Reducing Greenhouse Gas Emissions Through Improved Accessibility

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Abstract

Greenhouse gas emissions from the transportation sector are a result of sprawling urban areas that create a heavy reliance on the automobile. Reliance on the automobile is calculated in terms of vehicle miles traveled, of which can be converted into greenhouse gas emissions. The purpose of this research is to establish a framework for estimating greenhouse gas emissions based on characteristics of the built environment. The creation of this framework helps transportation practitioners better understand the impact various transportation projects have in relation to greenhouse gas emissions and highlights important components for reducing vehicle miles traveled. This research develops and displays a model that uses accessibility measures to predict outcomes in household vehicle miles traveled. Results suggest that accessibility measures (e.g. access to jobs, access to non-work points of interest) are more useful predictors of vehicle miles traveled than traditional built environment measures, and that compact development combined with well-connected transportation networks promotes lower levels of vehicle miles traveled. This report also evaluates the success of a new bus route in Madison, Wisconsin, predicting it to reduce household VMT up to 14 percent for adjacent neighborhoods.

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Introduction

Scientists are confident that many of the Earth's climate changes are linked to levels of greenhouse gases in our atmosphere, which have increased because of human activities (U.S. Environmental Protection Agency 2016). Since 1990, the United States Environmental Protection Agency (EPA) has compiled greenhouse gas (GHG) emissions for all man-made sources in the United States. At 27 percent in 2015, transportation ranked as the second largest source of all GHG emissions just behind electricity generation at 29 percent (U.S. Environmental Protection Agency 2017). Sixty percent of those transportation emissions came from the use of passenger cars and light-duty trucks.[1]

Federal and state government efforts have focused on vehicle fuel economy and the carbon content of fuel itself as solutions for reducing the amount of emissions from passenger cars and light-duty trucks. Ewing et al. (2008) demonstrated in his book *Growing Cooler*, that the U.S. transportation sector cannot meet emission targets through vehicle and fuel technology alone, but must work to reduce vehicle miles traveled (VMT) across the nation's sprawling urban areas.[2] VMT, adjusted for fleet mix and fuel efficiency, is a common indicator for the level of carbon dioxide emissions for which a person or vehicle is responsible. Since the EPA began compiling GHG emissions, transportation emissions have risen as a share of total vehicle miles traveled. From 1992 to 2017, total annual VMT on United States roads increased by 43 percent (Federal Highway Administration 2017). Meanwhile, from 1990 to 2015 the number of vehicles registered increased by only 37 percent (U.S. Department of Transportation 2017).

Ewing's findings indicate a need for GHG emission reduction efforts at the local government level because of their ability to influence planning practices that work to reduce VMT. Using VMT as a common proxy for GHG emissions, Ewing suggested that the key to reducing VMT is through urban planning which promotes compact development. He described compact development as higher averages of blended densities, a mix of land uses, employment centers, interconnected streets, and the design of spaces at a pedestrian scale (Ewing et al. 2008).

Compact development can be thought of as a function of the built environment. This is why many researchers (Stevens 2017; Ewing and Cervero 2010; Heres-Del-Valle and Niemeier 2011) have already explored various relationships between the built environment and VMT; suggesting the built environment to have influences on VMT. To measure the built environment, researchers commonly use metrics that they refer to as the D-variables. The D-variables consist of five metrics: density, diversity of land uses, design of street networks, destination accessibility, and distance to transit.

Accessibility in decision making

While the D-variables have historically been used to quantify the built environment, new technologies have allowed us to improve metrics that better assist in this regard. Accessibility,

[1] Light duty trucks: minivans, passenger vans, pickup trucks, and sport-utility vehicles.
[2] VMT: miles traveled by vehicles within a specified time.

as it relates to transportation, is the ease with which citizens may reach a variety of opportunities for employment and services (Wachs and Kumagai 1973). In other words, how easily can people get from point A to point B. While destination accessibility is one of the D-variables, the metric we're talking about is more robust and flexible. The new form of accessibility doesn't just consider how many "places" one can reach, but also how easy is it for one to reach those places. For example, the D-variables form of accessibility analyzes how many places are within a certain radius, while the new form of accessibility analyzes how many places an individual can reach given the current transportation network. Hypothetically, this new form of accessibility captures all the D-variables in one metric. While todays practitioners have shown interest in accessibility, they have been slow to put it into practice (Boisjoly and El-Geneidy 2017; Levine, Merlin, and Grengs 2017; Proffitt et al. 2017).

