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ABSTRACT: Vehicle miles traveled (VMT) in the U.S. have exhibited an upward trend over time similar to that observed for GDP and personal income. While conventional wisdom suggests that economic growth leads to more driving and thus higher VMT, it is theoretically possible that the causation could also be the other way around. If causation is from VMT to GDP, then legislation to reduce VMT could potentially have an adverse impact on economic activity. This study uses times-series techniques to empirically test for Granger causality between VMT and various measures of economic activity over time and additionally incorporates a derived demand model that finds factors such as lane miles, personal income, population density, fuel cost, transit use, etc. to significantly contribute to the demand for urban area VMT. Results show that GDP leads VMT during economic upturns and in very large, large and medium sized urban areas, suggesting that exogenous shocks to VMT would not negatively impact GDP. However, VMT tends to lead GDP at the national level during recessions and in more rural areas.

The Relationship Between Vehicle Miles Traveled and Economic Activity

by

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Nathan Eckstein, Author

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CONTRIBUTION OF AUTHORS

Brian J. Gregor, P.E. assisted with the project idea and provided a data source. Dr. B. Starr McMullen was involved with the design, editing and writing, and additionally assisted in the interpretation of the data. Additional editing for this paper was provided by Gail Kesner and Rachel Strickland.

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Abbreviations

VMT:	Vehicle Miles Traveled
GDP:	Gross Domestic Product
PI:	Personal Income
GHG:	Greenhouse Gases
TTI:	Texas Transportation Institute
UMR:	Urban Mobility Report
FHWA:	Federal Highway Administration
HPMS:	Highway Performance Monitoring System
BEA:	Bureau of Economic Analysis
MSA:	Metropolitan Statistical Area
VAR:	Vector Auto-regression
FPE:	Final Prediction Error
AIC:	Akaike's Information Criterion
SBIC:	Schwarz's Bayesian Information Criterion
HQIC:	Hannan and Quinn Information Criterion
LR:	Likelihood Ratio

The Relationship Between Vehicle Miles Traveled and Economic Activity

I. INTRODUCTION

Understanding the relationship between vehicle miles traveled (VMT), economic activity, and other determinant factors of the demand for driving is essential in the development of an efficient U.S. transportation system. The idea that a transportation system can reduce VMT without reducing mobility or economic activity has recently been a controversial topic in transportation discussions. This study explores this question through an analysis of the relationship between VMT and economic activity. This is done through a statistical analysis of historic U.S. national and urban area VMT, gross domestic product (GDP), and personal income, followed by a more in-depth look at individual urban areas and key factors' effects on the demand for VMT.

The paper is organized as follows. First a review of recent VMT reduction goals in the U.S. is shown and recent trends in VMT's behavior over time are identified. The next section introduces and explains the statistical methodology pursued in this study and discusses the two datasets: one national and the other a sample of urban areas included in the Texas Transportation Institute's (TTI's) Urban Mobility Report (UMR). Results of Granger causality tests are presented for the national dataset for both the 1929-2009 time period and the 1949-2007 time period that was included in a recent similar study (Pozdena 2009). Then the causality issue is explored in context to the business cycle and with a sample of 98 urban regions. The analysis is furthered by exploring derived demand of VMT in 87 urban areas in order to help interpret the rational for variations in the Granger causality results. The study concludes with a summary of the primary results, implications for policy, and topics for future research in this area.

A. VMT Reduction Goals

Both the federal and state governments have proposed reducing VMT to achieve policy objectives. 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 percent below 1990 levels by the year 2035 (Winkelman, Bishins and Kooshian 2009). The Oregon state legislature mandated reductions in greenhouse gases (GHG) of 10% percent 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 (74th Oregon Legislative Assembly 2007).

Considering that the U.S. transportation sector accounts for 27 percent of U.S. GHG emissions, 60 percent of which are from light-duty vehicles (Greene and Plotkin 2011) and that population is expected to increase. Even with increases in fuel efficiency and alternative fuel use such GHG reduction targets are not likely to be met without some decrease in VMT (Gregor 2009).

VMT and measures of economic activity such as GDP, personal income, or employment, tend to move together leading to concerns that policies aimed at reductions in VMT will negatively impact economic activity (Pozdena 2009). However, it has also been argued that demand for VMT is a derived demand, so that changes in income lead to changes in VMT and not the other way around. Further, there are many other factors, such as the increased availability of transit, telecommuting, and on-line retail activity that provide substitutes to mobility, weakening any possible causal link from VMT to GDP (Puentes and Tomer 2008), (Litman 2010).

Given that VMT reduction is a critical part of several transportation policies, it is essential that the relationship between VMT and economic activity be better understood. If VMT reduction has an adverse impact on economic activity, alternative policy goals need to be considered. It is also possible that the relationship between VMT and economic activity may differ between regions due to differing levels of congestion, transit availability, commute distances, and other factors, so that VMT reduction policies could have different impacts in different locations.

B. VMT Growth and Economic Activity

VMT in the U.S steadily increased between 1929 and the early 2000’s when VMT growth began to plateau, experiencing decreases after 2005. The moderation in VMT growth has been noted by others (Polzin, Chu, and Toole-Holt 2004) and attributed to a variety of factors, notably the maturation of the transportation network and “saturation” of automobile travel in the latter part of the twentieth century relative to growth in earlier years. FIGURE 1 illustrates the upward growth trend in real GDP, real personal income and VMT over the 1929-2009 time period.

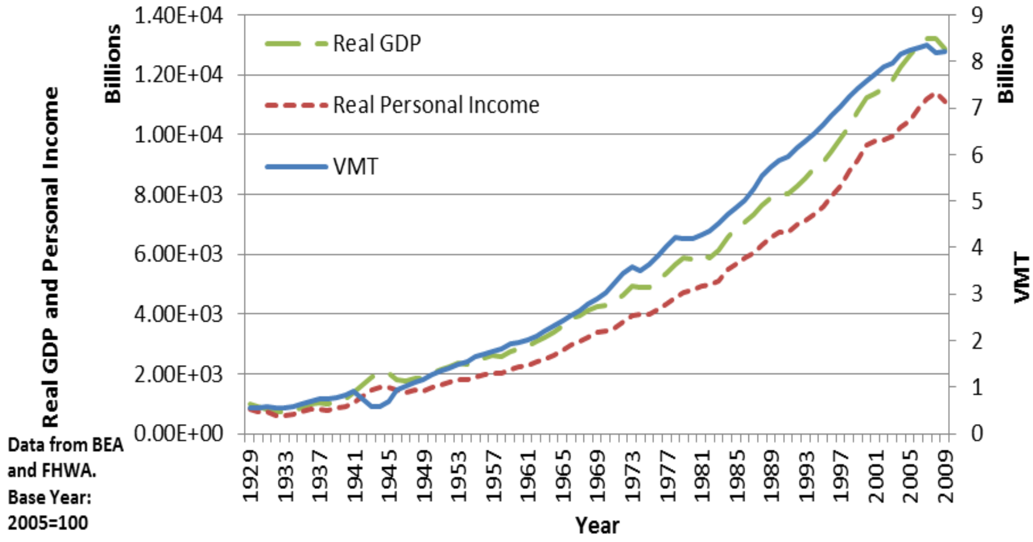

FIGURE 1: U.S. National Real GDP, Real Personal Income and VMT (1929-2009)

The Texas Transportation Institute (TTI) has been collecting and estimating VMT for urban areas since 1982 and finds that average daily VMT in urban areas has risen from just over 1.9 billion to over 3.7 billion in 2009, a 51 percent increase over a 28 year period. The U.S. Department of Energy predicts VMT to increase by 59 percent between 2005 and 2030 if policies are not significantly altered (Gregor 2009).

Prior to 2003 VMT grew at similar rates in urban and rural areas, VMT growth rates have since diverged, with urban area VMT continuing to grow whereas rural VMT has been falling (Puentes and Tomer 2008). Thus, the recent policies that aim to curb VMT growth are more relevant for urban areas, where continued VMT growth is predicted, as those are the places where congestion and GHG emission mitigation is most obviously required.

Most models that attempt to predict VMT for policy purposes use a variety of factors including demographics, automobile ownership, costs of driving, transit availability and real income as determinants of VMT demand (McMullen, et al. 2009), (Polzin, Chu, and Toole-

Holt 2004). The inclusion of real income is justified by economists because VMT demand is seen as a normal good, suggesting that the causal relationship runs from income to VMT demand (Puentes and Tomer 2008), (Litman 2010). Thus, in a growing economy an increase in per capita real personal income would be expected to lead to growth in per capita VMT unless changes in the price of other factors such as fuel cost, car ownership, insurance costs, costs associated with congestion and transit availability have partially offset this effect.

Conversely, VMT can also be considered as an input to production, moving labor, supplies and goods through commuting and freight transport resulting in additional economic activity, thus providing a means by which increases in VMT may lead to increases in income (Pozdena 2009). Because VMT is used as a proxy for mobility, policies that exogenously enforce decreases in VMT, and thus restrict mobility of the work force, could have a negative impact on economic activity as measured by income. The latter impact assumes that the decreasing VMT are not accompanied by offsetting levels of substitutes for VMT mobility such as increased use of alternative transport modes such as bicycling, transit, on-line retailing, or telecommuting (Puentes and Tomer 2008).

Puentes and Tomer assert that the causation is from output to VMT; not the other way around. They state that in modern times, decreases in VMT for large geographic regions will not be an indicator of declining economic activity. Additionally, Litman argues that while increased wealth often increases energy use and vehicle travel, this does not mean that increases in vehicle travel will increase wealth or reductions in vehicle travel reduce wealth (Litman 2010).

However, Pozdena contends that VMT significantly causes economic activity and that implementing VMT reduction to achieve GHG reduction mandates could have an adverse impact on the economy. He backs up these claims as he is the only one to employ a valid analytical econometric methodology to pursue this question, using pairwise Granger causality testing. During the 1949-2007 time period, he reports significant bidirectional causality, meaning that VMT and the economy Granger "cause" each other. Using impulse response functions, he estimates that a downward shock to VMT, such as one due to GHG regulation, would result in a reduction of GDP of 90 percent of the size of the VMT shock in the short run (2 years) and 46 percent of the size in the long run (20 years) (Pozdena 2009).

Although Pozdena uses statistical techniques to examine this causal relationship, his paper does not provide alternative specifications to determine the robustness of his results. As shown below, standard statistical tests can be used to select preferred model specifications. In particular, the lag structures recommended by standard tests differ from those reported by Pozdena, which may affect his reported results. Furthermore, results are also shown to be sensitive to the exact time period included in the statistical analysis.

