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Vehicle miles traveled and the built environment: New evidence from panel data

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Abstract: There has been considerable interest in the impact that the built environment has on vehicle miles traveled (VMT). While this issue has been extensively researched, due to the heavy reliance on cross-sectional data, there remains uncertainty regarding how effective local land-use planning and regulation might be in reducing VMT. Based on a 13-year panel of Florida counties, models are estimated that relate VMT to new measures of the spatial distribution of alternative land uses within counties and county urban expansion. Identification of causal effects is established by including year and county fixed effects, along with an extensive set of control variables, and instrumenting those land uses that may be endogenous. Incremental annual changes in the spatial concentration of alternative land uses are found to affect VMT. The policy implication is that appropriate land-use policy can reduce VMT and should be considered part of the strategy for dealing with the problem of global warming.

Keywords: Vehicle miles traveled, urban land use, global warming

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1 Introduction

One of the largest contributors to anthropogenic U.S. greenhouse gas (GHG) emissions is the transportation sector. In 2016, this sector accounted for 28 percent of total U.S. GHG emissions (United States Environmental Protection Agency, 2019). By far the largest source of transportation sector emissions is road vehicles (83 percent of the total). While total travel by these vehicles dipped nationally during the Great Recession and leveled off at the lower level until 2013, since then vehicle miles traveled (VMT) has resumed its secular upward climb (United States Department of Transportation, Bureau of Transportation Statistics, 2019). Because of growing concerns both domestically and internationally over global warming, there is considerable interest in policies that would reduce VMT.[1] A heavily researched issue has been whether changes in the built environment, in particular more compact development, could lower VMT. [2] The vast majority of studies have relied upon cross-sectional data where VMT has been measured either at the household level or for geographical areas. This reliance on cross-sectional

[1] As noted by Ewing and Cervero (2010), besides its relationship to climate change, VMT is also of interest due to its links to traffic safety, air quality, and energy consumption.

[2] According to Ewing and Cervero (2010), the relationship between the built environment and VMT is the most researched subject in urban planning.

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data has been heavily criticized for precluding establishing a clear cause and effect between a change in the built environment and a change in VMT. There have also been longitudinal studies, but their focus has not been strongly on the relationships that exist between changes in the built environment and VMT.

In this paper I take a completely different approach to the land-use/VMT issue. By exploiting the advantages of using panel data at the county level, I directly address the urban planner's problem regarding the placement of different types of new development: if the goal is to reduce VMT, is it better to further concentrate a land use within a county or is it better to achieve a more spatially balanced pattern of a land use throughout the county. While land use changes of a major proportion may not be feasible given the durability of the existing built environment, local governments can cause annual incremental changes in the spatial concentration of different land uses in making their project approval decisions. My focus on incremental changes that are realistically achievable from a policy perspective is a major departure from the existing literature. Stevens' (2017a) recent review of the literature identifies the following variables that the household VMT studies have sometimes employed as explanatory variables: distance to downtown, household/population density, job accessibility by auto, intersection/street density, land-use mix, job density, percentage of four-way intersections, distance to nearest transit stop, job accessibility by transit, and jobs–housing balance. His meta-regression analysis reveals that the VMT elasticities with respect to these variables are small in magnitude ranging from –.63 for distance to downtown to close to zero or not statistically significant for the last five variables listed. However, regardless of whether these variables actually influence VMT, the question is how feasible is it for local governments to change these variables.[3] Clifton (2017), in her commentary on Stevens (2017a), raises the issue of whether researchers are providing the answers to the questions that practitioners need.[4] Guidance regarding where to spatially target future development of different types toward greater or less concentration is something that planners would presumably find useful. Hence, if the incremental changes in land use that I consider do impact VMT, this carries considerable policy importance.

Using data from the state of Florida covering the years 2001 to 2014, I estimate log-linear models relating a county's VMT to countywide measures of the concentration/dispersal of eight alternative land uses: two residential types measured in units (single-family homes and units in multifamily properties), five commercial types measured as properties (office, retail, industrial, institutional, and parking lots), and one government property type.[5] Models are estimated for all counties and separately for urban versus rural counties. In another set of regressions estimated for just urban counties, I add measures of the concentrations of these same land uses within the central city of the metropolitan area that the county is part of. Central cities contain many destinations of interest not only to their own residents but also to residents throughout the MSA. Hence, changes in the spatial distributions of alternative land uses within these cities may impact county changes in VMT. I also estimate the impact of sprawl on VMT by including a measure of the physical expansion of the developed area of the county in my models. Concentration is measured in a novel and reliable fashion through the use of GINI coefficients (GC). Also unique is my measure of urban expansion (UE), which is obtained by annually counting the num-

[3] Whether the elasticities obtained from Stevens' meta-analysis or those of similar magnitude from Ewing and Cervero's (2010) earlier meta-analysis are large enough to be considered economically significant is disputed between the authors of these two studies. Stevens concludes they are not, but Ewing and Cervero (2017) disagree. Clearly, however, an elasticity of VMT with respect to distance from downtown of –.63 can be considered nontrivial in magnitude.

[4] There is also the question of whether this unmet need is furthered by the use of meta-analysis. This method of literature review has important limitations as outlined by Næss (2019). Criticisms specific to Stevens' meta-analysis and his defense are found in Stevens (2017b).

[5] Parking lots and garages are properties offering multiple individual parking spaces; hence the parking spaces that might be found on other properties (for example, single-family or multifamily properties) are not included.

ber of one-mile by one-mile square land area boxes that have been developed within the county. The estimated models include year and county fixed effects, along with an extensive set of household descriptive variables. Both OLS and 2SLS models are estimated, where in the latter case regressors suspected to be endogenous are instrumented with variables that strongly pass the standard validity checks. The evidence provided allows for more confidence in establishing the true causal connections between changes in the built environment and changes in VMT. The results show that varying the concentrations of a number of the land uses and changes in UE can result in nontrivial changes in VMT. Estimating separate models for urban and rural counties shows important differences in the results between the two types of counties.

In the next section (2), I review the literature that has focused on the impacts that the built environment has on VMT. Section 3 provides a conceptual framework for identifying the possible effects of changes in the concentration of a land use and urban expansion on VMT. The panel data are described in Section 4, which includes a discussion of the novel use of GCs to measure the spatial concentration of alternative land uses. Section 5 describes the log-linear, two-way fixed effects models, estimated by both OLS and 2SLS, used to explain daily vehicle miles traveled (DVMT). Levels and changes in DVMT, the GCs, and UE over the course of the panel are described in Section 6. Prior to presenting my findings from estimating the DVMT models in Section 8, I report results from conducting a variety of specification tests in Section 7 confirming the validity of the chosen methodology. A discussion of my findings is found in Section 9. Section 10 covers the limitations of my analysis and offers some suggestions for future research. Conclusions are found in Section 11.

