Determinants of VMT in Urban Areas: A Panel Study of 87 U.S. Urban Areas 1982-2009

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This paper uses econometric techniques to examine the determinants of vehicle miles traveled (VMT) in a panel study using data from a cross section of 87 U.S. urban areas over the period 1982-2009. We use standard OLS regression as well as two-stage least squares techniques to examine the impact of factors such as urban density, lane-miles, per capita income, real fuel cost, transit mileage, and various industry mix variables on per capita VMT. We use a distributed lag model to estimate long-run elasticities and find that the long-run price elasticity of demand for per capita VMT is approximately five times larger than in the short run. Preliminary empirical results show the per capita demand for VMT in urban areas is positively and significantly impacted by lane miles, personal income, and the percent of employment in the construction and public sectors. Fuel price and transit use and the percent of employment in manufacturing, retail, and wholesale sectors are all found to be statistically significant and negatively related to VMT per capita. After correcting for endogeneity, urban population density exerts a negative, but not always statistically significant, impact on per capita VMT. Finally, per capita VMT is found to differ significantly by geographic region, being higher the more western and the larger the population size of an urban area.

INTRODUCTION

Understanding the relationship between vehicle miles traveled (VMT), economic activity, and other determinants of the demand for driving is essential for the development of an efficient U.S. transportation system. This is particularly important given recent concerns regarding the major role the transportation sector plays in producing greenhouse gas emissions (GHG). As of 2007, over 27% of the GHG in the U.S. could be traced to the transportation sector and over 75% of those were attributable to highway transportation (USDOT 2010).

Legislation at both state and federal levels aimed to reduce GHG from transportation and reduction in VMT is one policy option frequently mentioned to attain this goal. For instance, the Federal Surface Transportation Policy and Planning Act of 2009 set a directive to reduce national per capita VMT and to increase public transportation usage, intercity passenger rail services, and non-motorized transportation (Commerce Committee 2009). At the state level, the Washington state legislature adopted a direct mandate to reduce per capita VMT to 25% below 1990 levels by the year 2035 in order to reduce GHG (Winkelman, Bishins, and Kooshian 2009), and the Oregon state legislature mandated reductions in greenhouse gases (GHG) of 10% below 1990 levels by 2020 and 75% below 1990 levels by 2050 and expects the transportation sector to play a crucial role in the achievement of this goal (Oregon House Bill 3543, 2007).

USDOT (2010) mentions VMT reduction as one of several ways to reduce GHG from transportation, with increased fuel efficiency, development of alternative fuels, and changes in vehicle and system operations being other important ways to help reduce energy consumption and GHG from transportation. As Boarnet (2010) notes, this is a complex issue since VMT reduction is really just a proxy for GHG reduction and thus should probably serve as one of many intermediate targets to help reduce GHG, not as the end goal itself.

Concerns have been expressed regarding the impact of VMT reduction policies. Pozdena (2009) has claimed that at the national level, VMT changes lead to reductions in GDP, thus suggesting that

VMT reduction policies could be detrimental to overall economic activity. However, recent research by McMullen and Eckstein (2012) has shown that at the national level, VMT changes derive from GDP changes and, when individual urban areas in the U.S. are examined, there is little significant causality found between VMT and income. Puentes and Tomer (2008) argue that other factors, such as the increased availability of transit, telecommuting, and on-line retail activity that provide substitutes to mobility, weaken any possible causal link from VMT to GDP.

The question then becomes what factors to consider when designing VMT reduction policies so as to minimize adverse impacts. Carlson and Howard (2009) point out that the impact of VMT reduction policies will differ depending on the geographical area considered. They argue that VMT reduction policies are best implemented in urban areas (rather than rural areas) where there are more viable options available for VMT reduction policies such as the availability of alternative modes of travel, including transit ridership, bicycling and walking, land use policies to increase urban density and reduce commute distances, increased use of carpooling, etc. Further, since the majority of the U.S. population lives in urban areas, it makes sense to first concentrate VMT efforts in urban locations.

Accordingly, we explore the relationship between VMT and economic activity using a panel data set of 87 U.S. urban areas from 1982-2009 provided by the Texas Transportation Institute (TTI). Multiple factors are hypothesized to contribute to VMT demand, including lane miles, personal income, population density, fuel cost, transit use, and the percent of employment in the public sector, finance, construction, manufacturing, and wholesale sectors. Results should assist policymakers in tailoring VMT reduction policies for urban areas in a way that will have the least adverse impact on mobility and economic activity.

LITERATURE REVIEW: DETERMINANTS OF VMT IN URBAN AREAS

Economic theory suggests some basic determinants of demand for a product: price, income, and population (when more than one consumer is considered). VMT per capita (VMTPC) will be considered as the good or product of interest in this paper.

Since VMT is usually considered to be a normal good, higher incomes are expected to result in more driving and thus VMTPC, ceteris paribus. Accordingly, personal income per capita (PIPC) is included as an indicator of the average income in urban areas. Positive income elasticities of demand are found consistently in the literature and range from 0.05 to 0.62 in the short run, and 0.12 to 1.47 in the long run (Goodwin, Dargay, and Hanly 2004).

Average annual state gasoline prices in real 2005 dollars (RFC) are used to represent the price or marginal cost of driving. Although there are certainly other components that are attributed to the price of driving (such as insurance, wear and tear on the vehicle, driving time, etc.), the price of gasoline is a large component and the data are easily available. Additionally, the real price of fuel (RFC) has been used in other studies as a proxy for the price of driving (Zhang et al. 2009; McMullen et al, 2010; Fulton et al. 2000; and Noland 2001). Price elasticities of demand for driving are expected to be negative and have been found to be in the range from –0.17 to –0.05 in the short run, and –0.63 to –0.10 in the long run (Goodwin, Dargay, and Hanly 2004).

Another possible determinant of VMTPC in urban areas is population density: as population becomes more dispersed and distances rise, VMT should rise. Accordingly, population density (DENSITY) is expected to be negatively correlated to VMTPC.

Increasing urban density through land use policy has been frequently mentioned as a possible VMT reduction policy based on evidence of the massive decentralization of employment in metropolitan areas between 1950 and 1990 that has led to longer commutes and more driving (Baum-Snow 2010). Research that examines smart growth, urban growth boundaries, and mixed development finds that denser development allows for shorter routes, more one stop shopping, and more walking and biking options, thus reducing the need for vehicle travel (Winkelman, Bishins, and

Kooshian 2009; Frank and Pivo 1995; and Litman 2010). However, increasing urban area densities through land use policies could cause increases in housing prices that would partially negate the desired VMT reduction (Moore et al. 2010). Boarnet (2010) concludes that VMT reduction will require a combination of pricing and land use policies and suggests that policies that are successful in some regions may not make sense for others.

To incorporate VMT substitutes (substitutes for driving) into the model, transit passenger miles traveled per capita (PMTPC) is included as an explanatory variable and is anticipated to have a negative elasticity, as found in similar studies (Pushkarev and Zupan 1980 and Holtzclaw 1991). Transit ridership in an urban area is expected to be negatively related to VMT as transit availability presents the consumer an alternative to driving.