II. METHODOGOLGY

The purpose of this study is to more fully explore the relationship between VMT and economic activity as measured by GDP and personal income using time-series techniques and testing for Granger causality. This study expands on previous work in several ways:

- The study uses well established statistical techniques for testing for stationarity, cointegration and the selection of the appropriate lag structure in the time-series data.
- The study tests for a structural change in the relationship between VMT and economic activity during the post WWII 1949-2007 time period.
- The study examines the sensitivity of the Granger causality results to the stage of the macroeconomic business cycle.
- Both national and urban area datasets are provided in this paper. Furthermore, urban area results are broken down and reported by urban area size as defined by TTI.
- Finally, demand for VMT is derived at the urban area level to provide additional rational to some of the variation in the Granger causality results for different areas.

The Granger Causality methodology is first introduced along with the various tests that must be performed in order to deal with time-series data and model specification.

A. Granger Causality

Granger causality provides an analytical tool with which time precedence can be established between variables (Granger 1969). Time precedence is one of the bases of causation; yet, due to Granger causality being defined in terms of predictability, it is not an acceptable definition of causation in its own right (Bunge 1959). The identification problem of differentiating between correlation and causation needs economic theory and institutional knowledge to be solved, but econometric testing through Granger causality can provide a good start (Stock 2001).

The Granger test provides probability>Chi^2 values for the F-statistics testing whether all the included lags of an endogenous variable in a vector auto-regression (VAR) are jointly significant. The reduced form vector auto-regression model is shown below in the system of two equations.

1) $\log(VMT_t) = c_1 + A_{11} * \log(VMT_{t-1}) + A_{12} * \log(VMT_{t-2}) + A_{13} * \log(GDP_{t-1}) + A_{14} * \log(GDP_{t-2}) + e_t$

2) $\log(GDP_t) = c_2 + A_{21} * \log(VMT_{t-1}) + A_{22} * \log(VMT_{t-2}) + A_{23} * \log(GDP_{t-1}) + A_{24} * \log(GDP_{t-2}) + e_t$

The null hypothesis is that the lagged variable's coefficients are equal to zero, or in other words that past values of one variable do not help explain the other variable's future movements. Therefore, any probability>Chi^2 result less than or equal to the significance level of five percent (0.05) affords the conclusion that the lagged variable Granger causes the dependent variable. Where causality is defined as Y causing X if X can be better predicted using all available information rather than if the information apart from Y had been used (Granger 1969).

B. Tests for Stationarity

Since time-series data such as that shown in FIGURE 1 tend to trend upwards over time, they must be tested for stationarity and made stationary, usually using differences, prior to use in a vector auto-regression (VAR) model. Data is said to be stationary when it displays a stable and observable mean and variance over time (Dickey and Fuller 1979). A stationary time-series is categorized as being integrated of order zero, written as I(0), or is said to have no unit roots; this quality in a time-series vector is a prerequisite for use in a standard VAR model. Alternatively, nonstationary data features a shifting mean and variance over time. Unit root tests provide the order of integration of a variable. A time-series that is categorized as integrated of order "P", written as I(P), would need to be differenced "P" times to become a stationary process or I(0) (Hamilton 1994).

An augmented Dickey-Fuller test with a null hypothesis that the variable contains a unit root and an alternative hypothesis that the variable was generated by a stationary process is applied to all time-series prior to use in the VAR. MacKinnon approximate p-values of the augmented Dickey-Fuller test statistic that are less than or equal to the significance level of ten percent (0.10) indicate that the null hypothesis can be rejected, suggesting stationarity.

C. Tests for Cointegration

Cointegration is said to occur when some linear combination of two or more time-series has a lower order of integration than the time-series have individually. This can happen if the two time-series share a common stochastic drift. If cointegration is present between two or more variables these variables should not be used in a standard VAR model (Engle and Granger 1987). To test for cointegration an Engle-Granger cointegration test is applied that uses an augmented Dickey-Fuller test on the residuals of a regression featuring two possibly cointegrated variables. Recall that all national variables are I(1), therefore if a linear combination of the two creates an I(0) time-series the two variables are defined as cointegrated.

D. Lag-Length Selection

The lag-length selection for the VAR model is made through the use of the several tests found in the “Varsoc” command in the Stata 11.1 (64-bit) Data Analysis and Statistical Software Program. Since Pozdena uses lags of four years, four years is used as the maximum possible lag-length tested for significance in this paper, although, prior studies on GDP consistently have used only one or two year lags for this type of VAR (Blanchard 2009). Five test statistics are used to help determine the longest lag that continues to contribute to the explanation of a VAR. Consequently, if three years is found to be the appropriate lag-length, lags of one, two, and three years all significantly explain the VAR and need to be included in the model specification.

The five statistical tests for lag-lengths include the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), the Hannan and Quinn information criterion (HQIC) and the Likelihood Ratio (LR). For further description of the tests see Ivanov and Killen (2005). In situations where all tests do not agree on lag-length AIC always selects the largest order, SBIC always selects the smallest and HQIC is somewhere in between (Lütkepohl 2005). When this occurs, the HQIC’s selection is used in this analysis.

III. DATA

A. National Data (1929-2009)

The Bureau of Economic Analysis (BEA) provides annual U.S. GDP and personal income data from 1929 to the present (U.S. Department of Commerce 2011). Both GDP and personal income are expressed throughout this study in terms of real 2005 dollars in order to control for inflation. The Federal Highway Administration (FHWA) publishes annual estimates of U.S. national VMT over the same time period (U.S. Department of Transportation 2011). In this study six variables are explored at the national level; vehicle miles traveled (*VMT*), real gross domestic product (*GDP*), real personal income (*PI*), and the per capita forms of these three variables (*VMTPC, GDPPC, PIPC*). TABLE 1 displays general summary statistics for the national data; providing mean, standard deviation, minimum, maximum, and percent annual growth from 1929-2009. This is the same data used by Pozdena expect that he used the 1949-2007 sub-period.

TABLE 1 National Data Summary Statistics (1929-2009)

Variable Name	Mean	Std. Dev.	Min	Max	% Annual Growth
Daily VMT(000,000)	3,540	2,600	542	8,350	3.64%
Daily VMTPC	15.21	8.03	4.16	27.94	2.45%
Annual VMT(000,000)	1,250,000	920,000	198,000	3,050,000	3.64%
Annual VMTPC	5,445	2,888	1,518	10,168	2.45%
GDP(000,000)	$5,160,000	$3,770,000	$716,000	$13,200,000	3.40%
GDPPC	$22,292	$11,228	$5,700	$43,800	2.21%
PI(000,000)	$4,260,000	$3,240,000	$594,000	$11,400,000	3.45%
PIPC	$18,261	$9,750	$4,730	$37,400	2.26%
Population(000,000)	203	57.1	122	308	1.16%

B. Urban and Metropolitan Data (1982-2009)

The data for urban areas has been collected and published by the Texas Transportation Institute (TTI) since 1982 for use in their annual Urban Mobility Report (UMR) (Texas Transportation Institute 2011). 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 substituted 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. Only 98 of these 100 urban areas were included in this study because two are not core urban areas inside a MSA, without this distinction personal income data is not available.

TABLE 2 provides summary average annual statistics for *VMT*, personal income (*PI*), and population variables in the 98 TTI urban areas for the period 1982-2009. While both *PI* and *PIPC* are larger in more populated urban areas, the fastest growth in both *PI* and population comes from the smallest areas. These 98 urban areas are incorporated into the study in several ways. All 98 areas are given as one aggregate time-series, as well as four population size groupings, they are analyzed individually and are further refined into a 87 urban area panel dataset in the derived demand chapter of this paper.

TABLE 2 Sample Urban Area's 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%

IV. RESULTS

Results are presented in five sub-sections. First, U.S. national VMT, GDP, and PI data are analyzed for 1929-2009 and then for the 1949-2007 time period for comparison with Pozdena's results. Next, a Chow test is used to test for and confirm a structural break in the relationship between VMT and GDP in approximately 1982, the year in which the TTI data for urban areas became available. The impact of the macroeconomic business cycle on the national Granger causality tests is then explored, followed by analysis of Granger causality for the sample of 98 U.S. urban areas. Finally, each of the 98 urban areas is tested individually for Granger causality.

A. National Results

The augmented Dickey-Fuller test was used to test for the stationarity of logged variables from aggregate national 1929-2009 data. Results shown in TABLE 3 indicate that all six national variables are integrated of order one, I(1), and thus are stationary as logged first differences.

TABLE 3 Augmented Dickey-Fuller Test: National Data (1929-2009)

Variable Name	MacKinnon approximate p-value for Z(t) =		Order of Integration
	Logged Levels	Logged Differences	
VMT	0.6337	0.0000*	I(1)
VMTPC	0.6067	0.0000*	I(1)
GDP	0.8512	0.0000*	I(1)
GDPPC	0.8371	0.0000*	I(1)
PI	0.9094	0.0000*	I(1)
PIPC	0.9031	0.0000*	I(1)

** Represents statistical significance at 10% level (H1: stationarity)*

TABLE 4 displays the MacKinnon approximate p-value for the augmented Dickey-Fuller test statistic found in the Engle-Granger cointegration test. Results indicate that that no cointegration exists between any of the relevant variable pairs because linear combinations of the variable pairs do not have lower orders of integrations than the individual I(1) variables. Thus, a standard reduced form VAR model may be applied to this national dataset.

TABLE 4 Engle-Granger Cointegration Test using ADF: National Data (1929-2009)

Variable Name	MacKinnon approximate p-value for Z(t) = Logged Levels	Order of Integration	Cointegration
VMT-GDP residuals	0.1690	I(1)	No
VMTPC-GDPPC residuals	0.1765	I(1)	No
VMT-GDPPC residuals	0.2032	I(1)	No
VMTPC-GDP residuals	0.1579	I(1)	No
VMT-PI residuals	0.1601	I(1)	No
VMTPC-PIPC residuals	0.1717	I(1)	No
VMT-PIPC residuals	0.1774	I(1)	No
VMTPC-PI residuals	0.1652	I(1)	No

No results statistically significant at the 10% level (Null hypothesis of no cointegration fails to be rejected)

The results of all five tests for lag structure were analyzed in TABLE 5. Although not all test statistics agree on lag-length, the HQIC test indicated a two year lag-length in every regression at the national level. Thus a two year lag-length is used; a choice consistent with past GDP time-series studies (Blanchard 2009), but not with Pozdena's choice of two and four year lags (Pozdena 2009).

