Trip and Parking Generation Rates for Different Housing Types: Effects of Compact Development

Guang Tian, PhD
Department of City and Metropolitan Planning, University of Utah
375 South 1530 East, RM 235 ARCH, Salt Lake City, UT 84112, USA
Tel: 801-581-8255
Fax: 801-581-8217
Email: guang.tian@utah.edu

Keunhyun Park
Department of City and Metropolitan Planning, University of Utah
375 South 1530 East, RM 235 ARCH, Salt Lake City, UT 84112, USA
Tel: 801-581-8255
Fax: 801-581-8217
Email: keunhyun.park@utah.edu

Reid Ewing, PhD
Department of City and Metropolitan Planning, University of Utah
375 South 1530 East, RM 235 ARCH, Salt Lake City, UT 84112, USA
Tel: 801-581-8255
Fax: 801-581-8217
Email: ewing@arch.utah.edu

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ABSTRACT

Guidelines for trip and parking generation in the United States come mainly from the Institute of Transportation Engineers (ITE). However, their trip and parking manuals focus on suburban locations with limited transit and pedestrian access. This study aims to determine how many fewer vehicle trips are generated, and how much less parking demand is generated, by different housing types (single-family attached, single-family detached, and apartment and condo) in different settings, from low density suburban environments to compact, mixed-use urban environments.

Using household travel survey data from 21 diverse regions of the United States, we estimate a multilevel negative binomial model of vehicle trip generation and a multilevel Poisson model of vehicle ownership, vehicle trip generation and vehicle ownership being logically modeled as count variables. The models have the expected signs on their coefficients and have respectable explanatory power. Vehicle trip generation and vehicle ownership (and hence parking demand) decrease with the compactness of neighborhood development, measured with a principal component that depends on activity density, land use diversity, intersection density, transit stop density, and employment accessibility (after controlling for sociodemographic variables). The models capture the phenomena of "trip degeneration" and "car shedding" as development patterns become more compact.

Reducing the number of required parking spaces, and vehicle trips for which mitigation is required, creates the potential for significant savings when developing urban projects. Guidelines are provided for using study results in transportation planning.

Keywords: trip generation, parking generation, car shedding, compact development, multilevel modeling

INTRODUCTION

Vehicle use and ownership are of interest from the standpoints of energy, environment and transportation. Over half of the world's oil and about 30% of total commercial world energy are consumed by the transport sector. In 2013, about 31% of total U.S. CO_2 emissions and 26% of total U.S. greenhouse gas emissions were generated by transportation (*1*). Vehicle trip generation and vehicle ownership models are used by policy makers to identify factors that affect vehicle miles traveled (VMT), and therefore address problems related to energy consumption, air pollution, and traffic congestion (*2*, *3*).

Guidelines for trip and parking generation in the United States come mainly from the Institute of Transportation Engineers (ITE). The ITE *Trip Generation Manual* and *Parking Generation* manual are considered "bibles" in transportation planning. However, these manuals focus on suburban locations with limited transit and pedestrian access. This study aims to determine how many fewer vehicle trips are generated, and how much less parking demand is generated, by different housing types in different settings, from low density suburban environments to compact, mixed-use urban environments.

It does so with the largest sample of travel and vehicle ownership data ever collected outside the National Household Travel Survey (NHTS) of 2009. And unlike NHTS, we have precise locational data for all households in our sample. Literally hundreds of studies have used household travel data to model travel outcomes and vehicle ownership in terms of built environmental data. So why one more study? The problem with the existing literature is simple. It lacks external validity. The use of data for single regions, specification of different models in each study, and use of different metrics to represent the built environment, precludes the use of models for general transportation planning purposes. By contrast, this study pools data from 21 diverse regions of the U.S. and uses consistently defined metrics to estimate best-fit vehicle trip generation and vehicle ownership models of three different types of housing (single-family attached, single-family detached, and apartment and condo).

LITERATURE REVIEW

The Built Environment

In travel research, influences of the built environment on travel have often been named with words beginning with D – density, diversity, design, destination accessibility, and distance to transit (*4*). While not part of the environment, demographics are the sixth D, controlled as confounding influences in travel studies.