One reason to stress the use of accessibility metrics over many of the D-variables is because of their potential to improve decision making. For example, imagine a new mixed-use development that is being considered as a form of compact development. In terms of the D-variables, the development might not improve density that much and only improve diversity a little. However, when analyzing the development with accessibility measures, one could see a significant increase in access to goods and services for residents of the development and surrounding neighborhoods. Accessibility makes the benefits of this new mixed-use development more transparent than when analyzing it with the D-variables. In this situation, accessibility is a measure that can capture all five of the D-variables.

Accessibility is even more important when considering its value in transportation decision making. The most common metric from the D-variables that is used to quantify any transportation network improvements is intersection density. Projects such as a road widening, transit improvements, new sidewalks, and new bike lanes won't necessarily change intersection density, but are still serving as a great improvement to the transportation network. The way accessibility measures access to goods and services allows it to capture these network improvements by understanding how easily people can move from place to place.

In this research, I work to establish a framework for measuring GHG emissions based on characteristics of the built environment and changes in transportation or land use. In doing so, the relationship between levels of accessibility created by the built environment and VMT (specifically targeting passenger cars and light duty trucks) is identified. Actual VMT data for individuals is difficult to obtain because of the lack of a recognized monitoring system. The lack of VMT data makes it difficult for transportation practitioners to analyze the impact of plans and policies focused on reducing VMT. Knowing how accessibility impacts VMT will help transportation practitioners better understand the impact of transportation projects on VMT and GHG emissions.

The goal of this research is to estimate VMT using accessibility measures. Reasons for using accessibility measures to estimate VMT are 1) accessibility measures are more readily available than VMT data, and 2) accessibility measures are better at capturing change in terms of transportation improvements than conventional built environment measures ("the D-variables").

Methods used

To understand how accessibility impacts VMT, a series of models was developed to estimate VMT based on accessibility scores while also comparing the usefulness of accessibility scores v. the D-variables. The study area for this research was Dane County, Wisconsin and the state of Virginia. The reason for conducting the research in these two areas was because accessibility data for the areas were readily available and currently of interest to transportation practitioners.

Model development

Variables that were tested in the model were classified into four categories: accessibility scores, built environment characteristics, household characteristics, and region effects. Accessibility scores were derived using the ArcGIS add-on *Sugar Access*. The built environment variables were representative of the D-variables and were derived from the U.S. EPA Smart Location Database (SLD). Household characteristics were included to control for demographics. Region effects were also included in the form of dummy variables. By including dummy variables, effects based on differences amongst the study areas could be accounted for.

The model was created using multiple linear regression and the least squares method. The goal of the model was to predict VMT using accessibility scores, while controlling for other variables. The foundation of the model was built on National Household Travel Survey (NHTS) data representing specific households. Each household represented a single point on a map of which contained household VMT and demographics. Other data such as accessibility scores and built environment characteristics consisted of different geographies (e.g. census tracts, census block groups, census blocks). To assign data values from these other sources of data to the specific households, a simple overlay was completed. For example, a household represented as a single point in Dane County would receive the built environment value of the census tract of which that single point is located in.

Originally, a large set of variables was collected to be analyzed. To determine which variables were the best predictors, I first identified the most useful variables from each category using standard stepwise regression. The remaining, or preferred, variables from each category were combined to create four models. Each of the four models featured different groupings of variables. Model 1 included all remaining, or preferred, variables that were selected in the previous step. Model 2 featured standard stepwise selection of all remaining, or preferred, variables. Model 3 featured stepwise selection with the three preferred accessibility measures forced into the model. Model 4 represents stepwise selection with accessibility measures forced into the model and built environment features omitted.

After testing the various models, I determined that the final, or preferred, model would include only the variables listed in Table 1.

Table 1. Descriptive statistics used in the final model.

