see Hamidi and Ewing (2014)	4.57	0.25
denfac	Natural log of density factor	Multiple sources—see Hamidi and Ewing (2014)	4.58	0.23
mixfac	Natural log of mix factor	Multiple sources—see Hamidi and Ewing (2014)	4.57	0.28
cenfac	Natural log of centering factor	Multiple sources—see Hamidi and Ewing (2014)	4.58	0.25
strfac	Natural log of street factor	Multiple sources—see Hamidi and Ewing (2014)	4.57	0.27

Note: FHWA = Federal Highway Administration; VMT = vehicle miles traveled.

regressed on the natural logarithm of population, and the resulting standardized residuals were converted into an index with a mean of 100 and standard deviation of 25. All urbanized areas fall on a continuum with compactness at one end and sprawl at the other. High values (over 100) correspond to compact urbanized areas, and low values (under 100) to sprawling areas. The ten most compact areas and ten most sprawling urbanized areas are shown in Table 6. These rankings are generally consistent with the rankings for census urbanized areas, and generally consistent with expectations, thus achieving face validity.

Hypothesis 1

The alternate hypothesis is supported by this analysis. The alternate hypothesis is that when vehicle use and density are measured independently, the relationship is not nearly so neat as in the curves of Newman and Kenworthy.

Figure 7 is a scatterplot of per capita VMT versus population density in persons per square mile for 157 urbanized areas. While the general pattern of data points looks exponential, per Newman and Kenworthy, the dominant impression is of wide variance around the best-fit curve.

The pattern of the data in Figure 7 is nonlinear. If a power function applies, it should be possible to produce a linear plot by taking the natural logarithm of each variable and plotting them against each other. This is done in Figure 8. The plot is now approximately linear. However, there is still tremendous scatter around the best-fit line. Regressing the natural log of per capita VMT on the natural log of population density yields the result in Table 7. The R^2 is 0.189, which means that the log of density explains only 19 percent of the variance in the logarithm of per capita VMT. The coefficient of density in this equation is −0.237. The coefficient in a log–log regression is just the arc elasticity of per capita VMT with respect to density. A doubling of density is associated with approximately a one-quarter decrease in per capita VMT. Not a huge effect compared with Newman and Kenworthy's, but a significant one. Results are similar when the analysis is limited to the 30 largest urbanized areas, a sample more equivalent to Newman and Kenworthy's. In a regression of the natural log of VMT per capita on the natural log of population density, the R^2 is higher, 0.267, but the elasticity of VMT per capita with respect to population density is lower, −0.181.

Hypothesis 2

The alternate hypothesis is confirmed by a multivariate analysis. When confounding variables are controlled, the relationship between density and per capita VMT remains significant and negative, but the significance level and

Table 5. Factor Loadings on Principal Components That Comprise the Compactness Index.

Component Matrix	2010 Factor Loadings
Density factor	
popden: gross population density of urban and suburban census tracts	0.964
empden: gross employment density of urban and suburban census tracts	0.895
lt1500: percentage of the population living at low suburban densities	−0.818
gt12500: percentage of the population living at medium to high urban densities	0.775
Urbden: net population density of urban lands	0.938
Eigenvalue	3.88
Explained variance	77.6%
Mix use factor	
jobpop: job–population balance	0.833
jobmix: degree of job mixing (entropy)	0.833
Eigenvalue	1.39
Explained variance	69.5%
Centering factor	
popcen: percentage of urbanized area population in CBD and/or subcenters	0.780
empcen: percentage of urbanized area employment in CBD and/or subcenters	0.787
varpop: coefficient of variation in census block group population densities	0.666
varemp: coefficient of variation in census block group employment densities	0.668
Eigenvalue	2.12
Explained variance	52.9%
Street factor	
smlblk: percentage of small urban blocks of less than 1/100th of a square mile	0.818
avgblk: average block size	−0.930
intden: intersection density	0.793
4way: percentage of 4-or-more-way intersections	0.703
Eigenvalue	2.66
Explained variance	66.4%

effect size drop. The addition of other relevant variables boosts the explanatory power of the model from an R^2 of 0.189 to an R^2 of 0.450 (see Table 8). At the same time, the effect size of the density variable, measured by the elasticity of VMT per capita with respect to density, drops from −0.237 to −0.164.

