Relationship Between Vehicle Miles Traveled and Economic Activity

B. Starr McMullen and Nathan Eckstein

Vehicle miles traveled (VMT) in the United States has exhibited an upward trend over time similar to that observed for the gross domestic product (GDP) and personal income. Although conventional wisdom suggests that economic growth leads to more driving and thus higher VMT, it is theoretically possible that the causation could be the other way around. If causation is from VMT to GDP, a directive from legislation such as the Federal Surface Transportation Policy and Planning Act of 2009 to reduce national per capita VMT annually could have an adverse impact on the overall economic activity. This study uses times series techniques to test empirically for Granger causality between VMT and various measures of the national economic activity over time. In most circumstances the causal relationship is found to be from economic activity to VMT; this relationship confirms conventional wisdom and suggests that exogenous shocks to VMT will not negatively affect the national GDP. The relationship between national VMT and GDP is found to be dependent on the stage of the business cycle, in particular, when GDP leads VMT in economic upturns or normal times but VMT tends to lead GDP recessions. For the 98 urban areas included in this study, no significant causal relationship was found between VMT and economic activity in either direction.

Both federal and state governments have proposed reducing vehicle miles traveled (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 use, intercity passenger rail service, and nonmotorized transportation (*1*).

At the state level, the Washington State legislature adopted a direct mandate to reduce per capita VMT to 25% below 1990 levels by 2035 (*2*). The Oregon state legislature mandated reductions in greenhouse gases (GHG) of 10% below 1990 levels by 2020 and 75% below 1990 levels by 2050 (*3*). Because the transportation sector accounts for 27% of U.S. GHG emissions, 60% of which are from light-duty vehicles (*4*) and populations are expected to increase, even with increased fuel efficiency and alternative-fuel use, such GHG reduction targets are not likely to be met without some decrease in VMT (*5*).

VMT and measures of economic activity such as the gross domestic product (GDP) and personal income (PI) tend to move together and lead to concerns that policies aimed at reductions in VMT will negatively affect economic activity (*6*). However, it has also been argued that the 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 online retail activity that provide substitutes for mobility and weaken any possible causal link from VMT to GDP (*7–9*).

Given that VMT reduction is an integral 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. To provide analytical evidence on this relationship between U.S. VMT and economic activity, Granger causality tests are conducted by using the vector autoregression (VAR) framework. Both national data and data from 98 urban areas in the United States are used to determine whether this relationship differs for urban areas in which VMT reduction policies are most likely to be implemented.

VMT GROWTH AND ECONOMIC ACTIVITY, 1929 TO 2009

U.S. VMT increased steadily between 1929 and the early 2000s, when VMT growth began to plateau and experience decreases after 2005. The moderation in VMT growth has been noted by others (*10*) 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 20th century relative to growth in earlier years. It is also possible that this slowdown was just a precursor of the recession that started in 2007. Figure 1*a* shows the upward growth trend in GDP, PI, and VMT over the 1929 to 2009 time period. Figure 1*b* shows this information as percentage changes, which illustrates the cyclical nature of VMT.

The Texas A&M 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 in 1982 to over 3.7 billion in 2009, a 51% increase over this 27-year period. The U.S. Department of Energy predicts VMT to increase by 59% between 2005 and 2030 if policies are not significantly altered (*5*).

Although before 2003 VMT grew a similar rate in urban and rural areas, VMT growth rates have since diverged: urban-area VMT continues to grow, whereas rural VMT has been falling (*7*). Thus, the recent policies that aim to curb VMT growth are more relevant for urban areas, where continued VMT growth is predicted, since those are the places where mitigation of congestion and vehicular emissions 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

Economics Department, Oregon State University, Ballard Extension Hall, Corvallis, OR 97331-3601. Corresponding author: B. S. McMullen, s.mcmullen@oregonstate.edu.