Category	Variable	Description	Source	Form	Mean (x)
Household	vmtWkdy	Weekday household VMT	2009 NHTS	log(x)	55.2
Household	nhtsInc	Total household income (mid-point value of NHTS-defined categories; $150,000 max.)	2009 NHTS	x	71,127
Household	nhtsAdults	Number of adult household members (18+)	2009 NHTS	x	1.94
Household	nhtsChildRatio	Ratio of children to adults in household	2009 NHTS	x	0.224
Household	nhtsVehs	Number of household vehicles	2009 NHTS	x	2.25
Accessibility	nonWork	Access to non-work destinations by walking	Sugar Access	$x^{0.5}$	19.5
Accessibility	jobsAuto	Access to jobs by automobile	Sugar Access	log(x)	214,069
Accessibility	jobsRatio	Ratio of *jobsTransit* to *jobsAuto*	Sugar Access	$x^{0.5}$	0.179

Application of the model

Once the model to predict household VMT using accessibility scores was determined, I used it to estimate the impact transportation projects in the City of Madison had on reducing VMT. Determining the impact projects had on household VMT allowed me to then estimate the anticipated reduction of GHG emissions based on VMT reductions.

When modeling project impacts, I didn't have household data for all the impacted households like I did with the NHTS data. Therefore, I relied on tract-level Census data as a proxy for individual household characteristics. The four household variables serving as a proxy to NHTS data come from the American Community Survey (ACS) (Table 2).

Table 2. Tract-level Census variables used as a proxy for NHTS household characteristic data.

Category	Variable	Description	Source
Household	incMed	Median household income	ACS
Household	adltPerHH	Average number of adults per household	ACS
Household	childRatio	Aggregate ratio of children to adults	ACS
Household	vehPerHH	Average number of vehicles per household	ACS

The Madison transportation project that I analyzed was the creation of a new transit route. The route, "Route 31", connects Madison's southeast neighborhoods to jobs on the city's eastside. Before this route was created, residents on the city's southeast side had few options to utilize public transit. The creation of this bus route dramatically improved access to jobs for many of the neighborhoods in the southeast part of the city (Figure 1).