Three of the other variables in the model are highly significant: the natural logarithms of urbanized area population, representing area size; freeway lane miles per 1,000 population, representing freeway capacity; and per capita income, representing area affluence. The average real price of fuel (gasoline), representing the cost of auto use, has the expected sign but is only significant at the 0.10 level. Per capita VMT increases with area size, freeway capacity, and income, and declines slightly with fuel price, all of which are expected.

Interestingly, the other roadway-supply variable, nonfreeway lane miles per 1,000 population, and the transit variables are not significant. Lower-order roads, such as collectors and local streets, do not appear to induce additional traffic. Transit supply does not appear to dampen VMT, perhaps because transit mode shares are small in most urbanized areas.

Parenthetically, multicollinearity may be an issue in this regression. The largest variance inflation factor (VIF) is 5.77 for the variable GPD. VIFs between 5.0 and 10.0 are suspect, and those over 10.0 are generally indicative of multicollinearity. This is the reason why Ewing et al. (2014a) used structural equation modeling in their earlier analysis. VIFs for all other variables are much smaller.

Hypothesis 3

The null hypothesis is that a more complete measure of urban compactness/sprawl than GPD bears a similar inverse relationship to per capita VMT. The alternate hypothesis is that a more complete measure of compactness/sprawl, which accounts for more aspects of land use and street design, actually has a stronger relationship to per capita VMT than does density. On this score, the evidence is mixed.

Table 9 presents the results of a regression of per capita VMT on the same set of variables as in Table 8, but substitutes the compactness index for GPD. The compactness index in Table 9 is more significant than gross density in Table 8, but the difference is not material. Likewise, the explanatory power of the model in Table 9 (represented by the R^2) is slightly greater than that of the model in Table 8. Again, the difference is not material. The main advantage of the new model over the old is in the area of multicollinearity. Because the compactness index is independent of population, as explained above, the largest VIF is now 2.209.

We wondered which of the dimensions of the compactness index accounts for its relationship to per capita VMT. So we regressed per capita VMT on each of the four compactness factors—density, mixed use, centering, and street factors—plus control variables. The results are presented in Table 10. To our surprise, the multivariate density factor (a more complete measure of density than simple gross density) is far more significant than Newman and Kenworthy's gross density measure, and the more complete measure of density alone, of the four factors, is statistically significant. The other factors have the expected signs but do not approach significance. The elasticity of per capita VMT with respect to the more complete measure of density is −0.612. This result can be taken as confirmation of Newman and Kenworthy's basic theory, that density, properly measured, is strongly related to vehicle use, at least at the large scale of urbanized areas.

Table 6. Compactness/Sprawl Scores for 10 Most Compact and 10 Most Sprawling Urbanized Areas in 2010.