Finally, the industry mix in different areas may result in more or less VMT, depending on the requirements of the industry. Given trends in the use of the Internet, we might expect certain industry sectors, such as retail where Internet shopping can occur at a remote location by computer as opposed to driving to a physical location, to generate less VMT than other economic activities that may require driving to a physical location. For instance, it is plausible that an industry sector like construction, which requires large amounts of movements of labor and supplies, may be more VMT-intense than an industry sector such as finance, which allows for money, advice, and services to take place either over the phone, fax, or Internet, replacing driving.

Baum-Snow's (2010) observation that firms that do not require a central city location (such as manufacturing or wholesale) often operate at the periphery of an urban area to be closer to where workers live, suggests lower VMT for workers employed in those sectors. While many firms have relocated outside the central city, thus possibly reducing commute distance for suburban workers, there are some sectors that may be more dependent on central city locations. For instance, public sector employees may have no choice but to commute to specific government work sites in central cities, making commute distances and VMT higher for those public sector employees living in the suburbs, relative to employees of private firms that have more flexibility to locate outside of the central city and closer to suburban workers.

Thus, this study incorporates industry employment mix variables, adding a new and important feature to the VMT derived demand model. Industry mix variables are defined here to be the percent of an urban area's economy that is employed in certain industries, allowing for direct evaluation of the per capita VMT intensity of industries during the production, distribution, and sales processes.

Finally, the most challenging variable to consider is that relating to the highway investment in an urban area, as usually measured by lane miles (LM) or lane miles per capita (LMPC). The literature suggests that LM is not truly exogenous in respect to VMT or VMTPC. It has been demonstrated that increases in VMT increase the demand for road capacity and can lead to more lane miles being built. Moreover, increases in lane miles of highway will reduce the cost of driving and induce more VMT, leading to a significant simultaneity bias (Noland 2001; Fulton et al. 2000; Goodwin 1996; and Pells 1989).

METHODOLOGY

Standard OLS Model

We follow previous studies and use VMTPC as the dependent variable for our econometric specification (Noland and Cowart 2000, Fulton, et al. 2000). Accordingly, the VMTPC equation is:

$$(1)\quad \log(VMTPC_{it}) = c + \alpha_i + \beta_t + \sum_k \lambda^k * \log(X^k_{it}) + \varepsilon_{it}$$

Where:

- $VMTPC_{it}$ is the average daily freeway and arterial vehicle miles traveled per capita for urban area *i* in year *t*;
- c is a constant term for the entire sample;
- α_i is the group-specific fixed effect for urban area *i*;
- β_t is the time-specific fixed effect for year *t*;
- λ_k is the coefficient of the k^{th} explanatory variable;
- X_{it}^{k} is the value of explanatory variable *k* for urban area *i* and year *t*.
- ε_{it} is the error term of a random variable for urban area *i* in year *t*, assumed to be normally distributed with mean zero.

The model transforms all variables (except for the fixed effect dummies) into natural logarithms, making the coefficients easily interpreted as elasticities and to help avoid heteroskedasticity. Note that the group-specific fixed effect can be defined as regional grouping, or TTI population size grouping instead of urban area (see Appendix A for categorical definitions and a list of urban areas in each group). These different group-specific fixed effects allow for interpretation of important relationships between VMTPC and region or population size, but provide less total information because they incorporate a smaller number of less specific dummy variables.

Distributed Lag Model

The distributed lag model, as used in Noland and Cowart (2000), is written as:

$$(2)\quad \log(VMTPC_{it}) = c + \alpha_i + \beta_t + \gamma * \log(VMTPC_{it-1}) + \sum_k \lambda^k * \log(X_{it}^{k}) + \varepsilon_{it}$$

Where all specifications are identical to the previous fixed effects OLS model, except for the inclusion of $VMTPC_{it-1}$, the one-year lagged value of average daily freeway and arterial vehicle miles traveled per capita for urban area *i* in year *t-1*, so this reduces the number of time periods used by one.

The distributed lag model differs from the basic model by incorporating a lagged value of the dependent variable (VMTPC) on the right-hand side of the equation. This allows for the calculation of long-term and short-term elasticities, where the long-term elasticities are defined as $\varepsilon = \frac{\lambda}{1-\gamma}$, where λ are the short-run elasticities (found in the regression's coefficients), and γ is the coefficient of the one-year lag of VMTPC. The model assumes an exponential lag structure that shows short-run impacts to be greatest and to diminish exponentially over time (Noland and Cowart 2000).

Two-Stage Least Squares Model

To deal with the endogeneity problem noted above for lane miles (LMPC), a two-stage least squares (2SLS) model is used, requiring the selection of an appropriate instrumental variable. Following Noland and Cowart (2000) and given data availability, urban land area (ULA) is selected as the instrument of choice. The first and second stages of the 2SLS model are written as:

$$(3)\quad \log(LMPC_{it}) = c + \alpha_i + \beta_t + \sum_k \lambda^k * \log(X_{it}^{k}) + \gamma * \log(ULA_{it}) + \varepsilon_{it}$$

$$(4)\quad \log(VMTPC_{it}) = c + \alpha_i + \beta_t + \sum_k \lambda^k * \log(X_{it}^{k}) + \gamma * \log(\overline{LMPC})_{it} + \varepsilon_{it}$$

Where all specifications are identical to the model already specified except that X_{it}^{k} no longer includes the endogenous variable, LMPC. ULA_{it} is the square miles of land area within urban area *i* in year *t*, and $\overline{LMPC}_{it}$ is the predicted estimate of LMPC within urban area *i* in year *t* taken from the first stage regression. Again all variables are natural logarithms.

As is expressed in the above set of equations, to incorporate 2SLS into the model, urban land area (*ULA*) is added to the first stage, which predicts LMPC using all available instruments. Then, the predicted estimate $\overline{LMPC}_{it}$ is applied to the VMTPC equation in the second stage, removing the simultaneity bias.

An appropriate instrumental variable must be both relevant, in that it is significantly related to the endogenous variable being instrumented, but also exogenous in that it is not correlated with the error term in the explanatory equation. Exogeneity ensures that the instrument's only influence on the dependent variable is through its effect on the endogenous variable and that it should not be an independent variable of the model in its own right (for further details on 2SLS and instrumental variables see Greene [2008]).

Econometric tests are performed to see if the model supports the use of ULA as an instrument. First, a Durbin-Wu-Hausman test for endogeneity of LMPC is performed. Next, tests are applied to determine the relevance of the instrument. Finally, the exogeneity of the instrument itself, ULA, is examined.

A Durbin-Wu-Hausman test for endogeneity uses the null hypothesis that the possible endogenous regressor, LMPC, is exogenous. It compares estimates from the corresponding 2SLS and OLS regressions to see if differences between the two estimates are statistically significant. With ULA as the instrument in the 2SLS model, the Durban-Wu-Hausman test gave a statistically significant Chi^2 (8) test statistic equal to 38.64. Thus, the null hypothesis is rejected, suggesting that LMPC is endogenous, indicating the use of a method such as 2SLS.