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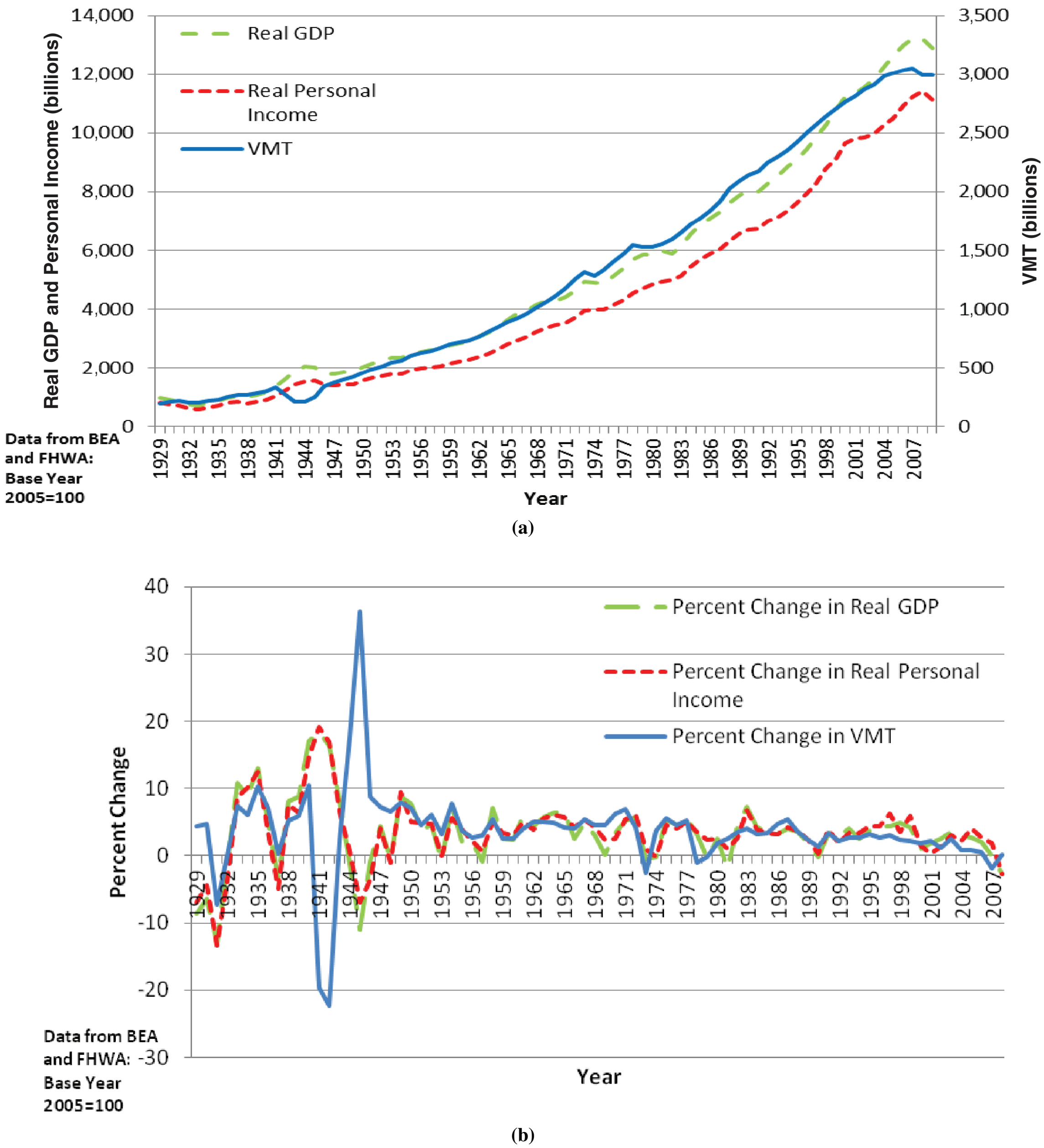

FIGURE 1 U.S. national GDP, PI, and VMT, 1929–2009: (*a*) national data and (*b*) percent change in national data.

of VMT demand (*10, 11*). The inclusion of real income is justified by economists since VMT demand is seen as a normal good; they suggest that the causal relationship runs from real income to VMT demand (*7, 8*). Thus, in a growing economy an increase in per capita real PI would be expected to lead to growth in VMT unless changes in the price of other factors such as fuel, car ownership, insurance, costs associated with congestion, and transit availability have partially offset this effect.

However, VMT can also be considered as an input to production; labor, supplies, and goods move through commuting and freight transport and result in additional economic activity, providing a means by which increases in VMT may lead to increases in income (*6*). Since VMT is used as a proxy for mobility, policies that exogenously enforce decreases in VMT and thus restrict the mobility of the work force could have a negative impact on economic activity as measured by income. This latter impact assumes that the decreasing VMT are not accompanied by substitutes for VMT mobility such as increased use of alternative transport modes [bicycling or transit, online retail, or telecommuting (*7*)].

Puentes and Tomer assert that the causation is from output to VMT and not the other way around (*7*). They state that decreases in VMT for large geographic regions will not be an indicator of declining economic activity. Litman argues that although increased wealth often increases energy use and vehicle travel, this finding does not mean that increases in vehicle travel will increase wealth or reductions in vehicle travel will reduce wealth (*8*).