Rank		Compactness Index	Density Factor	Mix Factor	Centering Factor	Street Factor
Ten most compact urbanized areas						
1	San Francisco–Oakland, CA	175.50	190.14	88.90	169.16	148.36
2	Reading, PA	162.19	120.74	128.44	126.47	138.92
3	Eugene, OR	155.08	118.34	128.22	123.68	127.25
4	Madison, WI	154.73	118.70	88.50	186.95	111.97
5	Salem, OR	153.88	123.04	135.33	112.19	123.12
6	Lexington–Fayette, KY	152.04	134.48	123.02	124.22	112.03
7	Huntington, WV-KY-OH	146.87	83.29	129.11	148.69	126.96
8	New York–Newark, NY-NJ-CT	146.62	186.88	75.10	185.54	124.87
9	York, PA	146.17	98.46	138.95	126.74	113.29
10	Allentown, PA-NJ	145.91	108.68	134.48	105.34	149.70
Ten most sprawling urbanized areas						
148	Nashville-Davidson, TN	66.05	94.10	64.31	97.93	79.97
149	Cleveland, OH	64.29	99.21	88.55	95.75	64.26
150	Lancaster-Palmdale, CA	63.88	98.34	97.30	54.81	61.05
151	Winston-Salem, NC	63.27	70.82	89.69	89.15	61.51
152	Fayetteville, NC	62.90	80.58	89.21	67.29	69.36
153	Chattanooga, TN-GA	61.63	70.13	67.38	100.48	71.59
154	Atlanta, GA	58.34	87.47	113.62	104.91	49.05
155	Baton Rouge, LA	57.67	74.57	107.36	71.05	57.73
156	Jackson, MS	55.90	63.24	94.84	104.76	36.48
157	Shreveport, LA	45.80	66.36	71.04	68.36	66.43

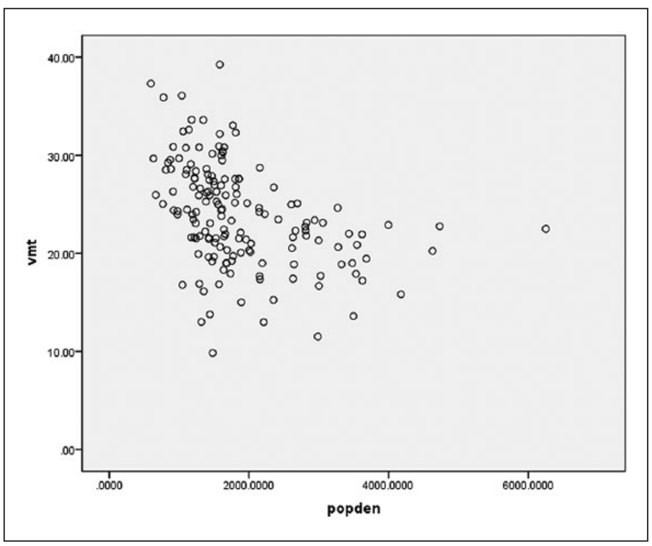

Figure 7. Daily per capita vehicle miles traveled versus population density of 157 US urbanized areas (variables not logged).

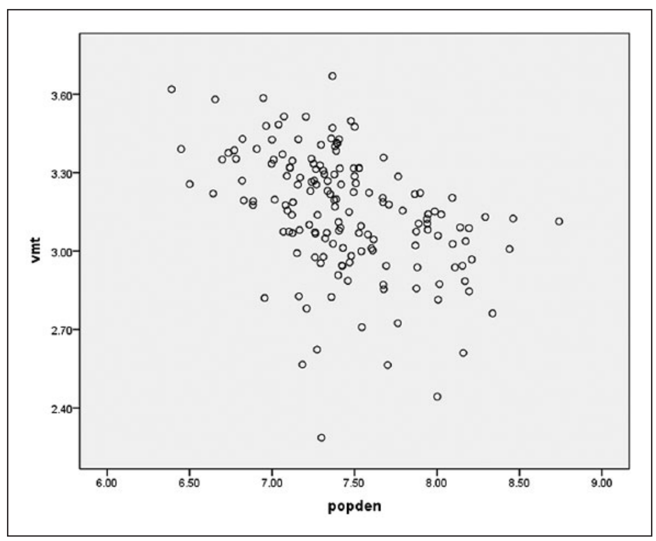

Figure 8. Daily per capita vehicle miles traveled versus population density of 157 US urbanized areas (logged variables).

Hypothesis 4

The alternate hypothesis is confirmed. However it is measured, density takes on disproportionate significance in aggregate studies that fail to account for all D variables. In the meta-analysis of Ewing and Cervero (2010), the weighted average elasticity of VMT per capita with respect to population density is only −0.04. At the same time, the weighted average elasticity of VMT per capita with respect of regional destination accessibility is −0.19. A recent update places the elasticity of VMT per capita with respect to density at −0.15 (Ewing and Cervero, forthcoming).