TABLE 5 Lag-Length Selection Results: National Data (1929-2009)

Regression Name	Suggested Lag-Length (Test Abbreviations)
VMT-GDP	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMTPC-GDPPC	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMT-GDPPC	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMTPC-GDP	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMT-PI**	2 lags* (LR, **HQIC**, SBIC) 3 lags (FPE, AIC)
VMTPC-PIPC**	2 lags* (LR, **HQIC**, SBIC) 3 lags (FPE, AIC)
VMT-PIPC**	2 lags* (LR, **HQIC**, SBIC) 4 lags (FPE, AIC)
VMTPC-PI**	2 lags* (LR, **HQIC**, SBIC) 3 lags (FPE, AIC)

** Represents the lag-length selected for use in the VAR*

***Represents that the variables were additionally tested using the longer lag-lengths; resulting in no significant changes in the Granger causality findings.*

The Granger causality results shown in TABLE 6 indicate economy activity consistently Granger causes VMT, but no statistically significant reverse causation from VMT to economic activity for the 1929-2009 time span. These results are significant at the five percent level and robust across alternative measures of economic activity (*GDP*, *GDPPC*, *PI* and *PIPC*). All Granger causality results presented in this study are taken from VARs with stable eigenvalues (see appendix C). These results follow the rationale that VMT is a normal good and further suggest that as economic activity increases so does personal vehicle driving. However, they do not support the hypothesis that reductions in VMT would significantly impact economic activity.

TABLE 6 Granger Causality: National Data (1929-2009)

Regression Name	Probability > Chi2	
	VMT causes Economy	Economy causes VMT
VMT-GDP	0.138	0.034*
VMTPC-GDPPC	0.158	0.028*
VMT-GDPPC	0.147	0.026*
VMTPC-GDP	0.148	0.037*
VMT-PI	0.109	0.010*
VMTPC-PIPC	0.181	0.013*
VMT-PIPC	0.167	0.011*
VMTPC-PI	0.119	0.011*

** Represents statistical significance at 5% level.*

B. Testing for a Structural Break in the Dataset

For direct comparison with Pozdena, Granger causality results for the 1949-2007 period are provided in Panel (A) of TABLE 7. Note that when Pozdena's sub-period is used, the bi-directional result that he reports is also found in this study. Thus, it appears that the results for Granger causality may be somewhat dependent on the specific time period considered. Possible reasons for this difference are examined in the next section.

TABLE 7 Granger Causality: National Data-Structural Break at 1982 (1949-2007)

Regression Name	Probability >Chi2	
	VMT causes Economy	Economy causes VMT
	Panel A: National Data (1949-2007)	
VMT-GDP	0.000*	0.000*
VMTPC-GDPPC	0.000*	0.000*
VMT-PI	0.000*	0.000*
VMTPC-PIPC	0.000*	0.005*
	Panel B: National Data (1949-1981)	
VMT-GDP	0.002*	0.000*
VMTPC-GDPPC	0.000*	0.001*
VMT-PI	0.001*	0.001*
VMTPC-PIPC	0.001*	0.014*
	Panel C: National Data (1982-2007)	
VMT-GDP	0.160	0.144
VMTPC-GDPPC	0.221	0.202
VMT-PI	0.411	0.172
VMTPC-PIPC	0.455	0.242
	Panel D: National Data (1982-2009)	
VMT-GDP	0.002*	0.120
VMTPC-GDPPC	0.005*	0.216
VMT-PI	0.002*	0.120
VMTPC-PIPC	0.005*	0.216

** Represents statistical significance at 5% level.*

In the early part of the twentieth century, the highway system was in its infancy. Following WWII, highway building accelerated, especially after the initiation of the interstate highway system in 1956 and its completion in the 1970s. The year 1982 is selected to subdivide the sample period for two reasons. First, it is reasonable assume that most of the long term location and development impacts from the investment in the interstate highway system were complete by that date. In comparing the periods pre- and post-1982, it can be seen that public road mileage grew at an annual percentage rate of .50% during the (1949-1981) time period, but only at a rate of .19% from (1982-2007). This dissimilarity, combined with lower real fuel prices, may have caused a larger induced travel demand impact in the earlier period. Since the more recent period is more directly relevant for prospective policymaking, it is important to know if there has been a change in the relationship between VMT and economic activity.

Second, the national level of aggregation may conceal important differences in the relationship between economic activity and VMT at the urban area level, at which most policies are likely to be formulated and implemented. The TTI data used to explore the relationship in urban areas were only available on an annual basis from 1982 to the present.

A Chow test was used to test for a structural break in the post-WWII national data using the 1949-1981 and 1982-2007 as the sub-periods (see Hamilton (1994) for a discussion of this technique). The resulting F-statistic(2, 55) of 74.07 suggests a significant improvement in the model's fit by splitting the sample at the year 1982 rather than pooling the data from 1929-2009 (Dougherty 2007). This confirms the hypothesis of a structural change in the relationship between *VMT* and *GDP* at the national level in 1982.

This study re-examines Granger causality results for the pre- and post- 1982 periods, and report the results in Panels (B) and (C) of TABLE 7. As noted above, bi-directional causality is found between *VMT* and *GDP* for the whole 1949-2007 period. However, when the sample is split into the pre-and post-1982 periods, bi-directional result is found for the 1949-1982 period, but the post-1982 period finds no significant causal relationship. This suggests that *VMT* is not a major determinant of economic activity in the latter period.

As an interesting aside, Appendix D features a similar impulse response analysis to Pozdena's using the data and methodology from this paper for the periods 1929-2009 and 1982-2009. It finds economic activity to have a much smaller response to the exogenous shock of VMT, and shows the response to dissipate after only ten years, contrasting the 20 year significant long-run effect found by Pozdena.

C. Impact of the Business Cycle on the VMT/Economic Activity Relationship

It should be noted that the results reported above are sensitive to the years included in the study. When the dataset is expanded to include 2008 and 2009 (years not included in Pozdena's study set), and the Granger causality results are updated, there is a surprising change. Now for the 1982-2009 period there is significant uni-directional Granger causation flowing from VMT to economic activity, see Panel (D) in TABLE 7. Typically the addition of only two years would not be expected to completely change the significance of the Granger causation, but the two years added were both in the heart of an economic recession (known to be caused by the financial crisis and not an exogenous drop in VMT).

To examine the hypothesis that the causal relationship between VMT and economic activity might be affected by the business cycle, the National Bureau of Economic Research's (NBER's) dating for peaks and troughs in the business cycle between 1929 and 2009 is used to create two subsamples: data for years are categorized as downturns if they occur during the time between a peak and a trough, and upturns if they occur during the time between a trough and a peak (The National Bureau of Economic Research 2011). This analysis shows that during economic downturns VMT Granger causes economic activity or bi-directional causation is seen, but during economic upturns only economic activity Granger causes VMT, see TABLE 8.

This explains why the addition of the years 2008 and 2009, two economic downturn years, completely changed the output. It is also interesting to note that changes in VMT are often used by macroeconomic forecasters as one indicator of turning points in the business cycle---although every large macroeconomic cycle has generally accepted causes other than exogenous reductions in VMT.

TABLE 8 Granger Causality: National Data Structural Break with Economic Downturns (1929-2009)

Regression Name	Probability >Chi2	
	VMT causes Economy	Economy causes VMT
National Data: During Economic Downturn (n=16 out of the years from 1929-2009)		
VMT-GDP	0.002*	0.159
VMTPC-GDPPC	0.005*	0.183
VMT-PI	0.007*	0.003*
VMTPC-PIPC	0.003*	0.026*
National Data: During Economic Upturn (n=62 out of the years from 1929-2009)		
VMT-GDP	0.113	0.000*
VMTPC-GDPPC	0.140	0.000*
VMT-PI	0.064	0.001*
VMTPC-PIPC	0.217	0.002*

** Represents statistical significance at 5% level.*

D. Urban Area Results (1982-2009)

The same methodology that was applied to the national level dataset is used again for the urban area dataset. First data is aggregated over all 98 urban areas in the study and examine Granger results. The urban areas are then divided into the TTI urban size sub-groups to see if there is a difference in the relationship observed between VMT and economics activity depending on urban area size.

TABLE 9 displays the order of integration for the aggregate urban area variables and the population size groupings for the 1982-2009 dataset. It show that *VMT* and *VMTPC* data are I(0) and thus regressed as levels, while all but one of the *PI* and *PIPC* variables are I(1) and are regressed as first differences. The one exception is the aggregate sample of 98 areas *PI* variable which was found to be I(2), and requires second differencing for stationarity.

As is noted in the bottom of TABLES 9 and 10 the urban area results were checked for robustness through the use of a more stringent five percent significance level for the augmented Dickey-Fuller test and through the incorporation of longer lag-lengths than HQIC's suggestion. The Probability>Chi^2 results for these robustness checks are not presented in the final Granger analysis in TABLE 11, but it should be noted that in no circumstance did *VMT* significantly Granger cause economic activity due to these changes. Yet, in the *VMTPC-PIPC* regression, economic activity did significantly Granger cause *VMT* when either longer lags were used or when a five percent significance level was used in the augmented Dickey-Fuller test.

TABLE 9 Augmented Dickey-Fuller Test: 98 Urban Area's Data (1982-2009)

Variable Name	MacKinnon approximate p-value for Z(t) =		Order of Integration
	Logged Levels	Logged Differences	
VMT	0.0000*	0.9863	I(0)
VMTPC	0.0000*	0.9352	I(0)
PI	0.1573	0.1168	I(2)
PIPC***	0.1875	0.0612*	I(1)
VMTPC(vlg)	0.0000*	0.8732	I(0)
VMTPC(lrg)	0.0000*	0.9604	I(0)
VMTPC(med)	0.0000*	0.6215	I(0)
VMTPC(sml)	0.0068*	0.3900	I(0)
PIPC(vlg)***	0.1571	0.0937*	I(1)
PIPC(lrg)***	0.1568	0.0962*	I(1)
PIPC(med)	0.1970	0.0251*	I(1)
PIPC(sml)	0.1806	0.0245*	I(1)

** Represents statistical significance at 10% level.*

****Represents that the variables were additionally tested using the 5% significance level for the ADF.*

Since the *VMT* variables are stationary and do not share the same order of integration as the *PI* variables, they cannot be cointegrated. Hence, similarly to the national data, the standard VAR model can be applied here. The urban area tests indicate a two year lag-length in every regression except *VMTPC-PI*, for which a third year was indicated and used, see TABLE 10. As before, when not all tests agree on lag-length the HQIC result is used.