Next, a highly significant negative t-statistics is found for ULA in the first stage of the 2SLS, implying that ULA is sufficiently related to LMPC to make it "relevant" and appropriate for use in the 2SLS. Additionally, ULA has a fairly low correlation with VMTPC of 0.32, which indicates its exogeneity and that it does not need to be included in the model in its own right. Hence, ULA is used as an instrument, because through a survey of the literature on this simultaneous relationship between lane miles and vehicle miles traveled, no clearly exogenous instrument is found to be more relevant than urban land area.[1]

DATA

In addition to VMT and VMTPC, explanatory variables used in this analysis are defined as:

- LMPC: freeway and arterial lane miles per capita
- PIPC: personal income per capita in 2005 dollars
- RFC: state average price of fuel in real 2005 dollars
- PMTPC: transit passenger miles traveled per capita for the urban area
- DENSITY: number of residents per square mile
- CON, MANU, FIN, WHOLE, RETAIL (industry employment variables): the percent of total employment in the relevant industry in the relevant MSA
- PUB: the ratio of public to private employees in relevant MSA

The data for urban areas have been collected and published by the Texas Transportation Institute (TTI) since 1982 for use in its annual Urban Mobility Report (UMR) (Texas Transportation Institute 2011). The definition of urban area does not change over time in this data set. From this dataset, average daily VMT on freeways and principal arterial roads is used as the urban area VMT variable for this study. These VMT estimates are compiled by TTI from the Highway Performance Monitoring System (HPMS) database and other local transportation data sources and are put into per capita form using population estimates from the U.S. Census Bureau.

Because urban area GDP data is unavailable, this study substitutes metropolitan statistical area (MSA) personal income data for the MSAs that coincide with the TTI urban areas. Note that at the national level, correlation between personal income and GDP is .999, making PI a good proxy for GDP. See U.S. Census Bureau (2010) and Office of Budget and Management (2010) for urban area and MSA definitions. Personal income, in real 2005 dollars, is also from the BEA (U.S. Department of Commerce 2011).

TTI collects detailed data on 100 individual urban areas in the U.S. and categorizes these urban areas into four population size groupings: very large (vlg), large (lrg), medium (med), and small (sml) (see Appendix A for categorical definitions and a list of urban areas in each group). These groupings are important, as it is likely that VMT reduction policies will be implemented in larger urban areas first, because they have the largest GHG reduction potential and also suffer the worst congestion delays. Thus, it is important to observe if variations in the size of an urban area affects the causal relationship between VMT and economic activity. Of these 100 urban areas, two are not core urban areas inside an MSA, and without this distinction personal income data were not available. Table 1 provides summary average annual statistics for *VMT*, personal income (PI), and population variables for the 98 TTI urban areas for the period 1982-2009.

Of these 98 TTI urban areas, some were not included in the 2007 UMR, and hence did not have annual data on two key variables needed in this analysis: urban land area (ULA) and population density (DENSITY). Thus, this study of derived demand includes only the 87 urban areas for which complete data sets were available for the entire time period. The panel data set used here includes specific DENSITY, LMPC, RFC, and PMTPC variables, all from the 2010 UMR (TTI 2011) for the sample of 87 urban areas. The source for PIPC and the industry employment statistics is BEA for the 87 associated MSAs (U.S. Department of Commerce 2011).

Table 2 presents summary statistics for the variables used in this paper. These statistics do not exactly match those found in Table 1 because this table includes data for only 87 of the 98 urban areas in Table 1. On average between 1982 and 2009, individuals in these 87 urban areas drove over 16 miles a day on freeways and arterial roads, were passengers on 124 miles of public transit annually, earned an average annual income of nearly $32,000 in real 2005 dollars, and paid nearly $2 a gallon for gas in real 2005 dollars.

The statistical package used for these estimations was STATA.

RESULTS

The inclusion of "two-way' fixed effects in which dummy variables are specified for both an observation's group (urban area) and time period (year) provides a static coefficient estimate for the entire sample, while dynamically shifting the constant term for each observation. This allows unmeasured or unknown cross-sectional (urban area) and time-series (year) factors to be explained through the fixed effects' coefficients and reduces any remaining bias due to omitted variables that are inevitably left out of the model (Dougherty 2007).[2]

The fixed effect coefficients in this study control for potential omitted variables, such as the number of women in the workforce, car ownership, population growth, climate, the existence of driving alternatives not measured by the PMTPC transit variable such as walking/biking paths, telecommuting, along with other unknown or unmeasured factors.

F-statistics are used to test the significance of the fixed effects, with the null hypothesis that the fixed effects are not jointly significantly related to VMTPC. First a comparison is made between a standard OLS model and a model with group-specific effects, resulting in a significant F-statistic of $F(86, 2267) = 104.72$. Then, the model with only the group-specific effects is compared to a model with group and time-specific or "two-way" effects fixed model, resulting in a significant $F(27, 2240) = 23.94$. Both results allow for a rejection of the null hypothesis and support the use of "two-way" fixed effects in the model estimation (Greene 2008).

Table 1: Urban Area Daily VMT Summary Statistics (1982-2009)

Variable Name	Mean	Std. Dev.	Min	Max	% Annual Growth
VMT	23,200,000	33,100,000	550,000	268,000,000	2.75%
VMT (vlg)	83,600,000	52,900,000	24,000,000	268,000,000	2.55%
VMT (lrg)	23,200,000	10,700,000	4,700,000	61,600,000	3.08%
VMT (med)	10,000,000	4,288,686	1,720,000	26,100,000	2.89%
VMT (sml)	4,914,278	2,563,854	550,000	11,800,000	2.96%
VMTPC	16.50	3.84	5.50	29.51	1.32%
VMTPC (vlg)	16.55	3.78	7.01	24.32	1.33%
VMTPC (lrg)	16.72	3.34	8.01	23.86	1.52%
VMTPC (med)	16.53	3.67	5.76	26.18	1.30%
VMTPC (sml)	16.14	4.58	5.50	29.51	1.14%
UA Pop.	1,436,062	2,267,139	95,000	18,800,000	1.34%
UA Pop. (vlg)	5,416,923	3,962,287	1,430,000	18,800,000	1.20%
UA Pop. (lrg)	1,366,139	510,278	365,000	3,048,000	1.54%
UA Pop. (med)	592,735	164,021	170,000	1,100,000	1.57%
UA Pop. (sml)	286,997	947,378	95,000	510,000	1.79%
PI (000,000)	$59,700	$95,300	$136,000	$959,000	2.70%
PI (vlg) (000,000)	$209,000	$45,700	$134,000	$282,000	2.67%
PI (lrg) (000,000)	$54,800	$12,900	$34,500	$74,700	2.83%
PI (med) (000,000)	$25,100	$5,030	$16,900	$33,100	2.48%
PI (sml) (000,000)	$13,600	$3,230	$8,750	$18,800	2.83%
PIPC	$31,204	$7,112	$11,822	$74,954	1.43%
PIPC (vlg)	$36,845	$4,577	$28,289	$44,396	1.48%
PIPC (lrg)	$32,174	$3,982	$25,039	$38,134	1.41%
PIPC (med)	$31,191	$3,618	$24,589	$37,022	1.41%
PIPC (sml)	$28,242	$3,306	$22,433	$33,333	1.34%
MSA Pop.	1,730,465	2,396,915	111,106	19,100,000	1.24%
MSA Pop. (vlg)	5,599,903	551,734	4,742,498	6,492,596	1.17%
MSA Pop. (lrg)	1,681,714	196,184	1,376,848	2,004,722	1.40%
MSA Pop. (med)	795,784	69,622	686,925	911,835	1.05%
MSA Pop. (sml)	475,742	58,862	389,911	578,215	1.47%