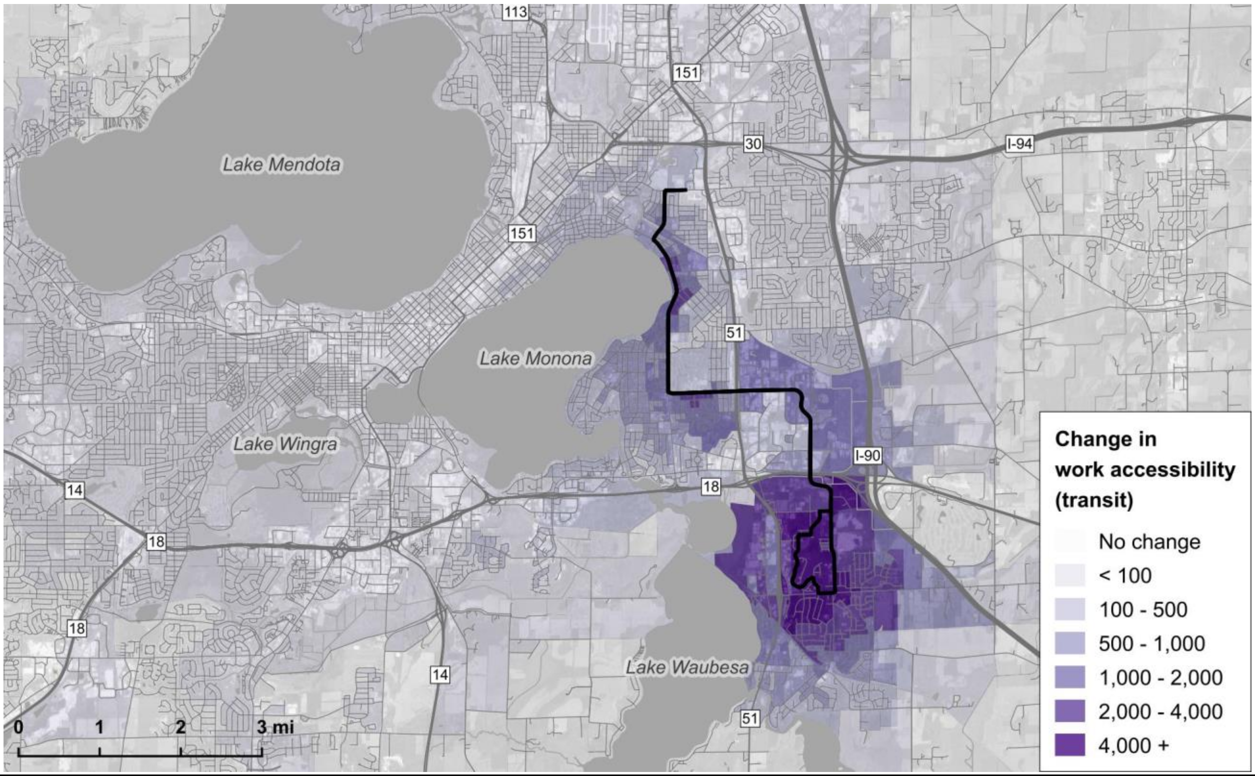

Figure 1. Increase in access to jobs by transit because of Metro Route 31 in Madison, WI.
Source: State Smart Transportation Initiative.

The change in access to jobs because of Route 31 can be analyzed using the model I developed in my research to predict reductions in VMT. To make these predictions, I ran the model using conditions before and after Route 31 was created to identify differences. The difference between the before and after analyses were the *jobsRatio* variables, which respectively contained the number of jobs accessible by transit before and after the creation of the bus route. Results of the before and after analyses were average household VMT displayed at the tract level. The averages were then multiplied by the number of households in each tract to determine total VMT per tract.

Results

Table 3. Explanatory factors of vehicle miles traveled for model 4 (final model).

Predictor	Est. coef.	Stan. coef.	t value	P-value	VIF	Elasticities
Intercept	1.9560		6.123	1.12e-09 ***		
nonWork	-0.0638	-0.12622711	-2.685	0.00731 **	5.049734	-0.14
jobsAuto	0.0580	0.05984275	1.910	0.05624 .	2.242801	0.03
jobsRatio	-0.4547	-0.09422222	-2.038	0.04173 *	4.887281	-0.10
nhtsInc	4.87E-06	0.20947074	9.137	< 2e-16 ***	1.201413	0.35
nhtsAdults	0.2868	0.18325899	7.547	7.02e-14 ***	1.347647	0.56
nhtsChildRatio	0.2036	0.08856341	4.191	2.91e-05 ***	1.020498	0.05
nhtsVehs	0.1280	0.13085287	5.109	3.58e-07 ***	1.499429	0.29
R^2	0.2099					
n	1,814					
F statistic	68.52					

Note: '***' 0.001 level of significance, '**' 0.01, '*' 0.05, '.' 0.1

When comparing the results of the final model to the other models that were tested, all models preformed similarly. For example, the R^2 for all models ranged from 21 percent to 21.4 percent. Therefore, a model containing only several accessibility scores and household characteristics performs as well as a model containing many different variables. This is particularly important for transportation practitioners because it suggests that you don't need all sorts of built environment measures to predict VMT, only a few accessibility metrics. Results also suggest that the most important determinants of VMT are household characteristics. However, household characteristics are not standalone, which is why accessibility is needed to account for the conditions of the built environment. Because of this, the preferred model for estimating includes accessibility scores and household characteristics Table 4.

Table 4. Description of explanatory factors for estimating vehicle miles traveled.

Accessibility scores
• Number of goods and services accessible by walking
• Number of jobs accessible by automobile
• Ratio of the number of jobs accessible transit compared to automobiles
Household characteristics
• Household income
• Number of adults
• Number of children to adults
• Number of vehicles

Elasticities are useful because they show the direct impact that an independent variable has on the dependent variable. Table 3 shows the elasticity of household VMT with respect to the predictor variables. They are calculated independently for each variable by determining the difference between the VMT estimate using all mean values and the VMT estimate using all mean values plus a one percent increase for that specific variable. For example, the elasticity of VMT with respect to *nonWork* was -0.14, which means that a one percent increase in *nonWork* corresponds with a 0.14 percent decrease in VMT.