TABLE 10 Lag-Length Selection Results: 98 Urban Area's Data (1982-2009)

Regression Name	Suggested Lag-Length (Tests Abbreviations)
VMT-PI	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMTPC-PIPC**	2 lags* (**HQIC**, SBIC) 4 lags (LR, FPE, AIC)
VMT-PIPC	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMTPC-PI	3 lags* (LR, FPE, AIC, HQIC) 1 lag (SBIC)
VMTPC(vlg)-PIPC(vlg)	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMTPC(lrg)-PIPC(lrg)	2 lags* (LR, FPE, AIC, HQIC, and SBIC)
VMTPC(med)-PIPC(med)**	2 lags* (FPE, AIC, **HQIC**) 4 lags (LR) 1 lag (SBIC)
VMTPC(sml)-PIPC(sml)**	2 lags* (**HQIC,** SBIC) 3 lags (LR, FPE, AIC)

** Represents the lag-length selected for use in the VAR*

***Represents that the variables were additionally tested using the longer lag-lengths.*

Granger causation at the urban area level for medium, large, and very large urban areas exhibits no significant causation in either direction, as shown in TABLE 11. While the aggregate urban *VMTPC-PI* regression shows economic activity to Granger causes VMT, and the small urban area grouping shows significant reverse causation flowing from VMT to the economy. Note that this table reports the 1982-2009 results which, for the national sample (see TABLE 7), actually exhibited reverse causation from VMT to economic activity. Thus, there seems to be a difference in the relationship between VMT and economic activity in larger urban areas as compared to smaller, more rural areas such as is seen in the national aggregation and the small urban area population grouping.

TABLE 11 Granger Causality: 98 Urban Area's Data (1982-2009)

Regression Name	Probability > Chi2	
	VMT causes Economy	Economy causes VMT
VMT-PI	0.524	0.357
VMTPC-PIPC***	0.116	0.101
VMT-PIPC~	0.151	0.454
VMTPC-PI	0.111	0.002*
VMTPC(vlg)-PIPC(vlg)***	0.197	0.552
VMTPC(lrg)-PIPC(lrg)***	0.067	0.359
VMTPC(med)-PIPC(med)**	0.368	0.125
VMTPC(sml)-PIPC(sml)**	0.042*	0.462

** Represents statistical significance at 5% level.*

***Represents that the variables were additionally tested using the longer lag-lengths; resulting in no significant changes in the Granger causality findings.*

****Represents that the variables were additionally tested using the 5% significance level for the ADF; resulting in no significant changes in the Granger causality findings.*

~Represents that testing using a 5% significance level for the ADF leads to PIPC uni-directionally significantly Granger causing VMTPC.

E. Individual Urban Areas

This section takes the 98 urban areas from the above analysis and separates them in order to study each area as an individual time-series. TABLE 12 shows Granger causation between *VMTPC* and *PIPC* in individual urban areas from 1982-2009. In looking at the 98 urban areas individually it was found that only nine showed uni-directional reverse causation from *VMTPC* to *PIPC* at the five percent significance level. These areas are diverse both geographically and in terms of population size making it hard to ascertain a pattern or theory as to how these nine areas differ from the other 89.

The areas that find reverse causation include Anchorage, AK, Birmingham-Hoover, AL, Buffalo-Niagara Falls, NY, Denver-Aurora-Broomfield, CO, McAllen, TX, Miami-Fort Lauderdale-Pompano Beach, FL, Poughkeepsie-Newburgh-Middletown, NY, Provo UT, and

Virginia Beach-Norfolk-Newport News, VA-NC. Additionally, significant bi-directional causation is found in Oklahoma City, OK and Portland-Vancouver-Hillsboro, OR-WA.

TABLE 12 Granger Causality: Individual Urban Areas (1982-2009)

Regression Name	Probability >Chi2	
	VMTPC causes PIPC	PIPC causes VMTPC
Akron, OH	0.379	0.949
Albany-Schenectady-Troy, NY	0.746	0.182
Albuquerque, NM	0.288	0.903
Allentown-Bethlehem-Easton, PA-NJ	0.749	0.177
Anchorage, AK	0.000*	0.298
Atlanta-Sandy Springs-Marietta, GA	0.068	0.498
Austin-Round Rock-San Marcos, TX	0.257	0.243
Bakersfield-Delano, CA	0.621	0.773
Baltimore-Towson, MD	0.967	0.304
Baton Rouge LA	0.224	0.041*
Beaumont-Port Arthur, TX	0.095	0.308
Birmingham-Hoover, AL	0.043*	0.440
Boise ID	0.301	0.078
Boston-Cambridge-Quincy, MA-NH	0.073	0.116
Boulder, CO	0.220	0.282
Bridgeport-Stamford-Norwalk, CT	0.128	0.332
Brownsville-Harlingen, TX	0.121	0.256
Buffalo-Niagara Falls, NY	0.013*	0.498
Cape Coral-Fort Myers, FL	0.205	0.006*
Charleston-North Charleston-Summerville, SC	0.878	0.573
Charlotte-Gastonia-Rock Hill, NC-SC	0.247	0.155
Chicago-Joliet-Naperville, IL-IN-WI	0.159	0.819
Cincinnati-Middletown, OH-KY-IN	0.723	0.388
Cleveland-Elyria-Mentor, OH	0.392	0.045*
Colorado Springs, CO	0.964	0.085
Columbia, SC	0.531	0.324
Columbus, OH	0.663	0.354
Corpus Christi, TX	0.068	0.737
Dallas-Fort Worth-Arlington, TX	0.486	0.189
Dayton, OH	0.312	0.152
Denver-Aurora-Broomfield, CO	0.006*	0.368
Detroit-Warren-Livonia, MI	0.116	0.497
El Paso, TX	0.063	0.989
Eugene-Springfield, OR	0.510	0.385
Fresno, CA	0.445	0.583
Grand Rapids-Wyoming, MI	0.612	0.136
Greensboro NC	0.539	0.817
Hartford-West Hartford-East Hartford, CT	0.798	0.090
Honolulu, HI	0.938	0.072

Houston-Sugar Land-Baytown, TX	0.889	0.531
Indianapolis-Carmel, IN	0.292	0.992
Jackson MS	0.425	0.788
Jacksonville, FL	0.322	0.832
Kansas City, MO-KS	0.966	0.083
Knoxville, TN	0.773	0.677
Laredo, TX	0.199	0.146
Las Vegas-Paradise, NV	0.060	0.288
Little Rock-North Little Rock-Conway, AR	0.063	0.271
Los Angeles-Long Beach-Santa Ana, CA	0.987	0.967
Louisville-Jefferson County, KY-IN	0.242	0.519
Madison, WI	0.192	0.017*
McAllen, TX	0.003*	0.756
Memphis, TN-MS-AR	0.303	0.064
Miami-Fort Lauderdale-Pompano Beach, FL	0.000*	0.655
Milwaukee-Waukesha-West Allis, WI	0.894	0.524
Minneapolis-St. Paul-Bloomington, MN-WI	0.084	0.646
Nashville-Davidson-Murfreesboro-Franklin, TN	0.593	0.942
New Haven-Milford, CT	0.093	0.353
New Orleans-Metairie-Kenner, LA	0.247	0.000*
New York-Northern New Jersey-Long Island, NY-NJ	0.086	0.002*
Oklahoma City, OK	0.017*	0.031*
Omaha-Council Bluffs, NE-IA	0.731	0.597
Orlando-Kissimmee-Sanford, FL	0.583	0.684
Oxnard-Thousand Oaks-Ventura, CA	0.100	0.069
Pensacola-Ferry Pass-Brent, FL	0.543	0.636
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.435	0.828
Phoenix-Mesa-Glendale, AZ	0.956	0.476
Pittsburgh, PA	0.187	0.217
Portland-Vancouver-Hillsboro, OR-WA	0.029*	0.029*
Poughkeepsie-Newburgh-Middletown, NY	0.000*	0.983
Providence-New Bedford-Fall River, RI-MA	0.697	0.117
Provo UT	0.022*	0.395
Raleigh-Cary, NC	0.259	0.131
Richmond, VA	0.820	0.511
Riverside-San Bernardino-Ontario, CA	0.826	0.869
Rochester, NY	0.262	0.019*
Sacramento-Arden-Arcade-Roseville, CA	0.629	0.219
Salem, OR	0.491	0.009*
Salt Lake City, UT	0.258	0.323
San Antonio-New Braunfels, TX	0.473	0.770
San Diego-Carlsbad-San Marcos, CA	0.311	0.237
San Francisco-Oakland-Fremont, CA	0.558	0.292
San Jose-Sunnyvale-Santa Clara, CA	0.052	0.964
Sarasota-Bradenton FL	0.206	0.640
Seattle-Tacoma-Bellevue, WA	0.910	0.756
Spokane, WA	0.337	0.173
Springfield, MA	0.479	0.877

St. Louis, MO-IL	0.551	0.022*
Stockton CA	0.381	0.090
Tampa-St. Petersburg-Clearwater, FL	0.222	0.322
Toledo, OH	0.301	0.708
Tucson, AZ	0.371	0.776
Tulsa, OK	0.801	0.329
Virginia Beach-Norfolk-Newport News, VA-NC	0.012*	0.364
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.626	0.123
Wichita, KS	0.888	0.745
Winston-Salem NC	0.242	0.371
Worcester MA	0.861	0.442
Urban Areas (Observations per panel)	98 (25)	98 (25)
Count of Significant Urban Areas at the 5% level	11	11
Percent of Areas that are Significant at the 5% level	11.22%	11.22%

** Represents statistical significance at 5% level (H1: Granger causation).*

V. DERIVED DEMAND

A. Introduction

The Granger causality results make it clear that there is significant variation in the findings depending on the areas analyzed. For example, during the time span from 1982-2009 reverse causation is found at the national level and in the small urban area population size grouping, but is not found for the sample of 98 urban areas, the very large, large, or medium urban area population size groupings or for a strong majority of the individual urban areas. If one takes into consideration that the national level sample includes rural and urban areas it becomes apparent that only the less densely populated regions are finding reverse causation.