Table 2: Sample of 87 Urban Area's Summary Statistics (1982-2009)

Variable Name	Mean	Std. Dev.	Min	Max
Vehicle Miles Traveled (VMT)	25,450,000	34,580,000	550,000	265,290,000
Vehicle Miles Traveled Per Capita (VMTPC)	16.44	3.83	5.50	29.51
Urban Area Population (POPu)	1,572,530	2,369,525	95,000	18,768,000
Population Density (DENSITY)	2,244	898	989	5,767
Urban Land Area (ULA)	643	659	25	4,810
Lane Miles (LM)	3,450,211	4,125,103	175,000	27,020,000
Lane Miles Per Capita (LMPC)	2.52	0.61	1.21	5.03
Real Fuel Cost (RFC)	$1.96	$0.54	$1.11	$3.72
Transit Pass. Miles of Travel (000,000) (PMT)	457	1,905	1.40	21,699
Transit Pass. Miles of Travel Per Capita (PMTPC)	124.30	148.72	1.97	1163.95
Personal Income (000,000) (PI)*	$65,373	$99,722	$1,364	$958,964
Personal Income Per Capita (PIPC)*	$31,613	$7,014	$11,822	$74,954
MSA Population* (POPm)	1,883,582	2,502,117	111,106	19,069,796
Public Private Employment Ratio (PUB)*	18.66%	7.56%	8.24%	58.71%
Percent Finance-Ins.-Real Estate Employment(FIN)*	8.34%	1.87%	0.34%	17.76%
Percent Construction Employment (CON)*	5.68%	1.36%	2.95%	14.85%
Percent Manufacturing Employment (MANU)*	10.91%	5.40%	1.01%	32.06%
Percent Wholesale Employment (WHOLE)*	4.51%	1.21%	1.83%	9.26%
Percent Retail Employment (RETAIL)*	14.88%	3.15%	7.46%	27.54%

**Represents that statistics are from MSAs and not UAs*

Standard OLS Results

Table 3 displays the estimated model with four sets of different industry employment variable specifications, ordered in columns from (A) to (D). Column (A) only includes the public-private employment ratio (PUB) and no other industry sector variables. This specification gives a large significantly positive coefficient for PUB and produces the largest R-squared of the four regressions, but fails to provide in-depth examination of specific industries effects on VMTPC—other than suggesting that urban areas with higher ratios of public to private employment have higher VMT.

To provide more insight on the impact of industry-specific variables within the private sector, we use the specification in Column (B), which includes all five of the industry employment variables, to see if they have any impact on VMT when public sector employment is not considered. Of these five variables, only construction (CON) has a positive and significant impact on VMTPC and only manufacturing (MANU) significantly reduces VMTPC. Column (C) omits the insignificant industry employment variables found in Column (B), leaving only construction and manufacturing; doing this increases the R-squared by about 1%.

Column (D) uses percent wholesale employment (WHOLE) instead of MANU, and has a much larger R-squared than Column (C). While the WHOLE sign is negative, it does not become significant until the simultaneity bias is removed, as shown below in the 2SLS model results. Column (D), which includes specific urban area and yearly fixed effects, does not report fixed effects coefficients for each individual urban area and year for the sake of brevity (available from authors on request).

LMPC, PIPC, RFC, and PMTPC all give expected signs and are statistically significant at the 5% level in all four columns of Table 3. However, the DENSITY coefficient sign varies between

Table 3: OLS Fixed Effects Model with Varying Employment Mix Variables (1982-2009)
Dependent Variable: VMTPC

Variable Name	(A) UA & Year Effects	(B) UA & Year Effects	(C) UA & Year Effects	(D) UA & Year Effects
Lane Miles Per Capita (LMPC)	.4902* (27.47)	.4865* (27.88)	.4941* (29.15)	.4994* (28.10)
Personal Income Per Capita (PIPC)	.3127* (9.68)	.1358* (3.97)	.1606* (4.82)	.2487* (7.38)
Population Density (DENSITY)	-.0087 (-0.55)	.0198 (1.26)	.0162 (1.05)	-.0152 (-0.96)
Real Fuel Cost (RFC)	-.1231* (-3.96)	-.1431* (-4.67)	-.1351* (-4.46)	-.1263* (-4.02)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0193* (-4.08)	-.0189* (-4.04)	-.0194* (-4.23)	-.0176* (-3.70)
Public Private Employment Ratio (PUB)	.0663* (3.49)			
Percent Finance-Insure-Real Estate Employment(FIN)		.0074 (0.70)		
Percent Construction Employment (CON)		.0697* (4.59)	.0607* (4.09)	.0338* (2.22)
Percent Manufacturing Employment (MANU)		-.1636* (-12.19)	-.1659* (-12.72)	
Percent Wholesale Employment (WHOLE)		-.0113 (-0.63)		-.0061 (-0.33)
Percent Retail Employment (RETAIL)		-.0521 (-1.43)		
Constant	-.6953* (-1.98)	.5619 (1.45)	.4066 (1.08)	-.0340 (-0.09)
Number of Urban Areas	87	87	87	87
Number of Years	28	28	28	28
Number of Total Obs.	2436	2344**	2422**	2361**
R-squared	0.5577	0.3958	0.4055	0.5529
Degrees of freedom	2314	2218	2299	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level.*
***Smaller number of observations due to missing observations from BEA employment statistics*

regressions and is not found to be statistically significant in any of the four models. This is not consistent with expectations or the results of previous studies (Noland and Cowart 2000) that find the coefficient of DENSITY to be negative and significant across all specifications. This may be because of DENSITY's strong correlation with LMPC, which is known to feature a strong simultaneity bias. Also, previous studies did not include variables to capture the impact of alternative modes such as transit or the employment mix of the urban area.