Application in project evaluation

The selected model is useful for estimating how transportation improvements can move a region toward lower levels of household VMT. The following example describes how accessibility can be used to reduce household VMT, which in return reduces GHG emissions.

The percent reduction in household VMT due to the addition of Route 31 is displayed in Figure 2. The largest average decrease in household VMT for a census tract was 14 percent (shown in dark blue).

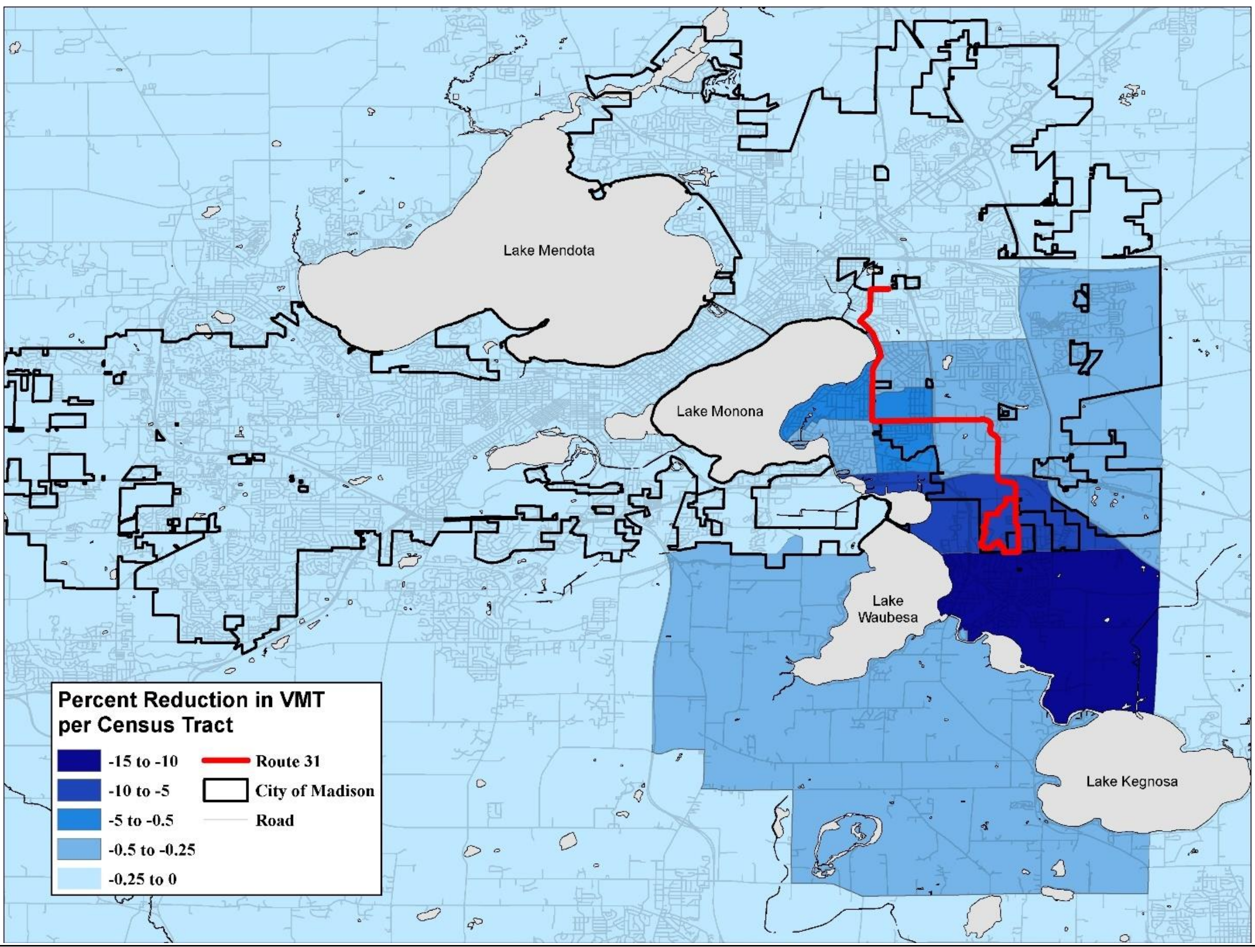

Figure 2. Percent reduction in VMT because of Metro Route 31 in Madison, WI.