2 Literature review

The methodological approaches of prior studies focused on explaining VMT include four types of studies. Most studies utilize cross-sectional, household level data obtained from travel surveys to regress subjective VMT estimates on the land-use characteristics of the respondent's neighborhood. These sometimes include such attributes as distances to points of interest and the types of land uses located within the home neighborhood; frequently, however, land use is described entirely by just one variable—residential density. Reviews of these studies (Brownstone, 2008; Transportation Research Board, 2009; Salon, 2014; Stevens, 2017a) and the assessments of others (Boarnet, 2011; Næss, 2015; Handy, 2017) have emphasized that the reliance on cross-sectional data of these studies has made it difficult to distinguish correlation from causality. The principal limitations associated with the use of cross-sectional household level data are well-known, consisting of possibly biased estimates resulting from residential self-selection and omitted variables.[6] Other limitations are measurement error in VMT resulting from respondents' recall of past travel behavior and the reliance on outdated surveys. The most frequently used surveys are the National Household Travel surveys of 2001 and 2009 and the National Personal Transportation Surveys of 1990 and 1995.[7] A second, much less frequently used methodological ap-

[6] Residential self-selection refers to the tendency of people who wish to drive less to locate in neighborhoods where there is less need to drive, which may result in an overestimate of the impact of the built environment on VMT. Not all of the studies relying upon household level data ignore the self-selection issue. Stevens (2017a) identifies ten studies that attempt to control for the problem. However, the results from a number of studies (Cao, Mokhtarian, & Handy, 2009; Wolday, Cao, & Næss, 2018) suggest that not controlling for residential selection results in little bias if controls include a rich set of demographic and socioeconomic variables.

[7] In addition to these national surveys, some studies rely upon surveys that have been done at the subnational level. A recent example is Boarnet and Wang (2019). Using household VMT data from the 2012 California Household Travel Survey, they find that access to jobs is negatively associated with household vehicle miles traveled within the Los Angeles Combined Statistical Area. Other studies use survey data on individual cities to address research questions particular to that city. An example is Henao and Marshall (2019), who do their own survey of ride-hailing passengers in Denver, Colorado. They find that ride-hailing increased VMT by 83.5 percent over what would have existed if ride-hailing did not exist.

proach also employs cross-sectional data, but instead of being measured at the household level, VMT is measured at an aggregate level for geographical units, such as traffic analysis zones (Miller & Ibrahim, 1998), census tracts (Yang, 2008), urbanized areas (Cervero & Murakami, 2010) and grid cells (Lindsey, Schofer, Durango-Cohen & Gray, 2011; Diao & Ferreira, 2014). However, as noted by the latter study (page 3007), finding a strong association between the built environment and travel patterns at a point in time is not the same as showing that a change in the built environment will lead to a change in travel behavior. Again, biases from self-selection and omitted variables could explain some of the observed correlation. Finally, there are studies that rely on longitudinal data. These studies can be divided into two types. One type involves following households that changed either their work location or residential location. Cao, Mokhtarian, and Handy (2009) review eleven longitudinal studies that focus on a variety of travel behaviors, with two yielding evidence on the built environment and VMT (Krizek, 2003; Handy, Cao, & Mokhtarian, 2005). Krizek found that a reduction in VMT is accompanied by an improvement in either workplace or residential accessibility to desired destinations, while the results of Handy et al. suggest that neighborhood characteristics have the greatest influence on VMT. A limitation of these studies is that they were unable to control for changes in attitudes that were correlated with moving that have an effect on mode choice, which may have biased their findings on the importance of the built environment in affecting VMT. Subsequent to Cao et al.'s review, van de Coevering, Maat, and van Wee (2015) used two waves of the same panel of respondents to test the relationships between the built environment, attitudes, and automobile travel. They find evidence of the "reverse causality" hypothesis, which they defined as the built environment affecting attitudes, which in turn influenced auto usage. The second type of longitudinal studies have used aggregate data to study VMT. Because my analysis falls into this category, these studies merit special attention in defining my contribution to the literature. Small and Van Dender (2005) employ a panel of all states for the years 1966 to 2001 to estimate the rebound effect for motor vehicles, by which improved fuel efficiency increases VMT, finding that the effect is much stronger in the long than the short run. Their study failed to account in changes in the built environment. Choo, Mokhtarian, and Salomon (2005) study the relationship between VMT and telecommuting using national data. In addition to excluding descriptors of the built environment as control variables, their study was severely handicapped by having only 11 years of data on the national number of telecommuters and therefore their regression models were estimated with only 11 observations. McMullen and Eckstein (2012) also used national data to determine Granger causality between GDP and VMT, where only these two variables were included in the analysis. The two longitudinal studies bearing the closest resemblance to the present study are by Ewing, Bartholomew, Winkelman, Walters, and Chen (2007) and Noland (2001). In the first study, using data on 85 urbanized areas, the percentage change in VMT measured over consecutive 10-year periods is regressed on the corresponding percentage changes in a wide range of variables, including lane miles, population, population density, and income. These variables are found to strongly affect VMT and are included among my set of control variables.[8] Ewing et al. do not include percentage changes in the concentrations of alternative land uses; hence, except for changes in population density, which may capture changes in the concentration of residual development for the urbanized area, changes in the built environment are not considered. In the second study, Noland uses state level data covering the years 1984 to 1996 to test the theory of induced travel demand (Downs, 1962), which hypothesizes that an increase in road capacity will induce additional growth in traffic. He regresses state annual VMT on lane miles, which is his measure of road capacity, a set of control variables (population, per capita income, and fuel cost) and state fixed ef-

[8] Ewing et al.'s analysis has been criticized over the coarseness of the level of analysis (urbanized area), the quality of the data, and questions about their model specification. See footnote 5, page 56 of Driving and the Built Environment (Transportation Research Board, 2009).

fects. His results provide support of the induced travel demand hypothesis. In summary, none of the longitudinal studies focus on the issues addressed in the present study of how incremental changes in the spatial concentrations of alternative land uses and incremental changes in the size of the urban area impact VMT.[9]

3 Land-use concentration, expansion, and VMT within counties

VMT has been described as a composite measure affected by trip length, trip frequency, and mode choice (Ewing & Cervero, 2010). The spatial concentration/dispersal of alternative land uses are expected to impact these measures and thereby VMT in different ways depending upon the relative strengths of two opposing forces. First, concentration results in agglomeration economies that reduce trip frequency and trip chaining travel distances between destinations. Many examples can be given, but four are well known: 1) the concentration of commercial establishments within a downtown, shopping center, or mall that reduces the number of trips and distances between destinations associated with the purchase of complimentary goods or services, 2) the concentration of offices, such as within an office park or the CBD, allowing less travel to attend multiple face-to-face meetings, 3) the existence of various types of business clusters (aka, "rows"), such as for automobile dealerships or antique stores, that minimize the travel associated with comparative shopping, and 4) clusters of firms in the same or related manufacturing industry, that minimize travel between producers and suppliers. Besides affecting trip frequency and travel distances, concentration above certain thresholds may also affect mode choice in favor of travel by means other than by motor vehicles. For example, concentrations of residences or jobs may enable the establishment of a public transit stop, which reduces motor vehicle dependence and VMT. Counteracting the tendency of the concentration of a land use to reduce VMT are two forces that raise VMT. First, concentration results in congestion that may require more driving to find an available parking space. Although unlikely an important factor until some high threshold is reached, a nontrivial amount of VMT is usually generated by drivers looking for parking within CBDs (Teng, Qi, and Martinelli, 2008).[10] Second, a more concentrated and less dispersed land use increases average distances between residential locations and non-specialized goods and services that consumers purchase on a regular basis, such as pharmaceuticals, groceries, and personal services, thereby increasing VMT. Because many residents work at the establishments that provide these non-specialized facilities, their concentration may also lengthen journeys to work. For example, in the classic case of a monocentric city, where all employment is concentrated within the CBD, suburban residents may have long trips to commute to their jobs and to do their shopping. Trip distances may also be long for suburban residents employed in the suburbs if jobs are concentrated within edge cities.