Table 7. Simple Regression of Per Capita Vehicle Miles Traveled on Gross Population Density (Log–Log Form).

	Unstandardized Coefficients			
Model	*B*	Standard Error	*t*	Significance
constant	4.908	0.293	16.740	.000
popden	−0.237	0.039	−6.015	.000
R^2	0.189			

Table 8. Regression of Per Capita Vehicle Miles Traveled on Gross Population Density and Control Variables (Log–Log Form).

	Unstandardized Coefficients			
Model	*B*	Standard Error	*t*	Significance
(Constant)	3.870	0.608	6.370	.000
popden	−0.164	0.080	−2.062	.041
pop	0.055	0.021	2.621	.010
flm	0.167	0.039	4.332	.000
olm	0.051	0.081	0.635	.526
fuel	−0.561	0.332	−1.689	.093
inc	0.299	0.087	3.455	.001
rtden	−0.020	0.032	−0.613	.541
tfreq	−0.024	0.035	−0.678	.499
R^2	0.450			

Table 9. Regression of Per Capita Vehicle Miles Traveled on Compactness Index and Control Variables (Log–Log Form).

	Unstandardized Coefficients			
Model	*B*	Standard Error	*t*	Significance
(Constant)	3.838	0.524	7.325	.000
compact	−0.203	0.071	−2.845	.005
pop	0.022	0.022	1.014	.312
flm	0.182	0.037	4.964	.000
olm	0.071	0.073	0.971	.333
fuel	−0.692	0.328	−2.112	.036
inc	0.351	0.088	4.002	.000
rtden	−0.037	0.026	−1.403	.163
tfreq	−0.034	0.033	−1.033	.303
R^2	0.464			

In the aggregate analysis in Table 8, the elasticity of VMT per capita with respect to population density is −0.164. It is even higher, −0.612, using the more complete measure of density in Table 10. The aggregate analyses, representing regional urban form strictly in terms of density, fail to account for the confounding influence of destination accessibility. Other reasons for this important difference are discussed below.

Table 10. Regression of Per Capita Vehicle Miles Traveled on Four Compactness Factors and Control Variables (Log–Log Form).

	Unstandardized Coefficients			
Model	*B*	Standard Error	*t*	Significance
(Constant)	5.342	0.741	7.205	.000
denfac	−0.612	0.156	−3.919	.000
mixfac	−0.017	0.055	−0.312	.756
cenfac	−0.058	0.065	−0.898	.371
strfac	−0.016	0.069	−0.233	.816
pop	0.072	0.022	3.329	.001
flm	0.156	0.037	4.213	.000
olm	−0.029	0.078	−0.367	.714
fuel	−0.567	0.330	−1.719	.088
inc	0.338	0.087	3.879	.000
rtden	0.024	0.030	0.791	.430
tfreq	0.015	0.035	0.426	.670
R^2	0.508			

Discussion and Conclusion

The contribution of Newman and Kenworthy to the planning field is undeniable. They were among the first to study the relationship between the built environment and transportation outcomes. Their work in the late 1980s, and that of Robert Cervero at about the same time, spurred a whole new area of academic inquiry. The relationship between the built environment and travel has become perhaps the most heavily researched topic in urban planning (Ewing and Cervero 2010). Newman and Kenworthy's iconic image of private transport energy use versus density, shown in Figure 1, has been reproduced in countless scholarly articles and government reports. While others had previously written about the interaction of land use and transportation, their work made the bidirectional relationship more tangible and quantitative.

Yet, given its importance, their basic theory that density (and the transit service it supports) almost uniquely determine automobile dependence has been subject to surprisingly little scrutiny. This study demonstrates that while density is correlated with per capita VMT, it accounts for relatively little of the variance in per capita VMT across US urbanized areas. Other variables such as personal income and freeway capacity are more significant and have greater elasticities.