Many studies provide economic and behavioral explanations of why built environments might be expected to influence travel choices. Basically, the first five Ds affect the accessibility of trip productions to trip attractions, and hence the generalized cost of travel by different modes to and from different locations. This, via consumer choice theory of travel demand (*5*), affects the utility of different travel choices. For example, destinations that are closer as a result of higher development density or greater land use diversity may be easier to walk to than drive to. As the D values increase (except distance to transit, with an inverse relationship), the generalized cost of travel by alternative modes decreases, relative utility increases, and mode shifts occur.

Vehicle Trip Generation and Degeneration

The ITE *Trip Generation Manual* itself states that its "[d]ata were primarily collected at suburban locations having little or no transit service, nearby pedestrian amenities, or travel demand management (TDM) programs" (ITE, 2012: page 1). As a result, ITE methods overestimate vehicle trips generated at urban sites. A sample of 17 residential transit oriented developments (TODs) averaged 44% fewer daily vehicle-trips than estimated by ITE (*7*). Another study found actual peak-hour trip rates to be between 26% and 50% lower than ITE rates for mid-rise apartments, general office buildings, and quality restaurants at urban infill sites (*8*). At thirty smart growth development sites in California, actual vehicle trip data showed 56-58% fewer vehicle trips than the ITE model predicted (*9*). In four out of five TOD cases, Ewing et al. (2017) found vehicle trip generation rates are about half or less of what is predicted in the ITE manual.

The ITE manual admits this limitation by saying: "At specific sites, the user may wish to modify trip-generation rates presented in this document to reflect the presence of public transportation service, ridesharing, or other TDM measures; enhanced pedestrian and bicycle trip-making opportunities; or other special characteristics of the site or surrounding area" (ITE, 2012: page 1). This kind of modification is seldom done in practice.

There are several trip generation methods developed as alternatives to the standard ITE method, primarily focusing on mixed-use developments. ITE (2014) provides trip generation for mixed-used developments using the procedure in NCHRP Report 684 (*12*), which is an enhancement of the current ITE multiuse method based on data collected at six sites and tested at three sites. However, it does not account for land use and transportation contextual factors. Initially developed for the United States Environmental Protection Agency (EPA) and later adapted by San Diego Association of Governments (SANDAG), the EPA Mixed-Use method is based on household travel survey data from large multi-use sites in six (updated to 13) metropolitan areas in the U.S. and includes various D variables to estimate external vehicle trips (*13*, *14*). However, most of these multi-use methods could not be applied to the same type of behavior at single-use urban developments (*15*).

There are currently a few adjustments available that account for vehicle trip generation at single-use developments in urban areas. Two studies (*16*, *17*) developed adjustments to supplement the current ITE method for specific land use types based on site-level data collections. In both studies, adjustments of trip generation rate are estimated as a function of the built environment. However, both of the studies are limited to small sample sizes in a single metropolitan area or a state and a selected few land-use types.

There are rich studies on the built environment and travel in the literature. A meta-analysis in 2010 found more than 200 individual studies of the built environment and travel (*4*). A more recent meta-regression analysis expanded this sample considerably (*18*). Generalizing across this vast literature, trip generation is a function of socioeconomic characteristics of travelers and the built environment. Compact developments that concentrate residents, workers, and retail shops in close proximity to one another can "de-generate" vehicle trips.

Vehicle Ownership, Car Shedding, and Associated Parking Generation

Vehicle ownership and associated parking generation are one and the same. A household with two vehicles will generate peak demand for two parking spaces. The ITE *Parking Generation* manual notes that study sites upon which the manual is based are "primarily isolated, suburban sites" (ITE, 2010). Studies show that vehicle ownership is lower in transit-served areas than those that are not transit-served (*20*, *21*). By comparing parking-generation rates for housing projects near rail stops with parking supplies and with ITE's parking-generation rates, Cervero et al. (2010) found there is an oversupply of parking near transit, sometimes by as much as 25-30 percent. Oversupply of parking spaces may result in an increase in vehicle ownership, which is supported by the strong positive correlation between parking supply and vehicle ownership and auto use (Chatman, 2013; Guo, 2013; Weinberger, 2012).

Vehicle ownership is generally treated as a function of households' sociodemographic characteristics. Some studies use income or income per capita to forecast national or global vehicle ownership (*2*). Some other sociodemographic characteristics have been reported as good predictors of vehicle ownership, like household size, number of children and workers, and even immigration status (*27*).