Table 4 includes the same independent variables as Column (D) of Table 3, but also includes variables indicating the size of the urban area (small, medium, large, and very large) and geographic location (eastern, central, and western). For instance, Column (B) uses regional groupings for urban areas in the eastern, central, and western part of the U.S.; so that western is omitted as the control

**Table 4: OLS Fixed Effects Model with Varying Group Effects (1982-2009)
Dependent Variable: VMTPC**

Variable Name	(A) No Group Effects	(B) Regional & Year Effects	(C) Pop. Size & Year Effects	Standard OLS (column D Table 3)
Lane Miles Per Capita (LMPC)	.4974* (28.37)	.4709* (27.27)	.5065* (29.67)	.4994* (28.10)
Personal Income Per Capita (PIPC)	.5363* (28.25)	.5413* (28.15)	.4351* (21.60)	.2487* (7.38)
Population Density (DENSITY)	.0408* (3.40)	-.0120 (-0.94)	.0084* (0.70)	-.0152 (-0.96)
Real Fuel Cost (RFC)	-.1681* (-3.32)	-.4547* (-8.00)	-.0450* (-0.88)	-.1263* (-4.02)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0274* (-5.52)	-.02667* (-5.51)	-.0461* (-8.73)	-.0176* (-3.70)
Percent Construction Employment (CON)	.2460* (15.01)	.1883* (10.80)	.2310* (14.01)	.0338* (2.22)
Percent Wholesale Employment (WHOLE)	.1324* (9.54)	.1581* (11.40)	.0699* (4.90)	-.0061 (-0.33)
Central Region (CENTRAL)		-.0918* (-8.57)		
Eastern Region (EASTERN)		-.1079* (-10.89)		
Very Large Population Size (VLG)			.0874* (6.73)	
Large Population Size (LRG)			.0588* (6.71)	
Small Population Size (SML)			-.0806* (-8.37)	
Constant	-2.216 (-9.83)	-1.561 (-6.48)	-1.254 (-5.38)	-.0340 (-0.09)
Number of Urban Areas	87	87	87	87
Number of Years	28	28	28	28
Number of Total Obs.	2361	2361	2361	2361
R-squared	0.6372	0.6552	0.6630	0.5529
Degrees of freedom	2238	2236	2235	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level.*

group (see Appendix A for a list of urban areas in each group). The negative coefficients on both the central and eastern regional dummies indicate that ceteris paribus, VMTPC is higher in the western urban area regional grouping. This could be due to smaller population density of western urban areas or larger land areas and distances between major cities, along with a number of other regional factors.

Column (C) uses population size groupings for very large, large, medium, and small urban areas as fixed effects; so that medium is omitted as the control group (see Appendix A for categorical definitions and a list of urban areas in each group). The coefficients indicate that VMTPC increases with population size. However, since policy is more likely to be implemented at the metropolitan area level than on a regional level or by urban area size specification, we have selected to use the urban area fixed effects rather than other geographic fixed effects for the rest of this analysis.

Finally, Table 4, Column (A) is included to show a regression with no group-specific fixed effects. However, as noted earlier, the F tests shows that the use of urban area-specific fixed effects and yearly fixed effects provide the best fit for the model, as in column D (reproduced from Table 3). Accordingly, we use urban area and yearly fixed effects rather than the population size or regional dummy variables, along with CON and WHOLE for industry mix, in the rest of this analysis.

Distributed Lag Results

Table 5 presents a distributed lag regression output and provides the calculated long-run elasticities for the independent variables. The long-run elasticities found in Column (B) are closely comparable to the coefficients from the standard fixed effects model Column (D) from Table 3, which is labeled in Table 5 as Column (D) for comparison. Alternatively, the short-run elasticities, which are found in the distributed lag regression's coefficients, and shown in Column (A) are considerably smaller.

Recall that the long-term elasticities are calculated as $\varepsilon = \frac{\lambda}{1-\gamma}$, where are the short-run elasticities (found in the regression's coefficients), and is the coefficient of the one-year lag of VMTPC. We find a very inelastic price elasticity in the short-run of -.0263 (the RFC coefficient in Table 5), while the long-run price elasticity is $\frac{-.0263}{1-.7961} = -.1290$, which is very close to the value of -.1263 [found in the standard fixed effects model in Column (D)].

Thus, the long-run price elasticity found here is approximately five times larger than the short-run elasticity of demand for VMTPC, as compared by Noland and Coward (2000), who found the long-term price elasticity to be about 3.5 times as large as the short-run elasticity. Note that the larger R-squared in the distributed lag model is simply an artifact of the strong relation between VMTPC and its lag and does not necessarily reflect a superior design.

Two-Stage Least Squares Results

This section depicts the instrumental variable two-stage least squares model that corrects for the endogeneity of LMPC.

Table 6 shows the first stage of the 2SLS model, with LMPC as the dependent variable being explained by the instrument, ULA, and all the other exogenous variables in the equation. In all four columns, ULA has a negatively significant coefficient. Additionally, in the first stage, one can see that DENSITY is strongly negatively correlated to LMPC. This relation helps explain why the DENSITY coefficient in the standard fixed effects model is biased away from its expected negative value.

The second stage regressions are presented in Table 7. All variables in the model specifications in Columns (A) and (D) are significant at the 5% level, and coefficients have signs consistent with expectations of economic theory. Finally, the specifications in columns (A) and (D) have the largest R-squared of any of the four 2SLS models, indicating the best econometric fit.

Table 5: Distributed Lag Model (1982-2009)
Dependent Variable: VMTPC

Variable Name	(A) Distributed Lag Model	(B) Long-Run Elasticity from (A)	Standard OLS (column D from Table 3)
Lagged VMTPC One Year (L1_VMTPC)	.7961* (66.65)		
Lane Miles Per Capita (LMPC)	.1050* (8.71)	.5150	.4994* (28.10)
Personal Income Per Capita (PIPC)	.0498* (2.44)	.2442	.2487* (7.38)
Population Density (DENSITY)	-.0210* (-2.24)	.1030	-.0152 (-0.96)
Real Fuel Cost (RFC)	-.0263 (-1.47)	-.1290	-.1263* (-4.02)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0038 (-1.33)	-.0186	-.0176* (-3.70)
Percent Construction Employment (CON)	.0104 (1.15)	.0510	.0338* (2.22)
Percent Wholesale Employment (WHOLE)	.0024 (0.22)	.0118	-.0061 (-0.33)
Constant	.1888 (0.80)		-.0340 (-0.09)
Number of UAs	87		87
Number of Years	28		28
Number of Total Obs.	2344		2361
R-squared	0.9673		0.5529
Degrees of freedom	2220		2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level.*

It is notable that, after correction for simultaneity, DENSITY is found to have a negative coefficient in all four model specifications, but it is only significant in models shown in Columns (A) and (D). The DENSITY coefficients in Columns (B) and (C) here are negative (as opposed to positive as found for these models in the OLS specification) but not statistically significant. Although this result is consistent with the hypothesis that increases in urban density reduce VMTPC, the lack of statistical significance and the large change in the size of the coefficient across models is of concern and deserves further study.

The 2SLS correction significantly decreased the LMPC elasticity from .4994 in the standard OLS model to .2524 in the 2SLS. This smaller result is more comparable to the LMPC elasticities found in the literature (Noland 2001; Fulton et al. 2000).

The estimated coefficient for transit ridership per capita (PMTPC) is consistently negative and significant across all specifications and the size of this coefficient actually increases slightly with the 2SLS estimation. This result is consistent with the expectation that urban areas with higher transit ridership per capita have lower VMT per capita.