How might these opposing forces affecting the directional impact of a land use's concentration on VMT vary across the eight land uses that I empirically investigate? One hypothesis suggested by my conceptual framework is that the dispersal of single-family homes reduces VMT. If housing is more spatially dispersed throughout the county, households will have more of an opportunity to locate where their overall travel by motor vehicles can be minimized. In particular, greater spatial choice of residence

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[9] A reviewer suggested as a fifth category of VMT/ built environment studies those that rely upon qualitative evidence or a combination of both qualitative and quantitative analysis. Clifton and Handy (2001a) discuss how focus groups, interviews, and participant-observer techniques can be used in conjunction with quantitative approaches or on their own to fill the gaps left by quantitative techniques. For an example of this approach see their paper (2001b) on the effect that local shopping opportunities have on VMT. For a more recent example, see Dill, McNeil, and Howland (2019) on the influence that peer-to-peer car sharing has on VMT.

[10] Where public transportation is a good substitute for auto travel, as in many European cities, parking difficulty may not increase VMT, but instead induce mode choice away from the automobile.

enables workers to minimize their journey to work.[11] Moreover, possible agglomeration economies that might reduce VMT would seem unimportant in the case of housing. With respect to the concentration of office and industrial properties, extant evidence indicates that agglomeration economies are relatively strong in the case of these two land uses (Rosenthal & Strange, 2006); hence, the expectation is that their concentration will result in a reduction in VMT. Parking lots and garages, while important users of land, are not final destinations.[12] They impact VMT by serving as a proxy for locations, both private and public, that drivers need or desire access to. This suggests the dispersal of parking properties decreases average travel distances between homes and points of interest, causing a reduction in VMT. To hypothesize about possible VMT effects related to the spatial distribution of government and institutional properties, it should be noted that a majority of each of these land uses are described by a single property type. For government it is public schools and for institutional it is churches. Dispersing these land uses reduces the average distances between them and homes; hence, the expectation is that this will reduce VMT.

There are two land uses for which it is difficult to establish a hypothesis regarding their probable effects on VMT. First, there is the case of retail properties. For those that sell less specialized goods and services (for example, grocery stores), concentration results in longer distances between homes and shopping, resulting in increases in VMT. The concentration of more specialized retail, while also reducing general accessibility, results in agglomeration economies that reduce trip frequencies. Examples are various "rows" of commercial activity (automobile dealerships, antique and furniture stores) where comparative shopping typically occurs prior to purchase and regional shopping malls and shopping centers providing one-stop shopping for a variety of goods and services. It is not clear how these various factors play out to either increase or decrease VMT. In the case of multifamily housing there are also conflicting forces. Like single-family housing, the dispersal of multifamily housing is expected to reduce average travel distances between home and work. However, because land use zoning allows a spatial coexistence between commercial establishments and apartments, apartment residents may have shorter distances to places of interest, such as restaurants and stores.[13]

Regarding the expected effect of an expansion in the developed land area of a county on VMT (controlling for population size), the idea is that, on average, trip origins and destinations will be more distant from one another, and therefore trip lengths will be longer, resulting in an increase in VMT. Longer trips may also increase VMT by making walking and bicycling less competitive alternatives to the use of automobiles. Hence, the expected effect is seemingly unambiguous: as the developed land area of the county rises relative to its population size, VMT increases. However, in recent years, new developments on the fringes of Florida's urban areas tend to be non-traditional in the sense that they reflect "new urbanism" design concepts which promote walkable neighborhoods containing a wide range of alternative land uses, offering employment opportunities and access to schools, churches, and recreational activities. Hence, residing in one of Florida's new fringe development communities may or may not indicate more need for automobile travel.

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[11] In the case of dual worker households spatially dispersed housing opportunities enable the joint minimization of travel, taking into consideration possible differences in the value of travel time between workers. For example, according to the Household Responsibility Hypothesis, the value of travel time is higher for women than for men because of the disproportionate burden of household responsibility on women (Gimenez-Nadal & Molina, 2016).

[12] On average, an urban county has between 1000 and 2000 individual parking properties.

[13] Mixed land use providing multifamily housing residents easy access to a range of possible desirable destinations is more common outside the U.S., especially in Europe and China.

4 Panel of Florida counties

The panel of Florida counties includes all 67 of the state's counties covering the years 2001 to 2014. It is a perfectly balanced panel, containing a total of 938 county/year observations. The panel is constructed from multiple sources. My dependent variable, Daily Vehicle Miles Traveled (DVMT), and an important control variable, Centerline Miles (CLM), come from the Florida Department of Transportation (FDOT).[14] The GCs are constructed using the property tax rolls that each county is required to submit each year to the Florida Department of Revenue (FDOR).[15] Land uses are divided into eight categories, which largely account for the entirety of the built environment within a county. Residential units are divided into single-family homes and units within multifamily properties, which can be either owned or rented. The units are individual homes and not the buildings that they may occupy. Commercial units are properties and consist of office buildings, retail buildings, parking lots/garages, industrial buildings, and buildings for institutional use. The final land use is government buildings. A unique characteristic of the tax rolls is that Public Land Survey System (PLSS) section boundaries are identified. The PLSS divides each county into unchanging one-mile by one-mile square areas.[16] The GCs are computed by counting the number of housing units, commercial properties, and government buildings within each square box for each year, as shown in Figure 1.[17] [18] If each box contains the same number of units or properties the GC equals zero, indicating a perfectly uniform spatial distribution of the land use across the county's developed land area. Larger GCs indicate that the land use is found disproportionately in some boxes relative to the rest of the boxes. In the limit, with all members of a land use located in a single box, the GC equals one. Of course, in no county are limits reached; however, as shown below land uses tend to be highly concentrated within a relatively small percentage of the boxes found within a county. The UE of a county is measured by counting for each year of the panel the number of PLSS boxes within the county that contain developed properties.

In addition to CLM, there are 21 control variables. The variables include real personal income from the U.S. Bureau of Economic Analysis and person and household characteristics from GeoLytics, a commercial vendor that provides inter-decennial census data. These characteristics, along with their descriptive statistics, are listed in Appendix A.[19]

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[14] The FDOT determines VMT using vehicle traffic volume and segment length (Cambridge Systematics, Inc. & Kittelson and Associates, 2014). The number of vehicle miles traveled is based on data obtained from traffic monitoring sites. These monitoring sites collect count data on an hourly basis. VMT is equal to the product of the daily or hourly volume and the roadway's length in miles. The county total is obtained by summing up the VMT of each of the county's roadways. DVMT is obtained by dividing VMT by the number of days in the year. CLM is the length of the county's roads in miles, without regard to the number of lanes.

[15] These rolls have a standardized format so that each county provides the same information on each property located in the county. The rolls are used by the FDOR to ensure that properties are being equitably assessed for the purpose of determining each property's property tax liability.

[16] More information on the PLSS can be found at https://nationalmap.gov/small_scale/a_plss.html..

[17] The GCs are computed using STATA's fastgini command. The fastgini command uses the formula
GC= $\frac{2}{\mu n^2}\left(\sum_{i=1}^{n} i x_i\right) - \frac{n+1}{n}$ where μ is the mean of the vector sorted on x from smallest to largest. The code can be found at https://www.researchgate.net/publication/4778196_A_Method_to_Calculate_the_Jackknife_Variance_Estimator_For_the_Gini_Coefficient, and was developed by Karagiannis and Kovacevic (2000).