However, there are many studies that have found additional relationships between vehicle ownership and built environmental variables. Households that live in dense, mixed-use, and transit served areas tend to own fewer automobiles, a phenomenon called car shedding; at the same time, they make more walk, bike and transit trips (*28*). Studies have found that the built environment affects vehicle ownership after controlling for the sociodemographic characteristics of households. All of the Ds have been related to vehicle ownership in one study or another (*23*, *24*, *29*, *30*).

Additionally, some other variables have also been reported to be related to vehicle ownership, like parking availability (Chatman, 2013), housing or neighborhood type (*23*, *30*), travel attitudes (*29*), and urban area size (*32*).

METHODOLOGY

This study addresses the external validity issues with existing models by pooling household travel and built environment data from 21 diverse U.S. regions and using a large number of consistently defined and measured built environmental variables to model vehicle ownership and use. In this study, improvements to standard vehicle trip generation and vehicle ownership models include:

- Accounting for the impacts of all D variables while controlling for sociodemographic characteristics;
- Using road network buffers around households' location to capture the built environment, instead of predefined and aggregated geographic units, like traffic analysis zones (TAZs), zip codes, census block groups;
- Using a count regression model (negative binomial regression or Poisson regression);
- Using multi-level modeling (MLM) to account for dependence of households in the same region on shared regional characteristics.

Household Travel Survey Data

The main criterion for inclusion of regions in this study was data availability. Regions had to offer regional household travel surveys with XY coordinates, so we could geocode the precise locations of residences and capture built environment for households more accurately than using predefined and aggregated geographic units. It is not easy to assemble databases that meet this criterion, as confidentiality concerns mean that metropolitan planning organizations are often unwilling to share XY travel data.

At present, we have consistent data sets for 21 regions. They are Atlanta, GA, 2011, Austin, TX, 2005, Boston, MA, 2011, Denver, CO, 2010, Eugene, OR, 2011, Greensboro, NC, 2009, Houston, TX, 2008, Indianapolis, IN, 2009, Kansas City, MO, 2004, Miami-Dade, FL, 2009, Minneapolis-St. Paul, 2010, West Palm Beach, FL, 2009, Phoenix, AZ, 2008, Portland, OR, 2011, Provo-Orem, UT, 2012, Rochester, NY, 2011, Salem, OR, 2010, Salt Lake City, UT, 2012, San Antonio, TX, 2007, Seattle, WA, 2006, Winston-Salem, NC, 2009. The resulting pooled data set consists of 76,596 trips by 766,995 households. The regions are diverse as Boston and Portland at one end of the urban form continuum and Houston and Atlanta at the other.

To our knowledge, this is the largest sample of household travel records ever assembled for such a study outside the National Household Travel Survey of 2009 (NHTS). And relative to NHTS, our database provides much larger samples for individual regions and permits the calculation of a wide array of built environmental variables based on the precise location of households. NHTS provides geocodes (identifies households) only at the census tract level.

Built Environmental Data

The regions included in our household travel survey sample were, in addition, able to supply GIS data layers for streets and transit stops, population and employment for traffic analysis zones, and travel times between zones by different modes for the same years as the household travel surveys.

All the Ds are represented in our model based on these data:

- Parcel level land use data with detailed land use classifications; from these we can compute detailed measures of land use mix.
- A GIS layer for street networks and intersections; from these we can compute street connectivity measures.
- A GIS layer for transit stops; from these data we can compute transit stop densities.
- Population and employment at the block or block group level; from these we can compute activity density.
- Travel times for auto and transit travel from TAZ to TAZ (so-called travel time skims); from these, and TAZ employment data, we can compute regional employment accessibility measures for auto and transit.

Point, line and polygon data from the different sources were joined with road network buffers of household locations to obtain raw data, such as the number of intersections within buffers. These were then used to compute refined built environmental measures such as intersection density, which is simply the number of intersections divided by land area within the buffer.

Variables

Using these datasets, the built environment around a household's home address was measured for buffers of different widths (¼, ½, and one mile street network distances). Ultimately, one-mile buffers were chosen to define the relevant built environment for purposes of vehicle trip and parking generation. In fact, according to the 2009 NHTS, the average walk trip length in the United States varies by trip purpose from 0.52 miles for shopping trips to 0.88 miles for work trips. The overall average is 0.70 miles, which implies a relevant environmental scale of ½ to one mile. Also, from NHTS, bike trips for most purposes average more than one mile, which implies a relevant environmental scale of at least one mile.