Table 6: 2SLS Model- First Stage (1982-2009)
Dependent Variable: LMPC
Instrument: ULA

Variable Name	(A) 2SLS	(B) 2SLS	(C) 2SLS	(D) 2SLS
Urban Land Area (ULA)	-.3948* (-21.67)	-.4112* (-22.27)	-.4226* (-23.07)	-.4128* (-22.25)
Personal Income Per Capita (PIPC)	.0705* (2.05)	.0041 (0.11)	-.0282 (-0.76)	.0407 (1.12)
Population Density (DENSITY)	-.4108* (-19.27)	-.4023* (-18.48)	-.4448* (-20.97)	-.4176* (-19.20)
Real Fuel Cost (RFC)	-.1428* (-4.34)	-.1260* (-3.75)	-.1505* (-4.50)	-.1199* (-3.55)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0009 (-0.17)	.0016 (0.31)	.0020 (0.40)	.0027 (0.53)
Public Private Employment Ratio (PUB)	.1904* (9.59)			
Percent Finance-Insure-Real Estate Employment(FIN)		-.0299* (-2.57)		
Percent Construction Employment (CON)		-.0080 (-0.48)	-.0161 (-0.98)	-.0223 (-1.36)
Percent Manufacturing Employment (MANU)		-.0623* (-4.22)	-.0552* (-3.82)	
Percent Wholesale Employment (WHOLE)		-.1002* (-5.10)		-.0937* (-4.76)
Percent Retail Employment (RETAIL)		-.1016* (-2.53)		
Constant	6.048 (13.79)	5.704 (11.86)	7.000 (14.94)	5.809 (12.18)
Number of UAs	87	87	87	87
Number of Years	28	28	28	28
Number of Obs.	2436	2344	2433	2361
R-squared	0.1506	0.1315	0.1504	0.1484
Degrees of freedom	2314	2218	2299	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level*

Column (D) in Table 7 is the final model used to calculate other elasticities. From this we observe that a 10% increase in personal income per capita (PIPC) results in just over a 2.6% increase in VMTPC (due to the coefficient of .263). LMPC behaves similarly, with a 10% increase in lane miles per capita, resulting in just over a 2.5% increase in VMTPC (due to the coefficient of .2524). RFC, DENSITY, and PMTPC all show significantly negative elasticities of -.1542, -.0431, and -.0228, respectively.

As far as the industry specific coefficients are concerned, from Column (A) we note that a 10% increase in the ratio of public to private sector employment results in a 1.2% increase in VMTPC. This is consistent with the hypothesis that public sector employees living outside of the central city may have longer commutes to work than private sector employees who may be able to live closer to their job locations in the suburbs.

Table 7: 2SLS Model with Different Employment Mix Variables (1982-2009)
Second Stage Dependent Variable: VMTPC
Instrument: ULA

Variable Name	(A) 2SLS with UA & Year Effects	(B) 2SLS with UA & Year Effects	(C) 2SLS with UA & Year Effects	!(D) 2SLS with UA & Year Effects
Predicted Lane Miles Per Capita ($\overline{LMPC}_{it}$)	.2753* (6.14)	.2684* (6.36)	.3315* (8.31)	.2524* (5.80)
Personal Income Per Capita (PIPC)	.3425* (10.14)	.1424* (4.02)	.1630* (4.79)	.2630* (7.47)
Population Density (DENSITY)	-.0343* (-2.03)	-.0026 (-0.16)	-.0077 (-0.47)	-.0431* (-2.52)
Real Fuel Cost (RFC)	-.1534* (-4.71)	-.1687* (-5.26)	-.1591* (-5.07)	-.1542* (-4.67)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0247* (-4.96)	-.0237* (-4.83)	-.0231* (-4.87)	-.0228* (-4.53)
Public Private Employment Ratio (PUB)	.1207* (5.44)			
Percent Finance-Insure-Real Estate Employment(FIN)		-.0004 (-0.04)		
Percent Construction Employment (CON)		.0716* (4.55)	.0595* (3.93)	.0332* (2.09)
Percent Manufacturing Employment (MANU)		-.1742* (-12.44)	-.1724* (-12.88)	
Percent Wholesale Employment (WHOLE)		-.0436* (-2.24)		-.0411* (-2.06)
Percent Retail Employment (RETAIL)		-.0774* (-2.04)		
Constant	-.4738* (-1.30)	.7233 (1.80)	.7300 (1.87)	.1920 (0.47)
Number of Urban Areas	87	87	87	87
Number of Years	28	28	28	28
Number of Total Obs.	2436	2344**	2422**	2361**
R-squared	0.5348	0.3251	0.3736	0.5339
Degrees of Freedom	2314	2218	2299	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level*
***Smaller number of observations due to missing observations from BEA employment statistics*

For private sector employment, we look at Column (D) and observe that CON has a coefficient of .0332, meaning that a 10% increase in the percentage of an urban area's work force that is employed in the construction industry corresponds to a 0.3% increase in VMTPC. The same change in WHOLE corresponds to a decrease in VMTPC of about 0.4%, possibly due to the wholesale sector's comparatively less vehicle intense production, distribution and sales processes, and location in the periphery of an urban area.

POLICY IMPLICATIONS AND FUTURE RESEARCH

This study provides a careful analysis of the determinants of driving, as measured by vehicle-miles per capita, VMTPC, using a panel data set of 87 urban areas in the U.S. We find that there are significant differences in VMTPC across urban areas as indicated by urban area-specific fixed effects. Further analysis indicates that urban areas with larger urban populations have higher VMTPC and that urban areas in the western part of the U.S. have higher VMTPC than those in other regions of the country.

After correcting for endogeneity issues, we find that urban density significantly reduces VMTPC in only two of our model specifications. This differs from previous literature, which has found the density measure to have a negative and significant impact on VMT under all OLS and 2SLS model specifications (Noland and Cowart 2000). This illustrates the importance of including other important VMT determinants such as the use of alternative modes, including transit and the employment /industry mix of the urban area in the analysis.

One problem with the DENSITY variable is that it is defined for the total urban area, whereas actual densities may vary considerably across the urban area. Although this is the only measure of density available for this data set, household level data might be used in the future to further explore this issue. Since urban form is something that evolves slowly over time, policymakers need to seriously consider policies that promote urban density as part of long-range planning, but given the mixed results here, further investigation of role of the complex relationship between land use (DENSITY) and road use is needed.

Increased transit ridership is found to be significantly associated with lower VMTPC, a finding consistent across all model specifications and also with a priori with expectations. This suggests that development of transit systems can play an important role in VMTPC reduction. However, research is needed to be able to target transit investments toward places where there is the most potential for diversion from auto ridership if this is going to be most effective in VMTPC reduction. Also, future studies that distinguish between bus and light rail ridership could help policymakers with investment decisions regarding transit.

Most interesting are the findings here that suggest the employment mix and industry mix of urban areas may have a significant impact on VMTPC reduction policies. In areas with more public employment relative to private employment, VMTPC appears to be higher. More research needs to address the reasons for this large and significant impact of public employment on VMTPC if successful VMT reduction policies are to be implemented.