As important, Newman and Kenworthy's measure of density, GPD, has not nearly the explanatory power of a more refined multivariate measure of density that captures the distribution of density across the urbanized area. The more complete density factor score is much more significant and has a much larger elasticity than GPD. We suspect the reason is that the density factor score as shown in Table 5 includes information beyond simple GPD. Lt1500 (% population living at low suburban densities) and gt12500 (% population living at medium to high urban densities) are more about the distribution of population than about simple density. A similar urbanized area-level study using population-weighted density by Lee and Lee (2014) reports an elasticity of transportation-related CO_2 per household with respect to density of −0.48, similar to our elasticity of VMT per capita with respect to the multivariate density factor. VMT is a good proxy for transportation-related CO_2. Thus, the distribution of population and employment might be more important than overall density at the regional level.

There are two troubling things about our results when compared to Newman and Kenworthy's and the literature generally. Perhaps the most troubling is the much higher elasticity of VMT per capita with respect to density in the aggregate studies, and additionally, the failure of other dimensions of compactness beyond density, namely, land use mix, population and employment centering, and street connectivity, to significantly relate to per capita VMT in the aggregate studies. These other dimensions are actually more important than density in disaggregate studies of the built environment and travel behavior (Ewing and Cervero 2010; Ewing et al. 2014c). There are several possible reasons for the difference.

One is aggregation bias, and the ecological fallacy that plagues aggregate studies like Newman and Kenworthy's. This is the reason so little of the built environment–travel literature has used aggregate data since the mid-1990s.

The second is that at the highly aggregate scale of the urbanized or metropolitan area, the variable density picks up the effects of other D variables (and other variables generally, such as parking availability). This is an omitted variable problem with the aggregate studies. We suspect, in particular, that at a highly aggregate scale, density and destination accessibility (one of the Ds) become interchangeable. For any given population size, a low-density area will have much greater extent than a high-density area. This will cause automobile trips, on average, to be longer irrespective of mode shifts to transit and walking (Downs 1992, 181). In our aggregate study above, we do not explicitly model destination accessibility because of lack of data for 157 urbanized areas. It would be a herculean task to acquire socioeconomic and travel time data, and to derive destination accessibility metrics, for such a large sample.

Finally, we suspect that the two types of studies provide different results because they are asking different questions. The question in disaggregate studies is, What is the travel-behavior impact of a change in one's immediate environment, holding metropolitan characteristics constant? These are focused on the impact of marginal change in a region. For example, What is the impact of living in a walkable neighborhood versus an auto-oriented neighborhood in sprawling Atlanta? This is a good framework if you are, for example, the EPA and you are trying to figure out how much emissions-reduction credit to allow this year for

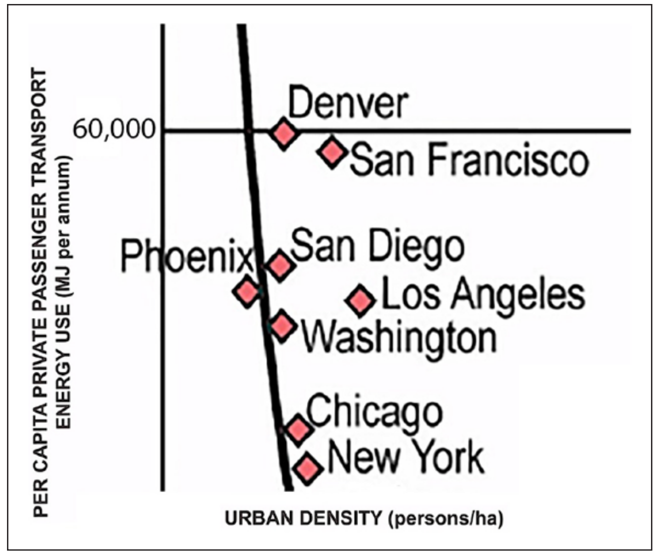

Figure 9. Per capita private passenger transport energy use and urban density in typical US cities (from Figure 2).

transit-oriented development. But since a larger portion (probably a majority) of one's travel is conditioned by metropolitan-level than neighborhood characteristics, the picture offered by the disaggregate framework is only partial (Jonathan Levine, personal communication).