The dependent and independent variables used in this study are defined in Table 1. Sample sizes and descriptive statistics are also provided. The variables in this study cover all of the Ds, from density to demographics. With different measures, a total of 13 independent variables are available to explain household vehicle ownership and use. All variables are consistently defined from region to region. We categorized the types of the house into three groups: single-family detached, single-family attached, and apartment and condo.

TABLE 1 Variables in This Study

Variable	***N***	***Mean***	***S.D.***
Dependent variables –household			
number of home-based vehicle trips for the household	76,596	4.03	2.87
number of vehicle owned by the household	76,596	1.93	1.03
Independent variables – sociodemographic characteristics			
household size	76,596	2.5	1.37
number of workers in the household	76,596	1.25	0.88
real household income (in 1000s of 2012 dollars)	76,596	77.4	49.85
Independent variables – built environment within one mile buffer			
activity density within one mile buffer (population + employment per square mile, in 1000s)	76,596	6.74	9.73
job-population balance within one mile buffer (Ewing et al., 2014)	76,596	0.63	0.25
land use entropy within one mile buffer (Ewing et al., 2014)	76,596	0.46	0.26
intersection density within one mile buffer	76,596	112.59	79.53
the percentage of 4-way intersections one mile buffer	76,596	26.1	18.47
transit stop density within one mile buffer	76,596	20.73	26.29
employment accessibility, percentage of regional employment within 10 min by car	76,596	6.91	10.22
Independent variables – region			
regional compactness index developed by Ewing and Hamidi (2014); higher values of the index correspond to more compact regions, lower values to more sprawling regions	21	95.68	26.71
regional population within the region (in 1000s)	21	2217	1663
regional average gasoline prices for 2010 at each region	21	2.89	0.12
Built environment variable loadings on the neighborhood compactness index			
Variable	***Factor Loadings***	***Factor Score Coefficients***	
activity density	0.842	0.32	
land use entropy	0.571	0.217	
intersection density	0.813	0.309	
transit stop density	0.83	0.316	
employment accessibility	0.493	0.187	
Eigenvalue: 2.629			
Explained variance: 52.59%			

Principal Component Analysis

Rather than relying on multiple, correlated variables to represent the built environment around households, we chose to reduce many correlated variables to one factor, called a neighborhood compactness index, representing the built environment around households. This factor was derived with principal component analysis (PCA), an analytical technique that takes a larger number of correlated variables and extracts a smaller number of factors that embody the common variance in the original data set.

The greater the correlation between an original variable and a principal component, the greater the loading and the more weight the original variable is given in the overall principal component score. The more highly correlated the original variables, the more variance is captured by a single principal component. The principal component selected to represent the built environment was the first one extracted, the one capturing the largest share of common variance among the component variables, and the one upon which the component variables loaded most heavily (Table 1). It is the only principal component with an eigenvalue greater than 1, a common cutoff point above which principal components are retained. This one principal component accounts for 52.59% of the variance in the dataset. All component variables load on this principal component with intuitively reasonable signs. Given the loadings, this principal component appears to represent the accessibility of residences to trip attractions outside the home.

We transformed the first principal component, which had a mean of 0 and standard deviation of 1, to a scale with a mean of 100 and standard deviation of 25, which we refer to as a neighborhood compactness index. To compute descriptive statistics and compare vehicle trip and parking generation rates with ITE, we categorized neighborhood settings into three groups based on this factor: sprawling neighborhoods (with index scores <= 90, 36.5% sample – 27,583 households), average neighborhoods (with scores between 90 and 110, 35.7% sample – 26,999 households), and compact neighborhoods (with scores >= 110, 27.8% sample - 21,033 households). Roughly equal numbers of households in our data set fall into each category.

RESULTS

Descriptive Statistics

Vehicle Trip Generation and Degeneration

To compare the residential trip generation in household travel surveys to ITE trip generation rates, we limited the trips and households using the following criteria:

- only included driver-based vehicle trips; trips made by passengers in a vehicle were not counted;
- only included home-based vehicle trips; trips made between non-home locations were not counted;
- only included households where every member of the household provided a travel dairy; many households provide incomplete trip records;
- only included households where the last trip for each person was home-based; many respondents forget to report the last trip of the day, the one that takes them home.

Table 2 provides vehicle trip rates from our 21-region database, for three different housing types and three different levels of neighborhood compactness. As expected, average trip rates per household are higher for single-family detached than single-family attached households, and for single-family attached than apartments and condos (multifamily units). Also as expected, average vehicle trip rates per household drop off with rising neighborhood compactness.