[18] Only boxes including at least one developed property are included. Empty boxes largely consist of those that are undevelopable because of natural features (e. g., lakes), parks, and national forests

[19] Note that all of the control variables are defined as county totals and are not percentages or expressed in per capita terms. The totals were found to maximize the explanatory power of the estimated DVMT models. This is expected because I am measuring the growth in the total county VMT. Through sheer expansion, more people, jobs and line miles are expected to increase total VMT and this is supported by the results obtained with the control variables.

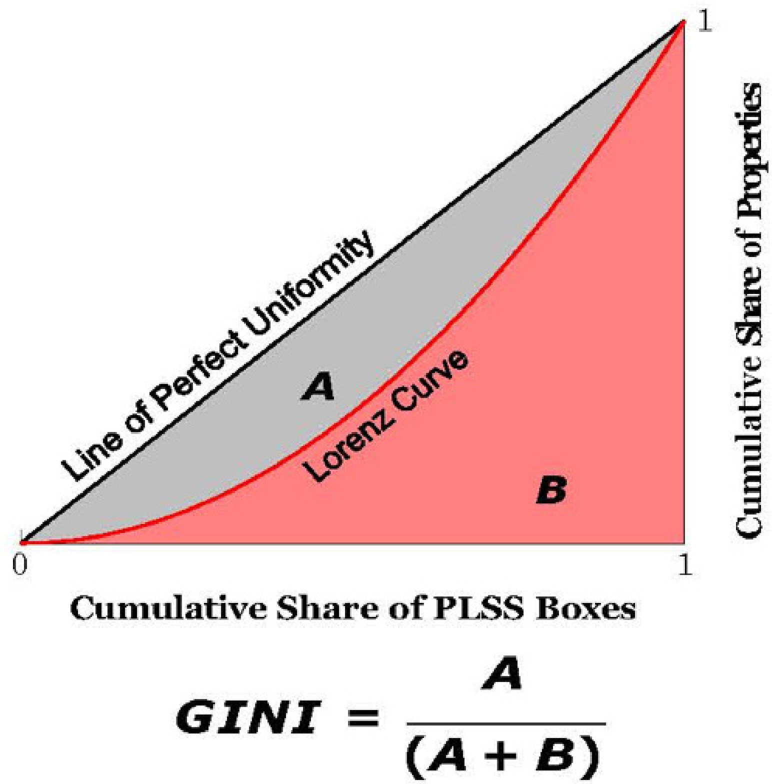

Figure 1. Spatial Gini coeffcient measurement of the concentration of land use

5 Estimated DVMT models

Two models are estimated. In the first model daily vehicle miles traveled (DVMT) for each county and year are regressed on the GINI coefficients measuring the concentration within the county of each of the eight different land uses, the measure of urban expansion, the economic and demographic control variables, and county and year fixed effects. The second model adds to the first model the GINI coefficients measuring the concentration of the land uses within the central city of the MSA that the county is part of.[20] Formally, the first model can be expressed as

$$lnDVMT_{it} = \gamma_t + \delta_i + \theta UE_{it-1} + \sum_{j=1}^{J} B_j GC_{it-1j} + \sum_{k=1}^{K} \alpha_k C_{itk} + \varepsilon_{i,t} \tag{1}$$

and the second model as

$$lnDVMT_{it} = \gamma_t + \delta_i + \theta UE_{it-1} + \sum_{j=1}^{J} B_j GC_{it-1j} + \sum_{j=1}^{J} \theta_j CGC_{it-1j} + \sum_{k=1}^{K} \alpha_k C_{itk} + \varepsilon_{i,t} \tag{2}$$

[20] The central city is identified by the U.S. Census Bureau as the city within the metropolitan area with the largest population.

where the dependent variable (DVMT) is in natural logs; *UE* is the urban expansion variable; *GC* and *CGC* are the Gini coefficients for the county and central city, respectively; and *i, t, j,* and *k* represent county, year, land- use type, and control variable, respectively. γ_t and δ_i are time fixed effects (year dummy variables) and county fixed effects, respectively. The assumed log-linear functional form conveniently yields the percentage change in DVMT from a unit change in an independent variable.

Note that the land use variables are entered into the model with a one-year lag ($t-1$), while the control variables are measured for the current year (t). This specification maximized the fit of the model, based on Akaike's Information Criterion (AIC). The one-year lag of the effects of changes in the built environment on travel behavior has intuitive appeal, since people may need time to adjust their driving habits.[21] Equation 1 is estimated for all counties (n=67), urban counties (n=39), and rural counties (n=28), while Equation 2 is estimated for urban counties. Both equations are alternatively estimated by OLS and 2SLS, as described in greater detail below in Section 7.

6 Variable means: Levels and changes

Table 1 reports the county means and standard deviations for DVMT, the UE measure (the number of PLSS boxes that are developed), and the GCs and CGCs for all years and selected years of the county panel. With panel data, a standard deviation (SD) change can be measured as either "between" or "within" the observational units. The between SD comparison can be thought of as selecting two counties from the same year, with one experiencing and the other not experiencing a standard deviation increase in one of the explanatory variables. The within SD compares two years for the same county, where in one of the years but not the other there is a standard deviation increase in the variable. Because the within SD is a better gauge of the policy importance of the estimated land-use effects on DVMT, I make use of this change in presenting my results and report it, along with the between SD, in Table 1.

[21] For example, loyalty to an old grocery store located farther away may delay an immediate response to switching to a new store located closer to home. There may also be a delay resulting from recognizing how the change can reduce travel time.

Table 1. Means and standard deviations for selected years of county panel

	DVMT (1000)	UE (Developed boxes)	
All years	7910	451	
	(10879)	(225)	
	[987]	[12]	
2001	6994	443	
	(9915)	(221)	
2005	8218	448	
	(11278)	(225)	
2010	8005	454	
	(10965)	(227)	
2014	8221	459	
	(11183)	(227)	
GC (County GINI coefficients)			
	Single-family	Multifamily	Retail
All years	.768	.700	.913
	(.098)	(.104)	(.060)
	[.013]	[.018]	[.008]
2001	.782	.711	.912
	(.091)	(.098)	(.061)
2005	.773	.702	.912
	(.096)	(.103)	(.064)
2010	.762	.697	.914
	(.102)	(.107)	(.057)
2014	.761	.693	.914
	(.104)	(.110)	(.056)
	Offices	Parking	Industrial
All years	.914	.920	.932
	(.054)	(.050)	(.035)
	[.005]	[.014]	[.008]
2001	.944	.919	.934
	(.053)	(.055)	(.032)
2005	.941	.915	.932
	(.055)	(.056)	(.034)
2010	.940	.921	.932
	(.054)	(.050)	(.039)
2014	.941	.925	.935
	(.053)	(.046)	(.033)
	Institutional	Government	
All years	.867	.948	
	(.058)	(.048)	
	[.011]	[.011]	
2001	.871	.953	
	(.055)	(.038)	
2005	.868	.951	
	(.056)	(.042)	

2010	.867	.945	
	(.061)	(.055)	
2014	.867	.944	
	(.058)	(.057)	

CGC (Central City GINI Coefficients)			
	Single-family	Multifamily	Retail
All years	.680	.607	.784
	(.113)	(.129)	(.092)
	[.025]	[.029]	[.013]
2001	.700	.616	.785
	(.105)	(.133)	(.100)
2005	.688	.610	.785
	(.108)	(.130)	(.098)
2010	.673	.605	.785
	(.122)	(.133)	(.089)
2014	.670	.604	.786
	(.123)	(.132)	(.086)
	Offices	Parking	Industrial
All years	.835	.839	.859
	(.072)	(.081)	(.067)
	[.019]	[.020]	[.015]
2001	.832	.830	.862
	(.083)	(.084)	(.067)
2005	.832	.834	.857
	(.085)	(.078)	(.061)
2010	.837	.841	.858
	(.066)	(.082)	(.075)
2014	.840	.844	.865
	(.065)	(.087)	(.064)
	Institutional	Government	
All years	.779	.851	
	(.084)	(.067)	
	[.027]	[.028]	
2001	.785	.867	
	(.081)	(.079)	
2005	.779	.860	
	(.083)	(.068)	
2010	.780	.844	
	(.096)	(.071)	
2014	.789	.840	
	(.069)	(.072)	

Notes: The number in parentheses is the between standard deviation and the number in brackets is the within standard deviation.