Thus, further exploration of the determinants of VMT in various urban areas is necessary for better understanding of how VMT may depend on other factors, such as the availability of alternative transportation modes, fuel price, road infrastructure, population density, and employment levels in certain industries. The evaluation of such factors should reinforce the deduction that VMT could be causally related to economic activity in less populated areas due to the prevalence of these factors in smaller areas.

If VMT reduction policies are implemented in areas where VMT cannot be substituted with other modes, then overall mobility would be reduced, leading to negative economic ramifications. Alternatively, the same policies in larger urban areas that feature more alternative modes of transportation might not have the same influence. The purpose of the following chapter on VMT demand is to help shed light on this and other VMT relationships at a more micro level.

i. Variable Selection and Expected Relationship with VMT

Prior to delving into the results of these models, reasoning is established for the presence of each independent variable included in the model. Independent variables included should have a direct effect on the demand for average daily freeway and arterial vehicle miles traveled per capita in urban areas. The dependent variable of interest in this paper is VMT, but most studies use VMT per capita (*VMTPC*) (Noland and Cowart 2000), (Fulton, et al. 2000).

Economic theory suggests some basic determinants of demand for a product: price, income, and population (when more than one consumer is considered). Average annual state gasoline prices in real 2005 dollars (*RFC*), is used to represent the price or marginal cost of driving. Although there are certainly other components that attribute to VMT's price such as insurance, wear and tear on the vehicle, driving time, etc., the price of gasoline is a large component and the data is easily available here. Additionally, the real price of fuel (*RFC*) has been used in other studies as a proxy for the price of driving (McMullen, et al. 2009), (Fulton, et al. 2000), and (Noland 2001). Price elasticities of demand for driving are expected by economic theory to be negative and are found in other studies to 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).

Since VMT is usually considered to be a normal good, higher incomes are expected to result in more driving and thus VMT, ceteris paribus. Accordingly, personal income per capita (*PIPC*) is included as an indicator of the average incomes 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).

Another possible determinant of *VMTPC* in urban areas is population density; as more spread out populations are expected to feature the more driving, ceteris paribus. Population density (*DENSITY*) is expected to be correlated to *VMTPC*, as various papers which analyze smart growth, urban growth boundaries, and mixed development demonstrate that more dense cities development allow for shorter routes, more one stop shopping, and more walking and biking options, reducing the need for vehicle travel (Winkelman, Bishins and Kooshian 2009), (Frank and Pivo 1995), and (Litman 2010).

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 Pushkarev and Zupan (1980) and Holtzclaw (1991). Transit ridership in an urban area should be correlated with lower VMT levels as transit availability presents the consumer an alternative to driving.

This study additionally incorporates industry employment mix variables, adding a new wrinkle to the typical VMT derived demand model. These variables indicate the percent of an urban area's economy that is employed in certain industries, allowing for direct evaluation of the VMT intensity of industries during the production, distribution and sales processes. 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, instead of requiring driving.

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).

ii. Multicollinearity Test

To reduce multicollinearity it was decided to define variables in per capita terms, notably, *PIPC*, *LMPC*, and *PMTPC*. Note that, industry employment variables are defined as ratios of employment in that industry to total employment. These changes help reduce multicollinearity from the otherwise large, consistent growth trend and cross-sectional collinearity. Finally, the exclusion of population as an independent variable further eradicates excessive collinearity.

The “Collin” command in the *Stata 11.1 (64-bit) Data Analysis and Statistical Software Program* computes several collinearity diagnostic measures including variance inflation factor (VIF), tolerance, eigenvalues, condition index, and R-squared. In the VIF and condition number tests any results greater than 10 are interpreted to contain significant collinearity. The final arrangement of variables, finds no VIF greater than 10, a mean VIF of only 1.75, and a condition number of 3.62. Therefore, the regression does not suffer from collinearity when specified in this manner.

The final set of explanatory variables described above is listed and defined here; these variables will make up the X_{it}^{k} matrix in the following model specification equation:

- $LMPC_{it}$, freeway and arterial lane miles per capita for urban area *i* in year *t*;
- $PIPC_{it}$, personal income per capita in real 2005 dollars for the relevant MSA *i* in year *t*;

- RFC_{it}, state average price of fuel in real 2005 dollars for urban area *i* in year *t*;
- $PMTPC_{it}$, transit passenger miles traveled per capita for urban area *i* in year *t*;
- $DENSITY_{it}$, the number of residents per square mile of urban area *i* in year *t*;
- CON_{it}, $MANU_{it}$, FIN_{it}, $WHOLE_{it}$, $RETAIL_{it}$ (industry employment variables), the percent of total employment that resides in an industry in the relevant MSA *i* and year *t*;
- PUB_{it}, the ratio of public employees to private sector employees in MSA *i* in year *t*.

B. Methodology

i. Standard OLS Model

The econometric specification for the *VMTPC* equation is estimated here as:

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

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 α_i can be defined as regional grouping α_i, or TTI population size grouping α_i instead of urban area α_i (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.

ii. Distributed Lag Model

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

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

Where all specifications are identical to the previous fixed effects 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*, and that T=27 for the distributed lag model, instead of T=28 as seen previously.

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 methodology allows for the calculation of long-term and short-term elasticities, where the long term elasticities are calculated 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).

iii. 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's (2000) methodology and available data, urban land area (*ULA*) is selected as the instrument of choice. The first and second stages of the 2SLS model are written as:

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

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

Where all specifications are identical to the model already specified expect 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 again given as 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].

[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.

C. Data

From the introduction and methodology of this chapter it is clear that a much more in-depth dataset is required for derivation of VMT demand than in the Granger causality analysis. This chapter uses the same data sources as the urban sample for the Granger causality analysis. However, only 87 of the 98 urban areas in the Granger sample are used because some areas 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*). The data used in this chapter is considered "panel data", as it incorporates both time-series and cross-sectional variation, whereas all previous data in this paper were purely time-series.

The panel data displays every urban area's specific *DENSITY*, *LMPC*, *RFC*, and *PMTPC*, which are all from the 2010 UMR (Texas Transportation Institute 2011). The source for *PIPC* and the industry employment statistics is BEA for the 87 associated MSAs (U.S. Department of Commerce 2011).

TABLE 13 present summary statistics for the variables used in this chapter. These statistics do not exactly match those found in TABLE 3 because this table only includes data for 87 of the 98 urban areas used previously. On average between 1982 and 2009, an individual in these 87 urban areas drove over 16 miles a day on freeways and arterial roads, was a passenger 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.

TABLE 13 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*

Only the percent industry employment variables have missing data. Number of missing observations is: Finance-Insurance-Real Estate=8, Construction=45, Manufacturing=14, Wholesale=85 and Retail=9.

D. Results

The inclusion of "two-way' fixed effects which applies dummy variables to both an observation's group (urban area) and time period (year) provides a static coefficient estimates 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).

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[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.

i. Standard OLS Results

TABLE 14 displays the 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 and produces the largest R-squared of the four regressions, but fails to provide in-depth examination of specific industries effects on *VMTPC*. Column (B) comprises all five of the percent industry employment variables; of which only construction (*CON*) is positively significantly correlated with *VMTPC*, and only manufacturing (*MANU*) is negatively significant. 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 one percent.

Column (D) integrates percent wholesale employment (*WHOLE*) in the place of *MANU*, and has a much larger R-squared than Column (C). Although, *WHOLE* takes on the expected sign, it does not become significant until the simultaneity bias is removed, as shown in the 2SLS model results.

LMPC, *PIPC*, *RFC* and *PMTPC* all give expected signs and are statistically significant at the five percent level in all four columns of TABLE 14. Whereas, the *DENSITY* coefficient sign varies between regressions and is not found to be statistically significant in any of the four columns, this is likely attributable to *DENSITY*'s strong correlation with *LMPC*, which is known to feature a strong simultaneity bias.

TABLE 14 Fixed Effects Model with Varying Employment Mix Variables
"Dependent Variable: VMTPC" (1982-2009)

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

** Represents statistical significance at the 5% level.*

***Represents smaller R-squared due to missing observations from BEA employment statistics.*

! Represents the optimal specification; to which other models can be compared.

All regressions in TABLE 15 include the same independent variables as Column (D) of TABLE 14, but with varying results for alternative ways of grouping and defining the fixed effects. 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 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 the more western the 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 (see discussion of possible omitted variables on pg. 37).

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 exhibit a linear upward trend; such that *VMTPC* is found to be higher the larger the population size bracket an urban area falls into, ceteris paribus.

Column (A) is included to show a regression with no group-specific fixed effects. It is apparent that the R-squared is much smaller and the coefficients are quite different in Column (A) when compared to Column (D) (which uses the standard urban area fixed effects). Column (D), similarly to all other regressions that feature urban area and yearly fixed effects, does not report fixed effects coefficients for each individual urban area and year for the sake of brevity (see Appendix B for urban area and yearly fixed effects' coefficients from the most refined model). TABLE 15 shows that the use of urban area-specific fixed effects and yearly fixed effects provides the best fit for the model, as indicated by the R-squared of approximately 0.94.

TABLE 15 Fixed Effects Model with Varying Group Effects
"Dependent Variable: VMTPC" (1982-2009)

Variable Name	(A) No Group-Specific Effects	(B) Regional & Year Effects	(C) Population Size & Year Effects	!(D) UA & Year Effects
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	0.9386

** Represents statistical significance at the 5% level.*

***Represents smaller R-squared due to missing obs. from BEA employment statistics.*

ii. Distributed Lag Results

TABLE 16 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 TABLES 14 and 15), which are labeled in TABLE 16 as Column (D) for comparison. Alternatively, the short-run elasticites, which are found in the distributed lag regression's coefficients, and shown in Column (A) are considerably smaller.

Recall the long term elasticities are calculated 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*. We find a very inelastic price elasticity in the short-run of -.0263 (the *RFC* coefficient in TABLE 16), 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 the 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.

TABLE 16 Distributed Lag Model "Dependent Variable: VMTPC" (1982-2009)

Variable Name	(A) Distributed Lag Model with UA & Year Effects	(B) Long Run Elasticities from (A)	!(D) UA & Year Effects
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

** Represents statistical significance at the 5% level.*

***Represents smaller R-squared due to missing observations from BEA employment statistics.*

! Represents the optimal specification; to which other models can be compared.

iii. Two-Stage Least Squares Results

This sections depicts the instrumental variable two-stage least squares model that corrects for the endogeneity of *LMPC*. The varying Columns (A) through (D) are to the exact same specification as the columns presented in the original fixed effects model in TABLE 14.