Two interesting patterns emerge. First, when vehicle trip rates are presented on a per person basis instead of a per household basis, differences among housing types and compactness levels partially disappear. That is to say, household size differences account for some (but not all) of the differences in vehicle trip rates. Second, the drop off in vehicle trip rates with compactness is far more pronounced between average and compact neighborhoods, than between sprawling and average neighborhoods. Comparing the extremes, single-family households in average neighborhoods generate 2.15 vehicle trips per person per day, while multifamily households in compact neighborhoods generate only 1.46 vehicle trips per person per day.

Table 2 also provides comparable (as nearly comparable as possible) vehicle trip generation rates from ITE and NHTS. Our rates are much lower than ITE's, even with the bulleted data limitations indicated above. Again, part of the difference has to do with household size. The differences between ITE and self-reported rates are not as stark on a per person basis. But even on a person basis, our rates and NHTS rates are lower than ITE's. This begs the question of why self-reported vehicle trip rates would be lower than automated driveway counts from individual housing developments. Self-reports could be biased downward, since people may forget about certain vehicle trips after the fact or may simply tire of inputting trip data. Also, our trip rates exclude package delivery trips to households in a development, visitor trips by friends and family, lawn and household maintenance trips, and other trips that would not show up in a household travel diary survey.

The large disparity in trip generation rates on a per household basis suggests that any adjustments to ITE trip generation rates to account for the D variables should be applied only to the household's own home-based trip rates, not to the difference between our rates and ITE's.

TABLE 2 Average Vehicle Trip Generation Rates by Housing Type from 21 Region Database, ITE *Trip Generation Manual*, and NHTS

21 regional database				
	Neighborhood Compactness Index	Sample Size	Vehicle trips (per unit)	Vehicle trips (per person)
Single-family Detached	1	17,196	5.05	2.09
	2	14,702	4.97	2.15
	3	9,174	4.17	2.03
	Average	41,621	4.82	2.10
Single-family Attached	1	1,252	3.64	2.19
	2	1,808	3.38	2.14
	3	2,074	2.81	1.60
	Average	5,170	3.21	1.93
Apartment and Condo	1	932	3.10	1.98
	2	2,384	2.80	1.88
	3	3,846	2.06	1.46
	Average	7,220	2.44	1.67
ITE Trip Generation Manual (weekday)				
			Vehicle trips (per unit)	Vehicle trips (per person)
Single-Family Detached (210)			9.52	2.55
Condominium/Townhouse (230)			5.81	2.49

Apartment (220)		6.65	3.31
2009 National Household Travel Survey (NHTS)			
	Sample size	Vehicle trips (per unit)	Vehicle trips (per person)
Single-family Detached	64,855	4.45	2.23
Single-family Attached	13,994	2.87	1.90
Apartment and Condo	4,089	3.27	1.97

Vehicle Ownership and Car Shedding

Parking generation is more complicated than vehicle trip generation. There is both supply of and demand for parking. There is off-street and on-street parking, only the former of which is captured by ITE. And, of course, there are ITE guidelines and actual parking numbers for surveyed households.

Table 3 presents average vehicle ownership per household as a function of housing type and compactness level. As expected, households in single-family detached housing own more cars than those in single-family attached housing, and those in single-family attached housing own more than those in apartments and condos (multifamily housing). Also, as expected, households in sprawling neighborhoods own more cars than those in average neighborhoods, while those in average neighborhoods own more cars than those in compact neighborhoods.

Again, two interesting patterns emerge. First, when vehicle ownership rates are presented on a per person basis instead of a per household basis, differences among housing types and compactness levels partially disappear. That is to say, household size differences account for some (but not all) of the differences in vehicle ownership rates. Second, the drop off in vehicle ownership rates with compactness is approximately the same between average and compact neighborhoods, as it is between sprawling and average neighborhoods. Comparing the extremes, single-family households in sprawling neighborhoods own 0.96 vehicles per person, while multifamily households in compact neighborhoods own only 0.66 vehicles per person.

Table 3 also provides comparable (as nearly comparable as possible) vehicle ownership rates from ITE and NHTS. Our rates are lower than ITE's. Again, part of the difference has to do with household size. The disparity in vehicle ownership rates on a per household basis suggests that adjustments to ITE vehicle ownership rates to account for the D variables are necessary.