The numbers in the first column of Table 1 show that from 2001 to 2005 DVMT strongly rose for the average county, registering a 17.5 percent increase. From 2005 to 2010 average DVMT declined somewhat, falling by 2.6 percent. Presumably, this decline was associated with the unemployment and curtailed consumption caused by the Great Recession. After 2010 DVMT rose by 2.7 percent, bringing the total back to what it was before the recession. The county averages of urban expansion (UE), shown in column two of Table 1, indicate that the number of developed PLSS boxes increased monotonically over the panel, growing from 413 in 2001 to 459 in 2014. Hence, worsening sprawl is clearly in evidence within Florida over this period.

A comparison of the county and central city GINI coefficient means yields similar conclusions regarding the most and least spatially concentrated of the land uses. At both the county and central city levels government, office, parking, and industrial properties are the most concentrated, with GINI coefficients larger than .80. Retail is also among the most concentrated land uses within counties, but less so within central cities. Institutional uses are next in order within both counties and cities. Unsurprisingly, within both cities and counties, the residential land uses (single-family and multifamily units) are the least spatially concentrated, with GINI coefficients of less than .70.

Regarding trends in concentration, single-family homes have become more dispersed over the years of the panel, both within counties and central cities. Apartments, on the other hand, have dispersed within counties but not within central cities. Within both areas, the concentrations of retail, office, industrial, and institutional properties have all remained fairly stable over the panel, while government properties have become more dispersed. While many of the GC means show little variation over time, there is considerable heterogeneity across counties in the time pattern of the GCs, which facilitates the estimation of their effects on DVMT.[22]

7 Specification checks

Before I report the results from estimating the DVMT models, the findings from tests supporting the specifications of my estimated equations merit comment. I report these tests for equation (1), but the same tests for equation (2) yielded similar results.[23] Three separate sets of tests were done. First, I conducted a joint *F*-test of all of the GC and UE terms. These terms are significant in the equation estimated for all counties (*p*-value=.042), for urban counties (*p*-value=.002), and for rural counties (*p*-value=.000), which provides strong support for the hypothesis that the geography of land uses within counties affects DVMT. Second, I tested the explanatory power of the control variables. Jointly they are significant at the 1% level for all equations and AIC provided strong support for their inclusion (see Appendix A).[24] [25] Finally, consistent estimation requires that the explanatory variables be strictly exogenous (Wooldridge, 2002, Chapter 10). If land use concentration is not strictly exogenous to DVMT, simultaneity or feedback bias may result. A strictly exogenous variable does not react to past changes in DVMT, displays no traditional simultaneity, and is not correlated with time-varying omitted variables.

[22] The difference between the 2014 and 2001 single-family GCs was positive in 12 percent of the cases. For the other land uses the difference was positive in the following percentages: 18 percent (multifamily), 37 percent (offices), 30 percent (retail), 61 percent (industry), 45 percent (institutional), and 52 percent (other commercial).

[23] The test results for equation (2) are available upon request.

[24] I also separately tested the long list of occupational variables and the other control variables and found that each set of variables merited inclusion in the model.

[25] Roughly half of the control variables are statistically significant in each of the estimated equations. The control variables display a high level of multicollinearity; hence, it is not surprising that not all of them obtain significance. As discussed below, the results obtained with the GINI coefficients are robust to whether insignificant variables are included or dropped from the estimated models.

To test for strict exogeneity, Wooldridge (2002, p. 285) recommends adding the leading values of the explanatory variables to the estimated models and testing their statistical significance. Since the UE and GC variables are measured with a one-year lag (*t–1*), this would involve adding their current values (*t*) to the models. The rationale for the test comes from the fact that if feedback is absent, concentration in *t* should not be correlated with DVMT in *t*, controlling for the other covariates. I tested the strict exogeneity of each of the UE and GC variables by adding their current values to equation 1 individually and as a group. *P*-values for a number of the variables approach one, strongly supporting their exogeneity. These include the single-family, multifamily, and parking GCs and UE. For a number of the other variables, *p*-values are .25 or larger, suggesting that they may not be strictly exogenous. These include the GCs for retail, office, government, industrial, and institutional properties. To obtain consistent estimates, 2SLS models were estimated, instrumenting these potentially endogenous variables. To develop a defensible instrumentation strategy, it is reasonable to argue that a change in one of the county GCs is driven by factors both within the county and statewide.[26] While these county factors may be endogenous to DVMT, statewide trends should not be affected by conditions within the home county, especially if the statewide trend is defined over the portion of the state which excludes the home county.

Based on this logic, the following instrumental variable is suggested: first, define a base year preceding the beginning of the panel. Then, using all counties within the state, except for the home county, calculate the percentage change in the average GC (GC_j) between the base and current years. These percentage changes are then multiplied by the base year value of the GC at the county level (GC_{jib}) to obtain a prediction of the current year value ($\widehat{GC}_{jit}$), assuming the growth in the GC followed the change that occurred at the state level. Formally,

$$\widehat{GC}_{jit} = GC_{jib} \times \left(1 + \frac{\overline{GC}_{jt} - \overline{GC}_{jb}}{\overline{GC}_{jb}}\right)$$

where $\overline{GC_t}$ and $\overline{GC_b}$ are current and base year statewide means, excluding in their construction the home county, *j* indexes the property type, *i* indexes the county, *t* indexes the current year, and *b* is the base year. While contemporaneous changes in DVMT could plausibly affect the GC, they should not affect the GC before the start of my panel during the base year either at the county or state level. Moreover, by excluding the home county from the statewide mean GC calculation, I mitigate any indirect channels through which county DVMT might impact statewide trends. Therefore, while changes in DVMT in year *t* may affect GC_{jit}, they should not have an effect on $\widehat{GC}_{jit}$.

Ultimately, however, the validity of $\widehat{GC}_{jit}$ as an instrumental variable depends on whether the county base year GC can be treated as exogenous to contemporaneous changes in DVMT. That is, there may be omitted variables correlated with the base year value which have a delayed impact on DVMT. In that case, the instrument would not be orthogonal to the error term of my estimating equation. To help rule out that possibility, I experimented with using a number of different base years to define my instrument. The results are robust to using base years that were 2 (1999), 3 (1998), and 4 (1997) years prior to the beginning of the panel and I report results in my tables obtained with 1997 as the base year. While it is still possible that events 4 years prior to the beginning of the panel could affect the current level of DVMT, this seems unlikely.

[26] One factor contributing to a statewide effect on county land-use patterns is that over all but the final years of my panel the state government had some control over county land use as the result of the Growth Management Act of 1985. This act mandated state-supervised, local-level, comprehensive planning based on principles of growth management.