The decrease in VMT as result of Route 31 can be modeled as a reduction in GHG emissions. *Moving Cooler* (Cambridge Systematics 2012) identifies the common model for predicting GHG emissions. Predicting GHG requires VMT, vehicle fuel efficiency, and fuel carbon intensity data. Vehicle fuel efficiency is miles per gallon (mpg). The national average for mpg of passenger and light duty vehicles is 22 mpg (U.S. Department of Transportation 2017). Fuel carbon intensity is the number of grams of carbon dioxide emitted per gallon of gasoline combusted. The EPA uses a common conversion factor of 8,887 grams of CO_2 emissions per gallon of gasoline consumed (U.S. Environmental Protection Agency 2015).

Based on VMT estimates before and after Route 31 completion, GHG emission reductions were identical to reductions in VMT. The most impacted census tract received on average a 14 percent reduction in household VMT.

Discussion and conclusions

This research established a framework for estimating GHG emissions by developing a model to estimate VMT. The reason for this research was to understand how levels of accessibility within urban environments impacts GHG emissions. My research created four models utilizing variables such as accessibility measures, built environment measures, and household characteristics to estimate VMT. Results of the model suggested that the most useful variables for estimating VMT were accessibility measures combined with household characteristics.

The preferred model (model 4 in Table 3) suggests that a simple model with accessibility measures and household characteristics performs like other models, making it particularly useful in predicting the VMT impacts of land use and transportation projects that directly impact accessibility. This suggests that key accessibility measures are as useful for predicting VMT as other built environment measures combined. The model also highlights the influence household characteristics, such as income and the number of vehicles, have on household VMT.

The amount of variation (R^2) explained by these models is low due to factors underlying VMT that aren't accounted for (e.g. day trips that are not part of that individual's normal routine and other random error). However, the model has strong, statistically significant directional relationships. These statistically significant predictors emphasize relationships between accessibility and VMT such as the importance of access to transit and access to amenities by walking. Understanding these relationships prove useful for transportation practitioners working to reduce GHG emissions.

Limitations for this research are centered around the lack of quality VMT data used to calibrate the model. The NHTS data used in this model represents travel for a household on one random day during the year. As previously mentioned travel for that day could include miles from trips that aren't typically traveled on a normal day (e.g. doctor appointments, work meetings, etc.). As *Sugar Access* was the tool used for determining levels of accessibility in this research, future technologies for analyzing accessibility may arise to provide more options for transportation agencies wanting to improve accessibility. As the popularity of accessibility grows, so should common metrics that can be used to explain what high levels of accessibility are.

Local governments can improve accessibility in many ways (Table 5). These strategies work to promote the compact development Ewing described as a mix of land uses, interconnected streets, and the design of spaces at a pedestrian scale (Ewing et al. 2008). One way to improve accessibility is by designing subdivisions that have a well-connected street network. For example, subdivisions which include cul-de-sacs and large block lengths score poorly in terms of walking accessibility. Subdivisions which include those design elements increase the difference between straight-line distance and the actual travel route distance to the destination (thus making a user walk further to a destination than should be required). Another way to improve accessibility is by creating new physical connections. For example, a neighborhood may be separated from a job center or commercial district by a freeway or road which may not be crossable due to traffic levels. Creating an over or under pass for that road better connects residents of that neighborhood to those destinations.

Table 5. Transportation strategies for improving levels of accessibility in an urban area.

Transportation network improvements
• Creating new physical connections for all modes of transportation
• Adding or improving crosswalks
• Completing first and last mile connections
Transportation system improvements
• Reducing transit headways
• Modifying/adding bus routes
• Street signal timings
• Increasing auto speeds
Land use improvements
• Subdivision design
• Adding new neighborhood retail/business

These improvements represent “on the ground” strategies that can be implemented at the local level to improve accessibility, thus lowering VMT and GHG emissions. Future urban planning research should work to identify new strategies for improving accessibility.