Our results show that there can be significantly different impacts on VMTPC depending on the private industry mix in an urban area. Construction employment is found to increase urban area-level VMTPC, whereas wholesale employment appears to result in lower VMTPC. Further delving into the VMTPC requirements of different industries is an important subject for future research. This study provides preliminary evidence that it may be necessary to develop different policies depending on the local industry mix of an urban area, especially if short-run impacts could adversely impact local industries that have high VMT requirements and few viable substitutes for driving.

Due to data availability, options for VMT reduction such as carpooling were not considered here. In particular, an urban area may have fewer vehicle miles per capita if there is effective carpooling taking place. For policy planning purposes it would be useful to know whether such policies have a significant impact on VMTPC as these policies can be relatively low cost. Studies using household survey data might be able to address this question in the future.

Finally, in all the model specifications, the price per mile of driving has a significant and negative impact on vehicle miles per capita that is much larger in the long run than the short run, consistent with expectations and results from previous studies. This suggests that pricing will play an important role in VMT reduction strategies.

This study has shown that there are significant factors that determine VMTPC in urban areas and underscores the point that because of difference in these factors across urban areas, any one VMT reduction policy may have a different impact in different places. We provide insight as to the source of those differences, which should help policymakers design region-specific policies that will be more successful in VMT reduction. However, it will probably take a combination of policies to reduce VMT enough to meet the GHG reduction goals set out by legislatures.

APPENDIX A: URBAN AREA POPULATION SIZE AND REGIONAL GROUPINGS

Table A.1: Urban Areas Population Size Groupings (98 TTI Urban Areas)

Group	Population Grouping	List of UAs (alphabetical)
Very Large (vlg)	More than 3 million	Atlanta GA, Boston MA-NH-RI, Chicago IL-IN, Dallas-Fort Worth-Arlington TX, Detroit MI, Houston TX, Los Angeles-Long Beach-Santa Ana CA, Miami FL, New York-Newark NY-NJ-CT, Philadelphia PA-NJ-DE-MD, Phoenix AZ, San Diego CA, San Francisco-Oakland CA, Seattle WA, Washington DC-VA-MD
Large (lrg)	Between 1 and 3 million	Austin TX, Baltimore MD, Buffalo NY, Charlotte NC-SC, Cincinnati OH-KY-IN, Cleveland OH, Columbus OH, Denver-Aurora CO, Indianapolis IN, Jacksonville FL, Kansas City MO-KS, Las Vegas NV, Louisville KY-IN, Memphis TN-MS, Milwaukee WI, Minneapolis-St. Paul MN, Nashville-Davidson TN, New Orleans LA, Orlando FL, Pittsburgh PA, Portland OR-WA, Providence RI-MA, Raleigh-Durham NC, Riverside-San Bernardino CA, Sacramento CA, San Antonio TX, San Jose CA, St. Louis MO-IL, Tampa-St. Petersburg FL, Virginia Beach VA
Medium (med)	Between 1/2 and 1 million	Akron OH, Albany-Schenectady NY, Albuquerque NM, Allentown-Bethlehem PA-NJ, Bakersfield CA, Baton Rouge LA, Birmingham AL, Bridgeport-Stamford CT-NY, Charleston-North Charleston SC, Colorado Springs CO, Dayton OH, El Paso TX-NM, Fresno CA, Grand Rapids MI, Hartford CT, Honolulu HI, McAllen TX, New Haven CT, Oklahoma City OK, Omaha NE-IA, Oxnard-Ventura CA, Poughkeepsie-Newburgh NY, Richmond VA, Rochester NY, Salt Lake City UT, Sarasota-Bradenton FL, Springfield MA-CT, Toledo OH-MI, Tucson AZ, Tulsa OK, Wichita KS
Small (sml)	Less than 1/2 million	Anchorage AK, Beaumont TX, Boise ID, Boulder CO, Brownsville TX, Cape Coral FL, Columbia SC, Corpus Christi TX, Eugene OR Greensboro NC, Jackson MS, Knoxville TN, Laredo TX, Little Rock AR, Madison WI, Pensacola FL-AL, Provo UT, Salem OR, Spokane WA, Stockton CA, Winston-Salem NC, Worcester MA

Each population size grouping includes 15, 30, 31, and 22 urban areas respectively from largest to smallest.

Table A.2: Urban Areas Regional Groupings (98 Urban Areas)

Group	List of UAs (alphabetical)
Western	Albuquerque NM, Anchorage AK, Bakersfield-Delano CA, Boulder CO, Colorado Springs CO, Denver-Aurora-Broomfield CO, Eugene-Springfield OR, Fresno CA, Honolulu HI, Las Vegas-Paradise NV, Los Angeles-Long Beach-Santa Ana CA , Oxnard-Thousand Oaks-Ventura CA, Phoenix-Mesa-Glendale AZ, Portland-Vancouver-Hillsboro OR-WA, Riverside-San Bernardino-Ontario CA, Sacramento-Arden-Arcade-Roseville CA, Salem OR, Salt Lake City UT, San Diego-Carlsbad-San Marcos CA, San Francisco-Oakland-Fremont CA, San Jose-Sunnyvale-Santa Clara CA, Seattle-Tacoma-Bellevue WA, Spokane WA, Tucson AZ.
Central	Atlanta-Sandy Springs-Marietta GA, Austin-Round Rock-San Marcos TX, Beaumont-Port Arthur TX, Birmingham-Hoover AL, Brownsville-Harlingen TX, Cape Coral-Fort Myers FL, Corpus Christi TX, Dallas-Fort Worth-Arlington TX, El Paso TX, Houston-Sugar Land-Baytown TX, Jacksonville FL, Kansas City MO-KS, Laredo TX, Little Rock-North Little Rock-Conway AR, Miami-Fort Lauderdale-Pompano Beach FL, Minneapolis-St. Paul-Bloomington MN-WI, New Orleans-Metairie-Kenner LA, Oklahoma City OK, Omaha-Council Bluffs NE-IA, Orlando-Kissimmee-Sanford FL, Pensacola-Ferry Pass-Brent FL, San Antonio-New Braunfels TX, St. Louis MO-IL, Tampa-St. Petersburg-Clearwater FL, Tulsa OK, Wichita KS
Eastern	Akron OH, Albany-Schenectady-Troy NY, Allentown-Bethlehem-Easton PA-NJ, Baltimore-Towson MD, Boston-Cambridge-Quincy MA-NH, Bridgeport-Stamford-Norwalk CT, Buffalo-Niagara Falls NY, Charleston-North Charleston-Summerville SC, Charlotte-Gastonia-Rock Hill NC-SC, Chicago-Joliet-Naperville IL-IN-WI, Cincinnati-Middletown OH-KY-IN, Cleveland-Elyria-Mentor OH, Columbia SC, Columbus OH, Dayton OH, Detroit-Warren-Livonia MI, Grand Rapids-Wyoming MI, Hartford-West Hartford-East Hartford CT, Indianapolis-Carmel IN, Knoxville TN, Louisville-Jefferson County KY-IN, Memphis TN-MS-AR, Milwaukee-Waukesha-West Allis WI, Nashville-Davidson-Murfreesboro-Franklin TN, New Haven-Milford CT, New York-Northern New Jersey-Long Island NY-NJ-PA, Philadelphia-Camden-Wilmington PA-NJ-DE-MD, Pittsburgh PA, Poughkeepsie-Newburgh-Middletown NY, Providence-New Bedford-Fall River RI-MA, Raleigh-Cary NC, Richmond VA, Rochester NY, Springfield MA, Toledo OH, Virginia Beach-Norfolk-Newport News VA-NC, Washington-Arlington-Alexandria DC-VA-MD-WV

Each regional grouping includes 24, 26 and 37 urban areas respectively from west to east.