One possible concern with an instrumental variable is that it may be "weak," meaning that its correlation with the included endogenous regressor is small. Weak instruments can cause biased estimates for independent variables and hypothesis tests with large size distortions (Stock &and Yogo, 2005). The statistic commonly used to detect weak instruments is the F-test of the joint significance of the instruments in the first -stage reduced form regression. However, for models with multiple endogenous variables, Baum, Schaffer, and Stillman (2003) have shown the standard F-statistic may not be sufficiently informative. A more informative test is the Sanderson-Windmeijer (SW) (2016) conditional F statistic that tests the weak identification of individual endogenous regressors. This statistic is constructed by "partialling-out" linear projections of the remaining endogenous regressors. Weak identification F test critical values have been established by Stock and Yogo (2005), but only in the case of a single endogenous variable. Nevertheless, researchers have commonly used *F* values of 10 as a safe number to reject the null hypothesis that an instrument is weak. As shown in Appendix Table B.1, all of the SW *F* values are greater than 10; hence, I have confidence that my results are not being affected by weak instruments. Another 2SLS statistic that is commonly reported is Sargan-Hansen's test of overidentifying restrictions. The joint null hypothesis is that the instruments are valid, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. A rejection of the null hypothesis casts doubts on the validity of the instruments. For none of the estimated equations is the null hypothesis rejected at any reasonable level of significance. [27]

A final econometric issue is that estimated values of the variance inflation factor indicated the presence of multicollinearity. As is well known, multicollinearity can result in unstable and unreliable regression estimates. One approach to dealing with the problem is to drop insignificant variables and re-estimate the regression models. However, there are often good reasons to leave insignificant effects in a model. The *p*-values are just one piece of information. Important information may be lost by automatically removing insignificant regressors, which may result in biased estimates. Therefore, in my tables I report the results obtained from including all variables and models including only those variables that have *p*-values smaller than .200. I chose the latter, rather liberal, p-value as an indicator of statistical significance to guard against obtaining biased estimates.

8 Results from estimating the DVMT models

Four sets of results are reported. Table 2 reports the results from estimating equation (1) for all counties (Panel A), urban counties (Panel B) and rural counties (Panel C). The results from estimating equation (2) for urban counties are reported in Table 3. In all cases both OLS and 2SLS results are reported, using for both estimators all explanatory variables (Full) and a reduced set of the latter variables (Reduced) that are significant at the 20 percent level in the Full model estimation. Reported are the estimated coefficient, the estimated robust standard error clustered at the county level (in parentheses), and the percentage change in DVMT from a within standard deviation change in the explanatory variable (in brackets).[28] From a policy perspective this last number is of particular interest, because it represents how DVMT might change in response to a one year, incremental change in an explanatory variable. Given their land-use powers, county governments could realistically make such a change.[29]

[27] To conduct the test of overidentifying restrictions there must be more instruments than endogenous variables. Adding an instrument for one of the variables not treated as endogenous was used to complete the test. The instrument was constructed in the same manner as those used for the endogenous variables and marginally improved first-stage diagnostics.

[28] Tests detected both serial correlation and heteroskedasticy in the errors of my estimated equations. In light of these test results, standard errors are clustered at the county level in order to obtain consistent estimates of the standard errors.

[29] With panel data, a standard deviation (SD) change in an explanatory variable can be measured as either "between" or "within" the observational units. Most researchers are aware of the between SD that is frequently used to compare the relative magnitudes of variables measured in different units. The between SD comparison can be thought of as selecting two counties from the same year, with one experiencing and the other not experiencing a standard deviation increase in one of the GCs. The within SD compares two years for the same county, where in one of the years but not the other there is a standard deviation increase in the GC.

8.1 Results from estimating the DVMT model for all counties

The OLS and 2SLS estimates based on the sample of all counties are quite similar and the Full and Reduced specifications yield similar conclusions. Across all four estimated models, the single-family and parking GCs are statistically significant at the 5 percent level or better. The industrial GC has the expected negative sign but is significant (10 percent level) only in the Full model.

Table 2. Results from estimating DVMT model (equation 1)

	Panel A All Counties			
	OLS		2SLS	
	Full	Reduced	Full	Reduced
Single-Family	1.162***	1.123***	1.264***	1.313***
	(.380)	(.378)	(.358)	(.342)
	[1.497]	[1.820]	[2.049]	[1.691]
Multifamily	–.095		–.072	
	(.126)		(.121)	
	[–.174]		[–.164]	
Retail	–.523		–.451	
	(.934)		(.907)	
	[–.398]		[-.342]	
Offices	–.410		–1.688*	–1.569
	(1.129)		(1.039)	(.911)
	[–.202]		[–.887]	[–.773]
Parking	.567**	.466**	.568***	.469**
	(.233)	(.206)	(.221)	(.200)
	[.783]	[.656]	[.799]	[.648]
Industrial	–.898*	–.033	–.870*	–.343
	(.466)	(.434)	(.494)	(.399)
	[–.710]	[–.030]	[–.781]	[–.271]
Institutional	.068		–.216	
	(.271)		(.382)	
	[.069]		[–.235]	
Government	.290		.052	
	(.539)		(.532)	
	[.310]		[.056]	
Developed area	–.014		.000	
	(.027)		(.000)	
	[–.163]		[–.009]	
R-square	.719	.683	.717	.692
Observations	938	938	938	938
Counties	67	67	67	67

	Panel B			
	Urban Counties			
	OLS		2SLS	
	Full	Reduced	Full	Reduced
Single-Family	1.152***	1.321***	1.199***	1.318***
	(.442)	(.428)	(.421)	(.430)
	[1.743]	[1.999]	[1.815]	[1.994]
Multifamily	–.302**	–.217**	–.259**	–.222**
	(.140)	(.097)	(.122)	(.099)
	[–.676]	[–.486]	[–.581]	[–.498]
Retail	–.543		–.378	
	(.801)		(.762)	
	[–.519]		[–.361]	
Offices	1.030		–.171	
	(1.197)		(1.065)	
	[.598]		[–.099]	
Parking	.585**	.541**	.581**	.544**
	(.267)	(.277)	(.267)	(.276)
	[.921]	[.851]	[.914]	[.857]
Industrial	–.817	–.565	–.837	–.614
	(.511)	(.477)	(.536)	(.502)
	[–.721]	[–.499]	[–.738]	[–.542]
Institutional	.244		.220	
	(.278)		(.333)	
	[.303]		[.273]	
Government	.480	.575**	.564*	.670**
	(.349)	(.294)	(.329)	(.315)
	[.657]	[.787]	[.771]	[.916]
Developed area	–.001**	–.001**	–.001**	–.001**
	(.000)	(.000)	(.000)	(.000)
	[–1.172]	[–1.112]	[–1.016]	[–1.121]
R-square	.750	.744	.749	.744
Observations	507	507	507	507
Counties	39	39	39	39

	Panel C			
	Rural Counties			
	OLS		2SLS	
	Full	Reduced	Full	Reduced
Single-Family	.403		.427	
	(.544)		(.495)	
	[.357]		[.378]	
Multifamily	.209		.083	
	(.266)		(.239)	
	[.209]		[.083]	

Retail	.270		.068	
	(1.310)		(1.529)	
	[.092]		[.023]	
Offices	−1.547	−1.071	−1.022	
	(1.255)	(1.271)	(1.440)	
	[−.516]	[−.357]	[−.341]	
Parking	−.169		−.162	
	(.207)		(.221)	
	[−.179]		[−.172]	
Industrial	−.466	−.286	−.724*	−.523
	(.312)	(.373)	(.418)	(.446)
	[−.301]	[−.185]	[−.468]	[−.338]
Institutional	−.082		−1.081*	−.683
	(.349)		(.583)	(.603)
	[−.047]		[−.619]	[−.391]
Government	2.586	2.422	2.751	2.191
	(1.730)	(1.540)	(2.151)	(1.589)
	[.923]	[.864]	[.982]	[.782]
Developed area	.001**	.001***	.001**	.001***
	(.000)	(.000)	(.000)	(.000)
	[.985]	[.752]	[.985]	[.825]
R-square	.950	.948	.949	.945
Observations	364	364	364	364
Counties	28	28	28	28