The aggregate studies are effectively asking the question, What is the effect of changing metropolitan-level characteristics? So rather than asking about the effect of dropping a new urbanist neighborhood into metro Atlanta, they ask what would travel behavior look like if metro Atlanta looked more like metro Boston. It stands to reason that the travel-behavior impact on a resident of a new urbanist neighborhood in Atlanta would be a whole lot greater if the rest of Atlanta had grown more like Boston than if Atlanta remained Atlanta. So the greater impact shown by the aggregate studies is, in large part, due to a change in scale (Jonathan Levine, personal communication). It is not that one type of study is inherently more accurate or relevant than the other, but that they ask and answer different questions.

The other thing that is troublesome about our findings relative to Newman and Kenworthy's has to do with variance within our samples. It would appear, on its face, to account for some of the difference in results. By limiting our sample to a small slice of their sample, those urbanized areas that fall within the density range characteristic of the United States, we have less variance in both the dependent variable, per capita VMT, and the independent variable, GPD. Any given scatter around the best-fit curve is accentuated when such a small slice of the VMT/density curve is considered (as shown in Figure 9, a slice of Figure 2).

Using per capita VMT and gross density data from Kenworthy and Laube's original data set (1989–1991), we

Table 11. Regression of Per Capita Vehicle Miles Traveled on the Gross Density and a US Dummy Variable (Log–Log Form).

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Standard Error	Beta	t	Significance
constant	12.8	0.585		21.896	.000
popden	−0.513	0.062	−0.705	−8.247	.000
us dummy	0.418	0.129	0.277	3.246	.002
R^2			0.776		

get an R^2 of 0.72 when running a regression for the entire data set, but only 0.096 when we run a regression with only US cases. Out of curiosity, we also ran a regression for the entire data set adding a single fixed effect variable for US cases, and got the results in Table 11. The log of population density is highly significant, but so is the fixed-effect variable for the US cases (with a positive sign). This suggests an apples and oranges problem in the data sets of Newman et al. Houston and Hong Kong differ in many ways other than density alone, or even density and transit service availability. They differ in terms of per capita income, fuel price, highway capacity per capita, and myriad other factors, including culture. This may be most serious limitation of Newman and Kenworthy's original analysis.

Returning to the question of scale, ultimately, we think that most planners aspire to systemwide change, not merely scattered islands of urbanism in a sea of sprawl. While the disaggregate framework is better fitted to "this-year-to-the-next" policy impacts, the aggregate framework better fits our long-run aspirations. This is the strongest argument for aggregate studies like Newman and Kenworthy's, and this one as well (Jonathan Levine, personal communication).

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Author Biographies

Reid Ewing is a professor and chair of City and Metropolitan Planning at the University of Utah. He also directs the Metropolitan Research Center. His research interests focus on the interactions between land use and transportation.

Shima Hamidi is an assistant professor and Director of the Institute of Urban Studies at University of Texas Arlington. Her research interests include transportation equity and affordability, urban sprawl and its quality of life impacts.

Guang Tian is a recent graduate of the Doctoral Program in Metropolitan Planning, Policy, and Design at the University of Utah. His research interests include travel behavior and built environment, active transportation, and GIS applications in planning.

David Proffitt is a doctoral student at the University of Utah. He studies the relationships between transportation planning, the built environment, and climate change.

Stefania Tonin is an associate professor in the Department of Design and Planning in Complex Environments at the University Iuav, Venice. Her research interests include economics of sustainability, land use and urban sprawl, and economic valuation.

Laura Fregolent is an associate professor in the Department of Design and Planning in Complex Environments at the University Iuav, Venice. Her research interests include territorial transformation and planning tools, land use and urban sprawl.