TABLE 17 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* takes on a negatively significant coefficient. Additionally, in the first stage, one can see that *DENSITY* is strongly negatively correlated to *LMPC*. This relation explains why the *DENSITY* coefficient in the standard fixed effects model is biased away from its true negative value, shown in the second stage of the 2SLS.

TABLE 17 2SLS Model with Varying Employment Mix Variables
First Stage "Dependent Variable: LMPC", Instrument: ULA" (1982-2009)

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
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)
R-squared	0.1506	0.1315	0.1504	0.1484

** Represents statistical significance at the 5% level.*

! Represents the optimal specification; to which other models can be compared.

The second stage regressions are presented in TABLE 18. It is noticeable that now all variables in the optimal model specification in Column (D) are significant at the five percent level and have the expected sign. The model reported in column (D) is considered to be the preferred model for three reasons. First, there is no longer a bias due to simultaneity, second because all coefficients are significant and consistent with expectations of economic theory. Finally this variable specification has the largest R-squared of any of the four 2SLS models, indicating the best econometric fit. The 2SLS correction significantly decreased the *LMPC* elasticity from .4994 in the standard OLS model down to .2524 in the 2SLS. This smaller result is more comparable to the *LMPC* elasticites found in the literature (Noland 2001), (Fulton, et al. 2000).

Column (D) in TABLE 18 is the final model used to calculate elasticities for this study. In consequence, a 10 percent increase in personal income per capita (*PIPC*) correlates with close to a 2.6 percent increase in *VMTPC* due to the coefficient of .2524. *LMPC* behaves similarly, with a 10 percent increase in lane miles per capita resulting in just over a 2.6 percent increase in *VMTPC*. *RFC*, *DENSITY*, and *PMTPC* all show significantly negative elasticities of -.1542, -.0431, and -.0228, respectively.

Finally, *CON* has an elasticity of .0332, meaning that a 10 percent increase in the percentage of an urban area's work force that is employed in the construction industry corresponds to a 0.3 percent increase in *VMTPC*. The same change in *MANU* corresponds to a decrease in *VMTPC* of about 0.4 percent, possibly due to manufacturing's comparatively less vehicle intense production, distribution and sales processes.

TABLE 18 2SLS Model with Varying Employment Mix Variables
Second Stage "Dependent Variable: VMTPC", Instrument: ULA" (1982-2009)

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

** Represents statistical significance at the 5% level.*

***Represents smaller R-squared due to missing observations from BEA employment statistics.*

! Represents the optimal specification; to which other models can be compared.

VI. CONCLUSIONS

The relationship between VMT growth and growth in economic activity is complex. This study uses time-series techniques and Granger causality to provide insight into these casual relationships. Historic national level data shows significant uni-directional Granger causation from economic activity to VMT from 1929-2009; a result consistent with the concept that VMT is a normal good. This differs from Pozdena's (2009) results that found bi-directional causation at the national level. Pozdena's bi-directional results are shown to be valid for the 1949-2007 and 1949-1982 periods, but during the time period of interest for prospective GHG and transportation system efficiency policymaking, 1982-2009, bi-directional causation is not found and significant variation is seen in the results between national and urban area data.

The causal relationship between VMT and GDP is found to be dependent on the macroeconomy and the stage of the business cycle. VMT tends to lead or cause economic activity in downturns, confirming the use of VMT related measures as indicators of turning points in the macroeconomic business cycle. However, in macroeconomic upturns uni-directional causation is seen flowing from economic activity to VMT growth. Although a majority of the findings suggest that policies designed to reduce VMT may be used without the threat of compromising national economic activity, results were found to differ for urban and non-urban geographic areas.

For very large, large, and medium size urban areas, no significant causal relationship was found between VMT and economic activity. Only for small urban areas and the national sample, which includes rural areas, was some reverse causation found; a result consistent with the hypothesis that smaller urban areas are still in the stage of growth where there is substantial feedback from increases in VMT and personal income. It is also possible that smaller urban areas lack the transit alternatives available in larger areas that help mitigate negative impacts from exogenous reductions in VMT.

Thus, the derived demand analysis is applied to explore the relationship between VMT and economic activity on a more micro level to determine where potential adverse impacts might arise and how policy could be formulated to mitigate those impacts. Multiple factors were found to significantly contribute to the demand for VMT in urban areas including lane miles, personal income, population density, fuel cost, transit use, and the percent of employment in the construction or wholesale sectors. Both transit use and population density are negatively related to VMTPC, reinforcing why smaller, less dense areas with less transit may not be able to provide substitutes for VMT, leading to a causal relationship with economic activity.

With all these factors held constant, per capita VMT is found to be higher the more western and the larger the population size of an urban area. However, VMT reduction policies should methodically examine each of these factors on an area by area basis. This study does not imply that VMT reductions can universally be introduced into a transportation system without reducing mobility or economic activity, but suggests that in under normal circumstances in well-developed urban areas, it is reasonable that GHG related VMT reduction policies would not result in significant drops in economic activity.

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APPENDICES

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.

Appendix B. Coefficients for the Group and Yearly Fixed Effects

TABLE B.1 Coefficients for the Group and Yearly Fixed Effects from TABLE 3-Column (D) (1982-2009)

Variable Name (Fixed Effects)	Coefficients	T-Statistics
Yearly Fixed Effects		
1983	0.0110	1.09
1984	0.0102	0.94
1985	0.0322*	2.77
1986	0.0146	0.82
1987	0.0286	1.57
1988	0.0475*	2.45
1989	0.0645*	3.46
1990	0.0757*	3.66
1991	0.0938*	4.56
1992	0.1118*	5.28
1993	0.1256*	5.63
1994	0.1300*	5.37
1995	0.1488*	6.56
1996	0.1637*	7.57
1997	0.1586*	6.68
1998	0.1444*	5.32
1999	0.1583*	6.1
2000	0.1888*	9.27
2001	0.1874*	8.65
2002	0.1833*	7.58
2003	0.2005*	8.85
2004	0.2351*	12.59
2005	0.2560*	14.99
2006	0.2550*	14.76
2007	0.2689*	15.53
2008	0.2733*	15.52
2009	0.2218*	12.94
Urban Area Fixed Effects		
Albany-Schenectady-Troy, NY	0.0456*	2.32
Albuquerque, NM	0.1933*	9.91
Allentown-Bethlehem-Easton, PA-NJ	0.0854*	4.37
Anchorage, AK	-0.0309	-1.43
Atlanta-Sandy Springs-Marietta, GA	0.4055*	19.27
Austin-Round Rock-San Marcos, TX	0.1980*	10.11
Bakersfield-Delano, CA	-0.0195	-0.88
Baltimore-Towson, MD	0.2719*	11.24
Beaumont-Port Arthur, TX	0.0678*	2.91
Birmingham-Hoover, AL	0.2714*	14.11
Boston-Cambridge-Quincy, MA-NH	0.2174*	9.31
Boulder, CO	-0.0535*	-2.10

Bridgeport-Stamford-Norwalk, CT	0.1234*	4.33
Brownsville-Harlingen, TX	-0.2388*	-7.75
Buffalo-Niagara Falls, NY	-0.1715*	-9.30
Cape Coral-Fort Myers, FL	0.0078	0.32
Charleston-North Charleston-Summerville, SC	0.2498*	10.63
Charlotte-Gastonia-Rock Hill, NC-SC	0.1560*	8.08
Chicago-Joliet-Naperville, IL-IN-WI	-0.0639*	-2.65
Cincinnati-Middletown, OH-KY-IN	0.1714*	9.29
Cleveland-Elyria-Mentor, OH	0.1187*	5.91
Colorado Springs, CO	-0.0068	-0.30
Columbia, SC	0.2414*	12.88
Columbus, OH	0.2909*	15.14
Corpus Christi, TX	0.0829*	3.64
Dallas-Fort Worth-Arlington, TX	0.3127*	16.60
Dayton, OH	0.1972*	10.65
Denver-Aurora-Broomfield, CO	0.2369*	11.33
Detroit-Warren-Livonia, MI	0.2904*	13.76
El Paso, TX	0.0837*	3.44
Eugene-Springfield, OR	0.1067*	5.20
Fresno, CA	0.0884*	3.99
Grand Rapids-Wyoming, MI	0.1482*	7.96
Hartford-West Hartford-East Hartford, CT	0.1206*	5.96
Honolulu, HI	0.2807*	8.77
Houston-Sugar Land-Baytown, TX	0.3109*	15.54
Indianapolis-Carmel, IN	0.3995*	21.87
Jacksonville, FL	0.3323*	18.00
Kansas City, MO-KS	0.3001*	15.58
Knoxville, TN	0.3702*	19.13
Laredo, TX	-0.2578*	-8.36
Las Vegas-Paradise, NV	0.1278*	4.56
Little Rock-North Little Rock-Conway, AR	0.2979*	16.06
Los Angeles-Long Beach-Santa Ana, CA	0.4855*	17.51
Louisville-Jefferson County, KY-IN	0.3435*	17.24
Memphis, TN-MS-AR	0.1323*	7.05
Miami-Fort Lauderdale-Pompano Beach, FL	0.2039*	9.39
Milwaukee-Waukesha-West Allis, WI	0.0660*	3.27
Minneapolis-St. Paul-Bloomington, MN-WI	0.2218*	11.13
Nashville-Davidson-Murfreesboro-Franklin, TN	0.3823*	20.86
New Haven-Milford, CT	0.1754*	9.28
New Orleans-Metairie-Kenner, LA	0.0033	0.14
New York-Northern New Jersey-Long Island, NY-NJ	-0.0532	-1.75
Oklahoma City, OK	0.2532*	13.55
Omaha-Council Bluffs, NE-IA	0.0098	0.49
Orlando-Kissimmee-Sanford, FL	0.3457*	17.89
Oxnard-Thousand Oaks-Ventura, CA	0.3603*	16.78
Pensacola-Ferry Pass-Brent, FL	0.1496*	6.99
Philadelphia-Camden-Wilmington, PA-NJ-DE	0.1114*	4.82
Phoenix-Mesa-Glendale, AZ	0.2234*	11.42

Pittsburgh, PA	0.0687*	3.53
Portland-Vancouver-Hillsboro, OR-WA	0.2500*	11.39
Poughkeepsie-Newburgh-Middletown, NY	0.2694*	14.23
Providence-New Bedford-Fall River, RI-MA	0.0100	0.51
Raleigh-Cary, NC	0.2412*	12.70
Richmond, VA	0.1755*	9.55
Riverside-San Bernardino-Ontario, CA	0.3578*	15.84
Rochester, NY	-0.1383*	-7.26
Sacramento-Arden-Arcade-Roseville, CA	0.3740*	15.65
Salem, OR	0.2981*	15.63
Salt Lake City, UT	0.0992*	4.28
San Antonio-New Braunfels, TX	0.2328*	11.52
San Diego-Carlsbad-San Marcos, CA	0.2878*	13.22
San Francisco-Oakland-Fremont, CA	0.4770*	19.17
San Jose-Sunnyvale-Santa Clara, CA	0.3984*	14.00
Seattle-Tacoma-Bellevue, WA	0.4073*	14.65
Spokane, WA	0.3381*	15.71
Springfield, MA	-0.0155	-0.77
St. Louis, MO-IL	0.0514*	2.78
Tampa-St. Petersburg-Clearwater, FL	0.1738*	8.70
Toledo, OH	0.0241	1.34
Tucson, AZ	0.1879*	7.90
Tulsa, OK	0.1333*	7.14
Virginia Beach-Norfolk-Newport News, VA-NC	0.1668*	7.65
Washington-Arlington-Alexandria, DC-VA-MD	0.2757*	9.14
Wichita, KS	-0.0654*	-3.49

Base year and area: 1982 and Akron, OH.