TABLE 3 Average Vehicle Ownership (and Associated Parking) by Housing Type from 21 Region Database, ITE *Parking Generation*, and NHTS)

21 regional database				
	Neighborhood Compactness Index	Sample Size	Vehicle Ownership (per unit)	Vehicle Ownership (per person)
Single-family Detached	1	24,278	2.34	0.96
	2	20,973	2.11	0.91
	3	12,848	1.81	0.87
	Average	58,922	2.14	0.92
Single-family Attached	1	1,561	1.64	0.91
	2	2,328	1.42	0.84

	3	2,723	1.26	0.67
	Average	6,663	1.41	0.79
Apartment and Condo	1	1,183	1.36	0.83
	2	3,129	1.17	0.76
	3	4,885	0.96	0.66
	Average	9,277	1.09	0.72
ITE Parking Generation (weekday)				
			Setting	Peak Demand (vehicles per unit)
Single-Family Detached (210)			—	1.83
Townhouse/Condominium (230)			Suburban	1.38
Low/Mid-Rise Apartment (221)			Suburban	1.23
			Urban	1.20
High-Rise Apartment (222): 5 or more floors			Central City, not downtown	1.37
2009 National Household Travel Survey (NHTS)				
		Sample size	Vehicle Ownership (per unit)	Vehicle Ownership (per person)
Single-family Detached		117,353	2.22	1.02
Single-family Attached		24,275	1.30	0.74
Apartment and Condo		8,056	1.82	0.95

Inferential Statistics

To increase statistical power and external validity, we pooled data from 21 diverse regions. The data and model structure are hierarchical, with households "nested" within regions. The best statistical approach for nested data is multilevel modeling (MLM), also called hierarchical modeling (HLM). MLM accounts for spatial dependence among observations (Raudenbush and Bryk, 2002). Households living in a region such as Boston are likely to have very different vehicle trip generation or vehicle ownership characteristics compared to a region such as Houston, regardless of household and neighborhood characteristics. The essence of MLM is to isolate the variance associated with each data level. MLM partitions variance between the household level (Level 1) and the regional level (Level 2) and then seeks to explain the variance at each level in terms of level-specific variables.

The number of vehicle trips generated by a household and the number of vehicles owned by a household are count variables, which can only assume the values of zero, one, two, or some larger positive integer. Although vehicle ownership has been widely modeled as a discrete choice in the literature (*34*), this may be not the best approach. We think count regressions may better fit the data. Two regression methods are used to model count variables – Poisson and negative binomial regression. They differ in their assumptions about the distribution of the dependent variable. Poisson regression is appropriate if the dependent variable is equi-dispersed, while negative binomial regression is appropriate if the dependent variable is overdispersed. Popular indicators of overdispersion are the Pearson and $\chi 2$ statistics divided by the degrees of freedom, so-called dispersion statistics. If these statistics are greater than 1.0, a model is said to be overdispersed (Hilbe, 2011: pages 88 and 142). By these measures, we have overdispersion of vehicle trips and near equi-dispersion of vehicle ownership rates, so the negative binomial model is appropriate for the former and the Poisson model is appropriate for the later. Models were estimated with HLM 7, Hierarchical Linear and Nonlinear Modeling software. Only the intercepts were allowed to vary randomly across level 2. All the regression coefficients at level 2 were treated as fixed and are called random intercept models (Raudenbush and Bryk, 2002).

Vehicle Trip Generation and Degeneration

The best-fit multilevel negative binomial regression models for vehicle trip generation by different housing types are shown in Table 4. For all three types of housing, the number of vehicle trips generated by a household increases with household size, number of working members, and household income. Bigger households with more workers and higher incomes tend to generate more vehicle trips.

We see evidence of trip degeneration as well. Controlling for socioeconomic variables, vehicle trip generation declines with neighborhood compactness. This relationship suggests that areas with high population and employment density, diverse land uses, good street connections, great transit service, and high accessibility allow direct substitution of transit, walk, and bike travel for automobile travel. At the regional level, for single-family detached and attached housing, vehicle trips decline with regional population. Larger regions typically offer much better transit service, which leads to substitution of transit trips for automobile trips.