Notes: Standard errors clustered at the county level are in parentheses. Percent change in DVMT from a within standard deviation change in explanatory variable is in brackets. Full refers to the model including all explanatory variables. Reduced is the model retaining only those variables with *p*-values less than .20.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The office GC is significant (10 percent level) only in the Full, 2SLS model. The signs on the estimated GCs indicate that increasing the spatial dispersal of single-family homes and parking lots/garages decreases DVMT. Of the four significant GCs, a within SD change in the single-family GC produces the largest absolute percentage change in DVMT (2 percent).[30] The results for single-family homes are consistent with the hypothesis that the dispersal of single-family homes reduces DVMT by giving households more of an opportunity to locate where their overall travel by motor vehicles can be minimized.[31] A within SD change in the parking properties GC reduces DVMT by .7 to .8 percent. This is consistent with the hypothesis that the parking GC impacts DVMT by serving as a proxy for locations, both private and public, that drivers need or desire access to.[32] While less robust, the findings for the concentration of office and industrial properties are consistent with the idea that agglomeration economies within these land uses reduce trip frequency and thereby DVMT. Within SD changes in these properties cause roughly a 1.0 and 0.5 percentage reduction in DVMT, respectively. The urban expansion measure (UE) is not significant. This likely reflects the findings reported below that UE has opposite effects on DVMT between urban and rural counties.

8.2 Results from estimating the DVMT model for urban counties

As in the case of the equation estimated for all counties, the results for urban counties are generally robust between the OLS and 2SLS estimators. Also, there are only small differences in the magnitudes of the estimates obtained from the Full and Reduced sets of explanatory variables and variables that are significant in one model are also significant in the other model. Hence, I will focus on the results obtained with the 2SLS Full model. The results again show that the dispersal of single-family homes and parking properties reduce DVMT. The percentage reductions from a within SD change equal 1.8 and .9, respectively. Also statistically significant are the GCs for multifamily housing and government buildings, while the industrial properties GC is borderline insignificant, with the expected negative sign. A within SD change in the concentration of multifamily units causes a .6 percent reduction in DVMT. The multifamily result contrasts with the lower DVMT generated from the dispersal of single-family housing. As hypothesized in Section 3, multifamily housing concentrations tend to co-exist with nearby shopping and employment opportunities, especially within urban areas; hence, both smaller travel distances and trip frequencies among the residents living in apartments may explain the contrasting results obtained for single-family and multifamily units.[33] A greater dispersion of government buildings reduces DVMT, suggesting that this provides improved convenience to consumers of public services. A

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[30] For the median (mean) county, a 2 percent decline in DVMT equals 72,120 (158,200); hence, the impact is nontrivial in magnitude.

[31] A reviewer suggested that the finding that the dispersal of single-family homes reduces DVMT may be due to a correlation between the single-family GC and the proportion of housing units that are within multifamily properties. To investigate this, I added the latter variable (PMF) to both the OLS and 2SLS models. PMF had little influence on the results reported in Table 2. The OLS and 2SLS estimates for the single-family GC equaled 1.25 and 1.35, respectively, which are almost identical to the estimates reported in Table 2. Both estimates remained statistically significant at the one percent level. The estimated coefficients on PMF equaled –.0016 and –.0015, and both are significant at the one percent level. The latter results suggest that a shift in the county proportion of housing units in favor of those found within multifamily properties reduces DVMT.

[32] As a reviewer noted, there is an alternative explanation for the finding that the dispersal of parking lots reduces DVMT. If dispersal is associated with less parking available within commercial centers travelers may opt in favor of using an alternative to the automobile for making their trip, which reduces DVMT.

[33] A reviewer suggested using a GINI coefficient that measured the concentration of both single-family and multifamily housing units together. This variable was tried and is not statistically significant. Because the concentration of the two types of residential units are found to have opposite effects on DVMT, the insignificance of their combined concentration effect on DVMT is not surprising.

within SD change reduces DVMT by .8 percent. An expansion of the developed area of an urban county is found to reduce DVMT. A within SD change results in a 1 percent decline in DVMT. As suggested above in Section 3, a possible explanation for this result is that new residential developments within Florida tend to be multi-use, consisting of homes, churches, stores, and offices. Households choosing to live in these developments may have less need to travel. Further investigation of this possibility is reserved for future research.

8.3 Results from estimating the DVMT model for rural counties

Overall, the results obtained for rural counties show that the concentration/dispersal of the alternative land uses have little impact on county DVMT. Also, in contrast to the similarity in results obtained from estimating OLS and 2SLS models and from using the Full versus Reduced set of variables using the all counties and urban counties samples, results differ across these comparisons when restricting the sample to rural counties. While none of the GCs are statistically significant from using OLS, the GCs for industrial and institutional properties are significant in the 2SLS model (10 percent level), but only when employing the full set of variables. Increasing the concentration of these land uses reduces DVMT, with the percentage declines from a within SD increase equaling .5 and .6, respectively. These findings suggest that agglomeration economies are enabling less travel. An interesting difference in results between the models estimated for urban and rural counties is that the sign on UE flips between the two samples. While expanding the developed area of an urban county reduces DVMT, the opposite is true for rural counties. In both cases the absolute percentage change in DVMT is roughly one percent from a within SD change. Residential development occurring within rural counties differs from that found within urban counties in that non-residential land uses generally are not part of the development. New subdivisions look like the traditional variety that include just single-family homes. [34] This difference in the mix of land uses may account for these contrasting results.

8.4 Results from estimating the DVMT model for urban counties including the central city GCs

The results from estimating equation (2) are reported in Table 3. Once again, the single-family and parking GCs measured at the county level are positive and significant and closely match in magnitudes of the estimates obtained from equation (1). The county GC for institutional properties is also now significant in both the Full and Reduced versions of the 2SLS model. A within SD change causes roughly a .6 reduction in DVMT. The industrial properties GC is also significant (10 percent level) in the Full 2SLS model with the expected negative sign.

Among the GCs measured for central cities, the concentration of government properties is found to increase DVMT. The magnitude of the effect is similar to that found for urban counties from the estimation of equation (1). The finding that the central city government GC matters to DVMT while the corresponding county GC does not, suggests that it is the dispersal of government within central cities that accounts for its negative impact on county DVMT. Having a contrasting effect on DVMT is the concentration of institutional properties within central cities and counties. As noted above the county effect is negative, while the central city effect is positive. Recall that the majority of properties within the institutional category are churches. A comparison of the properties comprising the institutional category between central cities and counties shows that churches make up a larger percentage of the total within central cities. Other land uses that are important parts of the institutional category are clubs, lodges, and union halls, which account for a larger percentage of the total within counties.

[34] This conclusion is drawn from an online sampling of new residential developments within urban and rural counties.

Their concentration may yield agglomeration economies that reduce the frequency of trips and account for the opposite effects that concentrations of institutional properties have on DVMT between central cities and counties.