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Endnotes

1. Previous works have noted difficulty in finding an appropriate instrumental variable, saying "all the variables that may correlate with lane miles also tend to be correlated with VMT" (Noland 2001). Hansen and Huang (1997) also were unable to locate an appropriate instrument for their analysis.

2. Two models are considered in setting up the panel data: random effects and fixed effects. A rejection of the Hausman test confirmed that a random effects estimator is not consistent with the fixed effects coefficients, and is thus not efficient (Dougherty 2007). Additionally, the Breusch and Pagan Lagrangian Multiplier test for random effects confirmed that the model does not meet a primary assumption of a random effects model because the variance of error term "u" does not equal zero (Breusch and Pagan 1980). Thus, a fixed effects model was selected, similarly to Noland (2001), Fulton, et al. (2000) and other papers in the literature on VMT's derived demand.

References

Baum-Snow, N. "Changes in Transportation Infrastructure and Commuting Patterns in Metropolitan Areas, 1960-2000."*American Economic Review (Paper and Proceedings)* 100 (2), (2010): 378-382.

Boarnet, M.G. "Planning, Climate Change, and Transportation Thoughts on Policy Analysis." *Transportation Research Part A* 44 (8), (2010): 587-595.

Breusch, T.S. and A.R. Pagan. "The LM Test and Its Applications to Model Specification in Econometrics." *Review of Economic Studies* 47, (1980): 239–254.

Carlson, D. and Z. Howard. "Impact of VMT Reduction Streatgeies on Selected Areas and Groups." WSDOT Research Report WA-RD 751, December 2010.

Dougherty, C. *Introduction to Econometrics*, *Third Edition*. Oxford University Press, New York, 2007.

Fulton, L.M., R.B Noland, D.J. Meszler, and J.V. Thomas. "A Statistical Analysis of Induced Travel Effects." *Journal of Transportation and Statistics* 3 (1), (2000): 1-14.

Frank, L.D. and G. Pivo. "Impacts of Mixed Use and Density on Utilization of Three Modes of Travel: Single-Occupant Vehicle, Transit, and Walking." *Transportation Research Record: Journal of The Transportation Research Board* 1466, (1995): 44–52.

Goodwin, P., J. Dargay and M. Hanly. "Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review." *Transport Reviews* 24 (3), (2004): 275–292.

Goodwin, P. "Empirical Evidence on Induced Traffic, a Review and Synthesis." *Transportation* (23), (1996): 35-54.

Greene, W.H. *Econometric Analysis Sixth Edition*. Pearson Prentice Hall, Upper Saddle River, NJ, 2008.

Hansen, M. and YL. Huang. "Road Supply and Traffic in California Urban Areas." *Transportation Research A* 31 (3), (1997): 205-218.

Holtzclaw, J. *Explaining Urban Density And Transit Impacts On Auto Use.* (California Energy Commission Docket No. 89), pp. 23., San Francisco: Natural Resources Defense Council, 1991.

Litman, T. "Are VMT Targets Justified?" Victoria Transportation Policy Institute, 2010.

McMullen, B. S., L. Zhang, and K. Nakahara. "Distributional Impacts of Changing from a Gasoline Tax to a Vehicle-Mile Tax for Light Vehicles: A Case Study of Oregon." *Transport Policy* 17 (6), (2010): 359-366.

McMullen, B.S. and N. Eckstein. "Relationship Between Vehicle Miles Traveled and Economic Activity." *Transportation Research Record: Journal of the Transportation Research Board* 2297, (2012): 21-28.

Moore, A., S.R. Bailey and R. Poole. "The Role of VMT Reduction in Meeting Climate Change Goals." *Transportation Research Part A* 44 (8), (2010): 565-574.

Noland, R.B. "Relationships Between Highway Capacity and Induced Vehicle Travel." *Transportation Research Part A* 35 (1), (2001): 47-72.

Noland, R. B. and W.A Cowart. "Analysis of Metropolitan Highway Capacity and the Growth in Vehicle Miles of Travel." *Transportation* 27 (4), (2000): 363-390.

Office of Budget and Management. *Standards for Delineating Metropolitan and Micropolitan Statistical Areas*. June 28, 2010. http://www.whitehouse.gov/sites/default/files/omb/assets/fedreg_2010/06282010_metro_standards-Complete.pdf.

Oregon House Bill 3543, 74th Oregon Legislative Assembly. "H.B. 3543 2." http://www.leg.state.or.us/07reg/measpdf/hb3500.dir/hb3543.en.pdf., Salem, OR, 2007.

Pells, S.R. "User Response to New Road Capacity: A Review of Published Evidence." Institute for Transport Studies, Leeds University, Working Paper 283, 1989.

Pozdena, R. "Driving the Economy." Cascade Policy Institute, 2009.

Puentes, R. and A. Tomer. "The Road …Less Travelled: An Analysis of Vehicle Miles Traveled Trends in the U.S." Washington: Brookings, 2008.

Pushkarev, B. and J. Zupan. *Urban Rail in America: An Exploration of Criteria for Fixed-Guideway Transit.* U. S. Department of Transportation, Report No. UMTA-NY-06-0061-80-1, Washington D.C.: Urban Mass Transportation Administration, 1980, p.31.

Texas Transportation Institute. *2010 Annual Urban Mobility Report*. 2011. http://mobility.tamu.edu/ums/.

U.S. Census Bureau. *2010 Census Urban and Rural Classification and Urban Area Criteria*. August 17, 2010. http://www.census.gov/geo/www/ua/2010urbanruralclass.html.

U.S. Department of Commerce Bureau of Economic Analysis. *Local Area Personal Income.* April 21, 2011. http://www.bea.gov/regional/reis/.

U.S. Commerce Committee. "Federal Surface Transportation Policy and Planning Act of 2009." (http://commerce.senate.gov/public/index.cfm).

U.S. Department of Transportation (USDOT). *Transportation's Role in Reducing U.S. Greenhouse Gas Emissions*, *Volume 1 Synthesis Report*. April, 2010. http://www.camsys.com/pubs/DOT_Climate_Change_Report_-_April_2010_-_Volume_1_and_2.pdf.

Winkelman, S., A. Bishins, and C. Kooshian. "Cost Effective GHG Reductions Through Smart Growth & Improved Transportation Choices." Center for Clean Air Policy, 2009.

Zhang, L., B.S. McMullen, K. Nakahara, and D. Valluri. "The Short- and Long-Run Impact of a Vehicle Mileage Fee on Income and Spatial Equity." *Journal of the Transportation Research Board* 2115, (2009): 110-118.

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