The pseudo-R^2s of the models range from 0.22 to 0.33. We have shown the pseudo-R^2 largely because urban planners are used to dealing with R^2s and may want this information. Pseudo-R^2s in multilevel regressions are not equivalent to R^2s in ordinary least squares regression, and should not be interpreted the same way. The pseudo-R^2 bears some resemblance to the statistic used to test the hypothesis that all coefficients in the model are zero, but there is no construction of which it is a measure of how well the model predicts the outcome variable in the way that R^2 does in conventional regression analysis.

Vehicle Ownership and Car Shedding

The best-fit multilevel Poisson regression models for vehicle ownership of different housing types are also shown in Table 4. For all three types of housing, the number of vehicles owned by a household increases with household size, number of working members, and household income.

We see evidence of car shedding as well. Controlling for socioeconomic variables, vehicle ownership declines with neighborhood compactness. This relationship suggests that areas with high population and employment density, diverse land uses, good street connections, great transit service, and high accessibility allow direct substitution of transit, walk, and bike travel for automobile travel, and thus car shedding. At the regional level, for apartments and condos, vehicle ownership declines with regional compactness index and population. Multifamily households living in compact and large regions own fewer vehicles than households living in sprawling and small regions. Again, the logical explanation is the ability to substitute transit trips for automobile trips in large regions with extensive transit service. The pseudo-R^2s of the models are 0.67 or higher. See the above discussion of pseudo-R^2s in multi-level models.

TABLE 4 Modeling Results of Household Vehicle Trips and Ownership

Multilevel negative binomial regression for household vehicle trip generation

	Single-family Detached	Single-family Attached	Apartment and Condo
intercept	1.089***	1.225***	1.098***
regional population	-0.00002***	-0.00003**	—
household size	0.167***	0.206***	0.187***
workers	0.117***	0.146***	0.209***
household income	0.002***	0.002***	0.003***
neighborhood compactness index	-0.002***	-0.006***	-0.007***
pesudo-R^2	0.33	0.28	0.22

"—" means this variable is not statistically significant.
**** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1*

Multilevel Poisson regression for household vehicle ownership

	Single-family Detached	Single-family Attached	Apartment and Condo
intercept	0.718***	0.312***	0.385***
regional compactness index	—	—	-0.0026***
regional population	—	—	-0.00003**
household size	0.057***	0.099***	0.107***
workers	0.148***	0.190***	0.208***
household income	0.002***	0.003***	0.005***
neighborhood compactness index	-0.005***	-0.006***	-0.005***
pesudo-R^2	0.87	0.83	0.67

"—" means this variable is not statistically significant.
**** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1*

DISCUSSION AND CONCLUSION

Smart growth, as an alternative to auto-oriented sprawling development, encourages mixed residential and nonresidential land uses in walkable communities with transit options and nearby essential destinations. Increasingly, planners, scholars, innovative developers, and local officials across the world promote smart growth as an antidote to many of the ills associated with urban sprawl. It is vitally important to accurately estimate the traffic impacts of a smart-growth development if communities are to reward such projects through lower exactions and development fees or expedited project approvals, and to right-size parking requirements. However, lacking a reliable methodology for adjusting trip and parking generation rates, communities relying on ITE guidelines are led to understate the traffic benefits of mixed-use development proposals and therefore discourage otherwise desirable developments.

This study explores how many fewer vehicle trips are generated, and how much less parking demand is generated, by different housing types in different settings, from low density suburban environments to compact, mixed-use urban environments. The results show that vehicle trip generation and vehicle ownership (and hence parking demand) decrease with the compactness of neighborhoods after controlling for sociodemographic factors. In other words, the posited phenomena of “trip degeneration” and “car shedding” are borne out.

Applications to Planning

How might the statistics in Tables 2 through 4 be used to plan for new developments? For the purpose of preliminary analysis or when the built environment and sociodemographic data are not available, a planner could estimate vehicle trip and parking generation from the descriptive statistics (Tables 2 and 3) showing average numbers aggregated from multiple regional household travel surveys. For three housing types – single-family detached, single-family attached, and apartment and condo – and three levels of compactness in built environment setting, planners could apply the average vehicle trips and average vehicle ownership (per unit or per person) to a specific development site.

On the other hand, with the complete data sets listed in Table 1, planners are able to predict more accurate and reliable values of vehicle trip and parking generation. The process of calculating these two values is laid out below.