Table 3. Results from estimating DVMT model for urban counties including the central city GCs (equation 2)

	OLS		2SLS	
	Full	Reduced	Full	Reduced
County GC				
Single-Family	1.282***	1.377***	1.639***	1.379***
	(.418)	(.379)	(.536)	(.424)
	[1.940]	[2.083]	[2.480]	[2.086]
Multifamily	−.363	−.217**	−.216	
	(.242)	(.088)	(.213)	
	[−.814]	[−.486]	[−.484]	
Retail	−.270		.303	
	(.805)		(.918)	
	[−.258]		[.290]	
Offices	.644		−1.795	−1.009
	(1.266)		(1.237)	(1.097)
	[.374]		[−1.043]	[−.586]
Parking	.588**	.507*	.782**	.774***
	(.279)	(.279)	(.308)	(.274)
	[.925]	[.798]	[1.231]	[1.217]
Industrial	−.749*	−.666	−1.219*	−.859
	(.442)	(.442)	(.664)	(.559)
	[−.661]	[−.588]	[−1.075]	[−.758]
Institutional	−.287		−1.386*	−1.039**
	(.378)		(.755)	(.510)
	[−.357]		[−1.725]	[−1.292]
Government	.193		−.145	
	(.401)		(.465)	
	[.264]		[−.199]	
City GC				
Single-Family	.140		−.039	
			(.410)	
			[−.100]	
Multifamily	−.021		−.112	
	(.272)		(.228)	
	[−.062]		[−.334]	
Retail	−.607		−.557	
	(.714)		(.709)	
	[−.765]		[−.702]	

Offices	1.029**	.824*	.800	
	(.642)	(.499)	(.718)	
	[1.935]	[1.550]	[1.564]	
Parking	–.064		–.005	
	(.208)		(.201)	
	[–.126]		[–.011]	
Industrial	.333		–.019	
	(.325)		(.358)	
	[.522]		[–.031]	
Institutional	.525*	.450***	.789**	.611***
	(.282)	(.129)	(.323)	(.216)
	[1.351]	[1.159]	[2.031]	[1.573]
Government	–.084		.598*	.444*
	(.142)		(.300)	(.270)
	[–.237]		[1.69]	[1.252]
Developed area	–.001***	–.001*	–.001*	–.001**
	(.000)	(.000)	(.000)	(.000)
	[–1.215]	[–.981]	[–.773]	[–1.020]
R-square	.765	.758	.742	.738
Observations	507	507	507	507
Counties	39	39	39	39

Notes: Standard errors clustered at the county level are in parentheses. Percent change in DVMT from a within standard deviation change in explanatory variable is in brackets. Full refers to the model including all explanatory variables. Reduced is the model retaining only those variables with *p*-values less than .20.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Among the results obtained with the control variables, one finding is particularly noteworthy. CLM is found to have a strong effect on DVMT within both urban and rural counties. An additional mile of CLM raises county DVMT by .07 and .09 percent in urban and rural counties, respectively. These findings are consistent with the prior evidence provided by Noland (2001) that supports the theory of induced travel demand (Downs, 1962), which hypothesizes that an increase in road capacity will induce additional growth in traffic. The added capacity reduces travel time, the largest component of the cost of driving, which increases the demand for travel.

9 Discussion

My results are based on a long panel, include new and effective measures of urban expansion and the spatial distribution of alternative land uses within the developed areas of counties, and an extensive set of household descriptors. The identification of causal effects is buttressed by the inclusion of year and county fixed effects and the instrumentation of regressors that may be endogenous.

The evidence provided suggests that changes in the concentration/dispersal of land uses within a county and changes in the size of the developed area of a county can impact DVMT. Overall, my results contrast to many of the findings reported in the literature suggesting that the relationships between VMT and the built environment are too weak for government land-use planning and regulation to play much of a role in reducing VMT. Moreover, the incremental within-county changes that I have investigated could reasonably be achieved through land-use policy.[35] Hence, there is cause for optimism in dealing with the heavy carbon footprint of motor vehicles and their effect on global warming. Project approval decisions of local government, however, need to be based on the whole range of factors that may impact social welfare and not only on their likely impact on VMT. For example, concentration of commercial and industrial properties may exacerbate negative externalities (such as air and noise pollution), while the dispersal of single-family homes may worsen racial or social segregation.

Many urban planners have taken the position that more compact urban form would yield important societal benefits, including a reduction in VMT. My results are both consistent and inconsistent with this position. The direction of effects depends on the type of land use and whether the area is urban or rural. Within urban counties the concentration of multifamily housing and industrial properties reduces VMT, while concentrating single-family housing and government-owned properties would produce the opposite effect. Concentrating industrial and institutional properties within rural counties would reduce VMT. A common finding between urban and rural counties is that the concentration of industrial properties reduces DVMT. The differences in the results obtained for urban and rural counties likely reflect the fact the Florida's rural counties are largely agrarian in nature. Government buildings and multifamily housing developments, which affect DVMT within urban counties, are sparse within rural counties; hence, there may be little to be gained by their spatial rearrangement in reducing DVMT. Results obtained for the models that include both county and central city GCs indicate that, apart from county levels of concentration, concentrations of selected land uses within the central city of the MSA that the county is part of can also impact DVMT.

10 Study limitations and suggestions for future research

My analysis of the relationships that exist between DVMT and the spatial concentrations of alternative land uses has both methodological and geographical limitations. While residential land uses are measured in units, other land uses are measured as properties. Obviously, properties can vary greatly in size and a preferred measure of land use (perhaps square feet of interior space) would account for this in constructing the GCs. In addition, my land-use typology is limited to only eight property types. Disaggregating these types into finer categories would enable a more comprehensive analysis. Finally, concentration might be better measured by a combination of land uses; for example, by combining the number of homes and offices into a single GC in order to capture concentrations of mixed land use. Like any sub-national study, the geographical limitation is that my results for Florida may not be applicable to other states.

The above limitations offer important opportunities for future research. More detailed locational data on a wider variety of property types can be obtained for all states from various commercial vendors, albeit at significant cost. VMT are required to be submitted every year by state transportation agencies to the Federal Highway Administration through the Highway Performance Monitoring System. In addition to Florida, PLSS surveys have been done in 29 other southern and western states. The methodology I have introduced in this paper for studying the impacts that incremental changes in the concentration/dispersal of alternative land uses have on VMT can therefore be replicated and improved with the available data. Given the importance of reducing VMT in order to address the growing concern over global warming, I encourage such future research efforts.

[35] The chief tool used by local governments to implement local land-use plans is zoning, but the planner's toolbox also includes a myriad of other land development regulations (Mills, 1979; Ihlanfeldt, 2004).

Conclusion

Changing the built environment is only one approach to reducing VMT. Alternative approaches include raising fuel and parking fees and imposing congestion taxes.[36] Based on the evidence provided in prior VMT studies that have focused on the built environment, these alternatives may appear relatively more attractive. They have the advantages of creating a stronger impact in the short run at a huge savings in upfront costs. However, the changes in the built environment that have been studied are generally of a monumental redesign of the urban landscape. What I have investigated in whether incremental annual changes in the concentration and dispersal of alternative land uses can make a difference to VMT. Such changes are not beyond what local governments could realistically obtain using their local land-use control and regulation powers. While my findings do not suggest that making these changes is necessarily the best approach toward reducing VMT, they do support keeping a focus on the built environment as part of a comprehensive strategy to deal with the problem of global warming.

[36] See Brownstone (2008) for a detailed review of these alterative VMT reduction policies.

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Appendix

Appendix available as a supplemental file at https://www.jtlu.org/index.php/jtlu/article/view/1647