** Represents statistical significance at the 5% level.*

Appendix C. Stability of the VAR Model

A post-estimation test is applied to observe the stability of the VAR model. Eigenvalues less than or equal to one are considered to be stable. TABLE C.1 shows the stability of the 14 aggregate VAR regressions described throughout the paper (four national regressions, six urban area regressions). All regressions were found to have “modulus” eigenvalues less than one, and thus satisfy the stability condition for a VAR. The stability of the regressions is also presented graphically in FIGURE C.2, which shows the unit circle graphs of the same eigenvalues from TABLE C.1. Eigenvalues are represented by dots on the graphs below, it is quickly apparent that none lie outside the unit circles in any regression and that all regressions are stable.

TABLE C.1 Stability of Eigenvalues

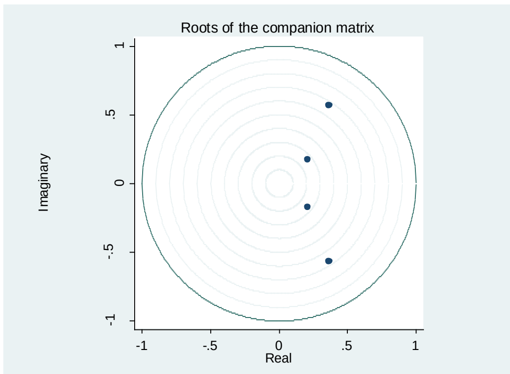
Regression Name	Eigenvalue	Modulus
National Data (1929-2009)		
VMT-GDP	.3670302 + .5666678i	.675147
	.3670302 - .5666678i	.675147
	.213231 + .1729945i	.274581
	.213231 - .1729945i	.274581
VMTPC-GDPPC	.3523781 + .5678486i	.668298
	.3523781 - .5678486i	.668298
	.2258035 + .1902826i	.295288
	.2258035 + .1902826i	.295288
VMT-PI	.386013 + .5729198i	.690828
	.386013 - .5729198i	.690828
	.2173896 + .164387i	.272546
	.2173896 + .164387i	.272546
VMTPC-PIPC	.3532957 + .5679065i	.668832
	.3532957 - .5679065i	.668832
	.2276286 + .1871313i	.294674
	.2276286 + .1871313i	.294674
Aggregated Subsample of UA's and Associated MSA's Data (1982-2009) (n=98)		
VMT-PI	.9173188 + .09394279i	.922117
	.9173188 - .09394279i	.922117
	-.496322	.496322
	.17858	.17858
VMTPC-PIPC	.8973181	.897318
	.6931843 + .3733022i	.787311
	.6931843 - .3733022i	.787311
	-.3695244	.369524
Urban Subsample Divided into Population Groupings (1982-2009) (n=98)		
VMTPC(vlg)-PIPC(vlg)	.8831655	.883166
	.7010097 + .3111598i	.766965
	.7010097 - .3111598i	.766965
	-.3236217	.323622
VMTPC(lrg)-PIPC(lrg)	.872843	.872843
	.7905867 + .283594i	.839912
	.7905867 - .283594i	.839912
	-.3983964	.398396
VMTPC(med)-PIPC(med)	.8902946	.890295
	.5018687 + .3658767i	.621078
	.5018687 - .3658767i	.621078
	-.2982423	.298242
VMTPC(sml)-PIPC(sml)	.9140482	.914048
	.5340066 + .3280137i	.626702
	.5340066 - .3280137i	.626702
	-.4276883	.427688

** Represents eigenvalues greater than one (*: do not satisfy stability condition).*

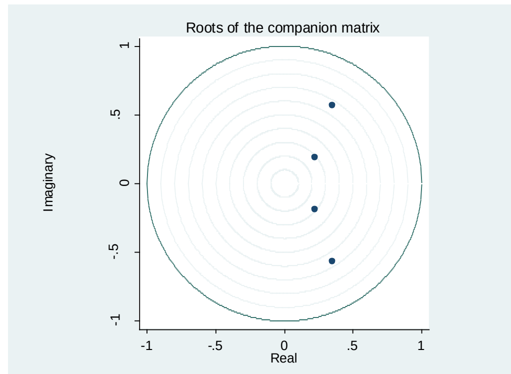
FIGURE C.2 Unit Circle Graphs for Stability of Eigenvalues

National Data (1929-2009)

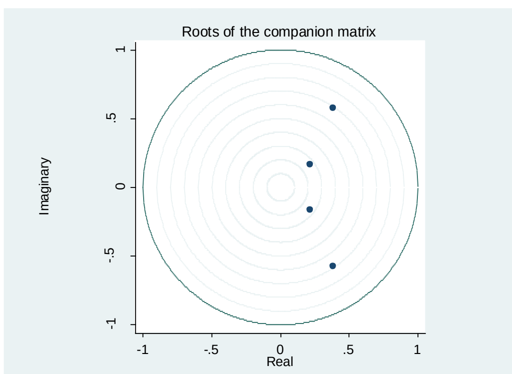
VMT vs. GDP



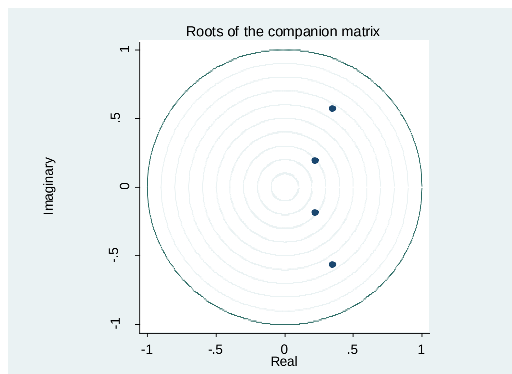
VMTPC vs. GDPPC



VMT vs. PI

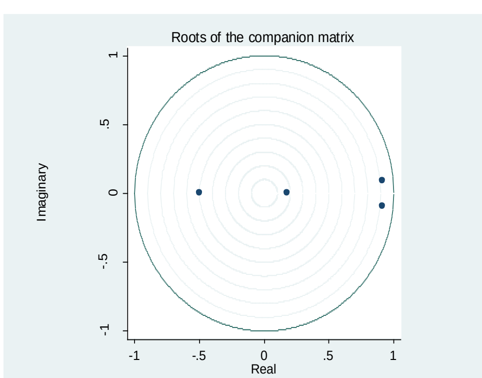


VMTPC vs. PIPC

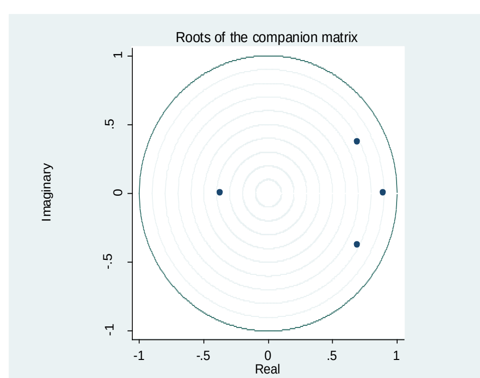


Aggregated Subsample of UA’s and Associated MSA’s Data (1982-2009) (n=98)

VMT vs. PI

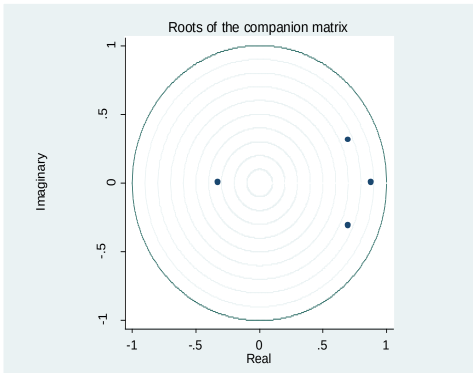


VMTPC vs. PIPC

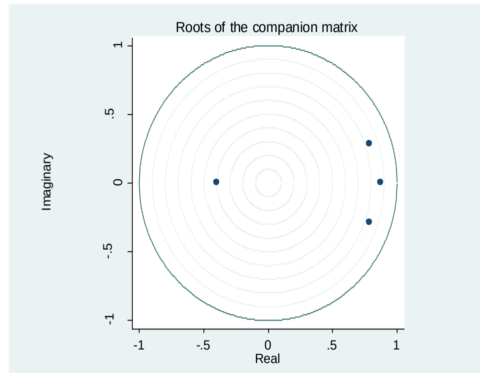


Urban Subsample Divided into Population Groupings (1982-2009) (n=98)

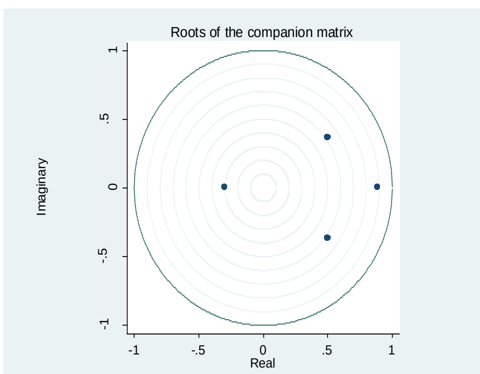
VMTPC(vlg)-PIPC(vlg)



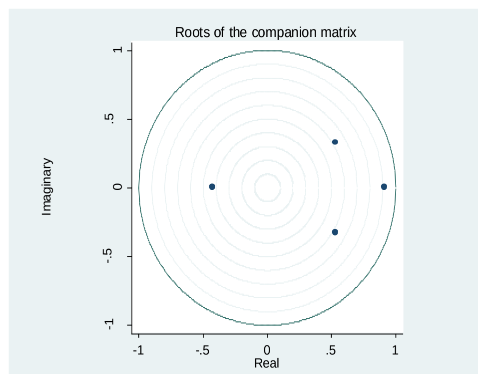
VMTPC(sml)-PIPC(lrg)



VMTPC(med)-PIPC(med)



VMTPC(sml)-PIPC(sml)



Appendix D. Impulse Response Analysis

Impulse response functions describe how a variable reacts over time to an exogenous shock or impulse. In this study the impulse will represent a negative shock to total VMT resulting from a policy passed in order to reduce GHGs or other externalities caused by excess driving. Accordingly, the one unit exogenous shock is placed on *VMT,* and the impulse response had by *GDP* or *PI* is observed, starting at the time of the shock and lasting as long as twenty years into the future.