First, planners need to collect all required built environment and sociodemographic data. Second, built environment variables must be converted to a compactness index for a neighborhood (1-mile buffer) around a given site. 1) Each D variable must be standardized using the means and standard deviations in Table 1. A standard (Z) score is calculated as (original value - mean) / (standard deviation). 2) The standard score of each variable is then multiplied by the factor score coefficient of that variable from Table 2 and all five multiplied scores are summed. 3) Lastly, the summed score can be converted into a final neighborhood compactness index (with a mean of 100 and a standard deviation of 25) by multiplying the summed score by 25 and adding 100 to the result. Third, all values of independent variables are entered into the regression equations in order to estimate vehicle trip generation or parking generation (Table 4). Note that the predicted values in negative binomial and Poisson models are the logs of the expected values of the outcome variables. Thus, to derive estimates of vehicle trip generation and vehicle ownership, one needs to exponentiate the values from the regression equations, that is, take the anti-logs of the values.

For example, in a region with a population of 2 million, we assume a given single-attached development has an average household size of 2.0 persons, has labor force participation of 1.0 worker per household, has a median household income of $60,000, and has a neighborhood compactness index either 75 or 125 (one standard deviation below and above the mean – bounding the result). Taking these values into the equation for vehicle trip generation in Table 4 (1.225 - 0.00003 * 2000 + 0.206 * 2 + 0.146 * 1 + 0.002 * 60 - 0.006 * 75 or 125), we compute values of 1.393 and 1.093. After exponentiation, the predicted vehicle trip generation is 4.03 vehicle trips per day for the sprawling neighborhood and 2.98 vehicle trips per day for the compact neighborhood. By contrast, the ITE trip generation rate per unit on a weekday for townhouses and condos is 5.81. The difference is partly due to package delivery trips, garbage collection trips, etc., but is also due to the unique characteristics of the development, including the compactness of the neighborhood in which the development is located. We would compare the computed vehicle trip generation rate to the average for the entire sample from Table 2 (3.21 vehicle trips in this case), and adjust the ITE rate accordingly.

Study Limitations

We acknowledge a few limitations of this study. First, it may be difficult for local planners and engineers to collect and process the built environment data required for use of our tables. Some GIS data in section 3.2 might not be available at the local level or may require collaborations among multiple agencies. Also, data processing requires GIS skills such as network analysis. Most desirably, metropolitan planning organizations (MPOs) would collect, process, and publish compactness metrics for subareas (traffic analysis zones perhaps) within their regions. We have done this for individual households in 21 regions, so it is doable.

Second, diverse impacts of built environment variables are glossed over by using a single measure of compactness to characterize the built environment. We acknowledge that the different D variables have different impacts on travel behavior and vehicle ownership. On the other hand, a single index has the advantage of simplicity when presenting rates for different housing types (see Tables 2 and 3). Planners can conveniently consult 3 x 3 tables to predict trip generation and parking demand for a new development project.

Third, relying on conventional household travel surveys, this study did not control for attitudinal variables or residential self-selection effects. Only three of regions included attitudinal variables in their survey. Residential self-selection occurs if the choice of residence depends in a significant way on preferences for owning automobiles or choosing one mode of transportation over another (*36*, *37*). Such attitudes confound the relationship between the residential environment and travel choices or vehicle ownership. The benefits associated with compact urban development patterns – trip degeneration and car shedding in this study – may be overestimated or underestimated. The evidence is mixed (Ewing et al., 2016; Ewing and Cervero, 2010; Stevens, 2017).

Fourth, while count regression models (negative binomial or Poisson regression) are commonly used in vehicle trip and parking generation studies, they treat car ownership as separate from vehicle trip generation when the two are actually linked (*34*). Car ownership plays a mediating role in the complex relationship between the built environment and travel behavior(*38*). Using structural equation models, future research might be able to measure both the direct effect of built environment on travel behavior and the indirect effect via car ownership.

Lastly, household travel surveys may not be the most accurate source of vehicle trip generation estimates for residential developments. There are significant differences between our results and ITE trip generation rates due presumably to under-reporting of trips in household diary surveys plus delivery and visitor traffic not captured in household travel surveys. These create systematic downward bias that needs to be corrected in trip generation analysis.

Still, we believe that our results have the potential to improve ITE trip generation and parking generation estimates by explicitly accounting for trip degeneration and car shedding in compact, mixed-use urban environments (as compared to ITE's sprawling, single-use suburban environments). They should not be viewed so much as a substitute for ITE rates but rather as a supplement to ITE rates that can be used by professional planners and engineers in project-specific trip and parking generation analyses.

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