It is important to remember “that the U.S. transportation sector cannot meet emission targets through vehicle and fuel technology alone, but must work to reduce vehicle miles driven across the nation’s sprawling urban areas” (Ewing et al 2008 p.). This is the reason why transportation practitioners, urban planners, and local decision makers should look to accessibility improvements as a method for reducing VMT and thus lowering GHG emissions.

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Appendix

Table 6. Descriptive statistics considered for all models.

Category	Variable	Description	Source	Form	Mean (x)
VMT	vmtWkdy	Weekday household VMT	2009 NHTS	log(x)	55.2
Household	nhtsInc	Total household income (mid-point value of NHTS-defined categories; $150,000 max.)	2009 NHTS	x	71,127
Household	nhtsSize	Number of household members	2009 NHTS	x	2.40
Household	nhtsAdults	Number of adult household members (18+)	2009 NHTS	x	1.94
Household	nhtsChildRatio	Ratio of children to adults in household	2009 NHTS	x	0.224
Household	nhtsVehs	Number of household vehicles	2009 NHTS	x	2.25
Household	nhtsDtch	Single family detached	2009 NHTS	1,0	0.827
Household	nhtsNonWt	Non-white household	2009 NHTS	1,0	0.156
Built environment	popDens	Population density (people per acre)	SLD	log(x)	5.21
Built environment	jobDens	Employment density (jobs per acre)	SLD	log(x)	1.51
Built environment	jobPerHh	Jobs per household	SLD	log(x)	0.885
Built environment	ntwkDens	Road network density (miles per sq. mi.)	SLD	x	12.5
Built environment	intDensStreet	Street intersection density (per sq. mi.)	SLD	x	51.2
Built environment	intDensMM3	Intersection density, multimodal three-leg intersections (per sq. mi.)	SLD	log(x)	7.18
Built environment	intDensMM4	Intersection density, multimodal four-leg intersections (per sq. mi.)	SLD	log(x)	3.52
Built environment	ptDist	Distance to nearest transit stop (m)	SLD	1/x	482.4
Built environment	ptFreq	Aggregate transit frequency per hour within 0.25 miles during evening peak	SLD	log(x)	17.9

Built environment	ptFreqDens	Aggregate transit frequency per square mile	SLD	log(*x*)	71.4
Accessibility	nonWork	Access to non-work destinations by walking	Sugar Access	$x^{0.5}$	19.5
Accessibility	jobsTransit	Access to jobs by transit + walking	Sugar Access	log(*x*)	63,378
Accessibility	jobsAuto	Access to jobs by automobile	Sugar Access	log(*x*)	214,069
Accessibility	jobsRatio	Ratio of *jobsTransit* to *jobsAuto*	Sugar Access	$x^{0.5}$	0.179
Region	Nova	Northern Virginia		1,0	0.034
Region	HamptonRoads	Hampton Roads, Virginia		1,0	0.580
Region	Lynchburg	Lynchburg, Virginia		1,0	0.281

Table 7. Results from all models.

Predictor	**Model 1**	**Model 2**	**Model 2**	**Model 3**
Intercept	1.485e+00*	2.317e+00***	1.861e+00***	1.956e+00***
nonWork	-2.689e-02	–	-4.813e-02	-6.376e-02**
jobsAuto	8.604e-02	–	6.621e-02*	5.803e-02 .
jobsRatio	-4.561e-01	-4.303e-01**	-4.356e-01	-4.547e-01*
popDens	3.857e-02	–	–	–
jobDens	-4.555e-02	-5.224e-02**	–	–
ntwkDens	-2.908e-03	–	–	–
intDensMM3	-4.175e-02	–	-4.747e-02*	–
nhtsInc	4.817e-06***	5.046e-06***	4.852e-06***	4.868e-06***
nhtsAdults	2.856e-01***	2.920e-01***	2.866e-01***	2.868e-01***
nhtsChildRatio	2.039e-01***	2.044e-01***	2.034e-01***	2.036e-01***
nhtsVehs	1.257e-01***	–	1.258e-01***	1.280e-01***
Nova	-2.863e-02	–	–	–
Lynchburg	7.680e-02	–	–	–
R^2	0.2137	0.2098	0.2121	0.2099
n	1,814	1,814	1,814	1,814

Note: '***' 0.001 level of significance, '**' 0.01, '*' 0.05, '.' 0.1