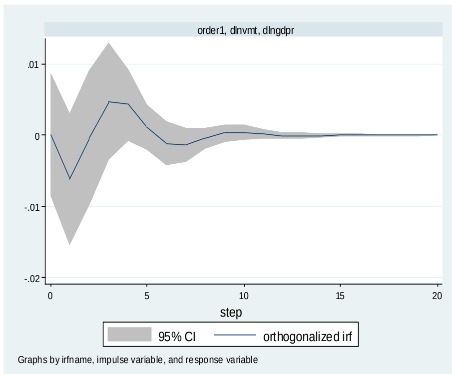
FIGURE D.2 presents graphs of the impulses responses of economic activity after a one unit positive shock in VMT. Due to time restraints and lack of impulse response function programming experience the exogenous shock to VMT is positive and not negative, as would be ideal in the simulation of a GHG policy. Yet, the impulse responses can be inverted in order to rudimentally forecast economic activity. What is more important to witness than the direction of the forecast, is the scale of the response, and that in every regression by the ten year mark almost all variation has subsided; contrasting Pozdena's finding that a downward shock to VMT, would result in a reduction of GDP of 90 percent of the size of the VMT shock in the short run (2 years) and 46 percent of the size in the long run (20 years) (Pozdena 2009).

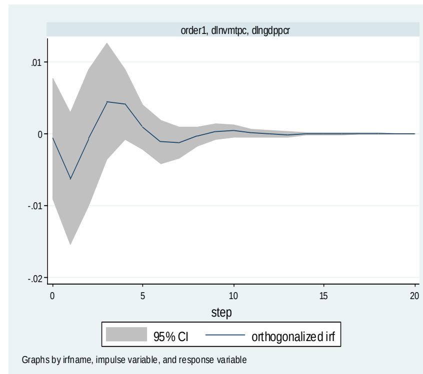
TABLE D.1 support the conclusion that GHG policies will not likely have large adverse effects on the economy due to VMT reduction by providing short-run (2 year), mid-run (10 year), and long-run (20 year) impulse response estimates derived from FIGURE D.2. At the national level, the impulse response functions report that a downward shock to *VMT* would result in an increase of *GDP* of .05 percent of the size of the VMT shock in the short run (2 years) and have no effect in the long run (20 years).

FIGURE D.1 Impulse Response Function Graph (0-20 yr. post exogenous VMT shock)

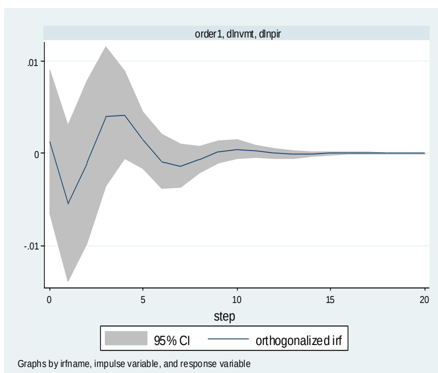
National Data (1929-2009)

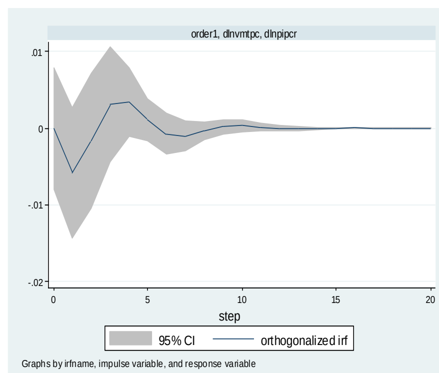
VMT vs. GDP | **VMTPC vs. GDPPC**





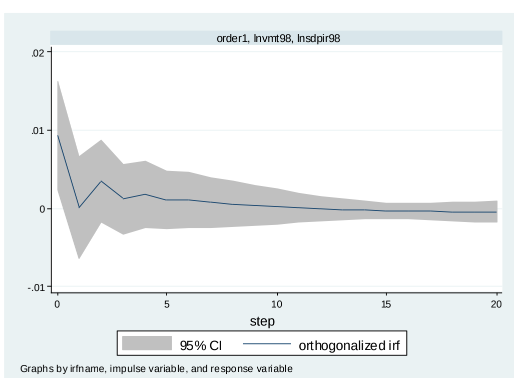
VMT vs. PI | **VMTPC vs. PIPC**

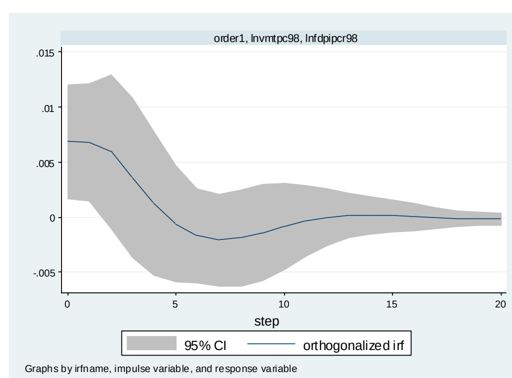




Aggregated Subsample of Urban Area's Data (1982-2009) (n=98)

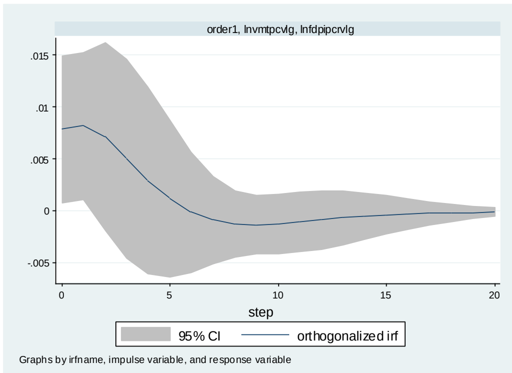
VMT vs. PI | **VMTPC vs. PIPC**



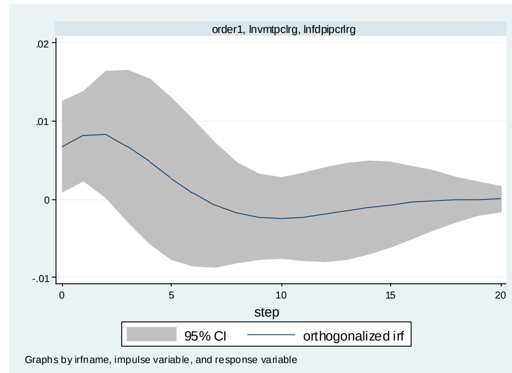


Urban Subsample Divided into Population Groupings (1982-2009) (n=98)

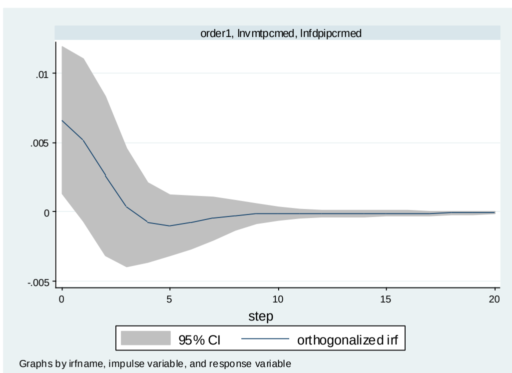
VMTPC(vlg)-PIPC(vlg)



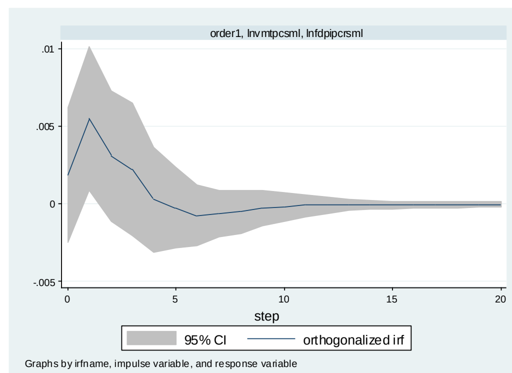
VMTPC(lrg)-PIPC(lrg)



VMTPC(med)-PIPC(med)



VMTPC(sml)-PIPC(sml)



All variables specified in stationarity form.

TABLE D.2 Impulse Response Functions (0-20 years post an exogenous VMT shock)

		National Data (1929-2009)		
Step	VMT-GDP	VMTPC-GDPPC	VMT-PI	VMTPC-PIPC
2 year	-.000371	-.000567	-.000972	-.001638
10 year	.000415	.000372	.000427	.000303
20 year	-7.5e-06	-4.9e-06	-.000011	-4.7e-06
		Aggregated Subsample of 98 Urban Area's Data (1982-2009) (n=98)		
Step	VMT-GDP	VMTPC-GDPPC	VMT-PI	VMTPC-PIPC
2 year	-	-	.003427	.005963
10 year	-	-	.000212	-.000837
20 year	-	-	-.000448	-.000171
		Urban Subsample Divided into Population Groupings (1982-2009) (n=98)		
Step	VMTPC(vlg)-PIPC(vlg)	VMTPC(lrg)-PIPC(lrg)	VMTPC(med)-PIPC(med)	VMTPC(sml)-PIPC(sml)
2 year	.007119	.008274	.002605	.003022
10 year	-.001277	-.002425	-.000119	-.000211
20 year	-.000151	.000046	-.000057	-.000071