However, Pozdena contends that VMT significantly causes economic activity and that implementing VMT reduction mandates could have an adverse impact on the economy (*6*). Pozdena's study is the only one to employ econometric methodology to pursue this question, using pairwise Granger causality testing (*6*). For the 1949 to 2007 time period he reports significant bidirectional causality, which means that VMT and the economy "Granger-cause" each other. By using impulse response functions, he estimates that a downward shock to VMT, such as one due to GHG regulation, would result in a reduction in GDP of 90% of the size of the VMT shock in the short run (2 years) and 46% in the long run (20 years).

Although Pozdena uses statistical techniques to examine this causal relationship, his study does not provide enough information on methodology and alternative specifications to determine the robustness of his results. Research here shows that results are sensitive to the exact time period considered, the business cycle, and the level of geographic aggregation.

The next section introduces and explains the statistical methodology pursued in this study and discusses the two data sets, one national and the other a sample of urban areas included in TTI's Urban Mobility Report. Results of Granger causality tests are presented for the national data set for both the 1929 to 2009 and the 1949 to 2007 time periods chosen by Pozdena (*6*), so that a direct comparison of the results from the two studies can be made. Next, the causality issue is explored over the business cycle and also for a sample of 98 urban regions. Conclusions include a summary of primary findings and their implications for policy.

METHODOLOGY

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

- Well-established statistical techniques are used to test for stationarity of the time series data and determine the order of integration to use in the analysis. Five tests are used in the selection of the appropriate lag structure.
- A Chow test is used to confirm that there is a structurally different relationship between VMT and economic activity in the period 1982 to 2007 for which data at the urban-area level are available relative to the earlier post–World War II 1949 to 1981 time period. The sensitivity of the Granger causality results to the stage of the macroeconomic business cycle is examined.
- Previous studies (*6*) reported results only for national data. This study provides results with both national and urban-area data sets. Urban-area results are further broken down and reported by urban-area size as defined by TTI.

In order to deal with time series data and model specification, the Granger causality methodology and the various tests that must be performed before statistical analysis are described.

Granger Causality

Granger causality provides an analytical tool with which time precedence can be established between variables (*12*). Time precedence is one of the bases of causation, yet because Granger causality is defined in terms of predictability, it is not an acceptable definition of causation in its own right (*13*). 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 (*14*).

The Granger test provides probability > chi-square values for the *F*-statistic that tests whether all the included lags of an endogenous variable in a vector autoregression (VAR) are jointly significant. The reduced-form VAR model is shown in the system of two equations:

$$\ln\left(\text{VMT}_t\right) = c_1 + A_{11} * \left(\text{VMT}_{t-1}\right) + A_{12} * \ln\left(\text{VMT}_{t-2}\right) + A_{13} * \ln\left(\text{GDP}_{t-1}\right) + A_{14} * \ln\left(\text{GDP}_{t-2}\right) + e_t \tag{1}$$

$$\ln\left(\text{GDP}_t\right) = c_2 + A_{21} * \left(\text{VMT}_{t-1}\right) + A_{22} * \ln\left(\text{VMT}_{t-2}\right) + A_{23} * \ln\left(\text{GDP}_{t-1}\right) + A_{24} * \ln\left(\text{GDP}_{t-2}\right) + e_t \tag{2}$$

where

VMT_t = VMT from period t,
VMT_{t-1} = VMT from period $t - 1$,
VMT_{t-2} = VMT from period $t - 2$,
GDP_t = GDP from period t,
GDP_{t-1} = GDP from period $t - 1$,
GDP_{t-2} = GDP from period $t - 2$,
c = constant,
A = coefficients to be estimated, and
e_t = error term for period 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-square result less than or equal to the significance level of 5% (0.05) affords the conclusion that the lagged variable Granger-causes the dependent variable. Where causality is defined as *Y* causing *X, X* can be better predicted by using all available information rather than if all available information excluding *Y* had been used (*12*).

Tests for Stationarity

Since time series data such as those shown in Figure 1 tend to trend upward over time, they need to be tested for stationarity and then transformed, usually by using differences, before their use in a VAR model to test for Granger causality. Data are said to be stationary when they display a stable and observable mean and variance over time (*15*). 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 its use in a standard VAR model. Alternatively, nonstationary data feature 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 $I(0)$ (*16*).

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 before their use in the VAR. MacKinnon approximate p-values of the augmented Dickey–Fuller test statistic that are less than or equal to .10 indicate that the null hypothesis can be rejected at the 10% significance level; this finding suggests stationarity.

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 has individually. Cointegration can happen if the two time series share a common stochastic drift. If cointegration is present between two or more variables, they should not be used in a standard VAR model (*17*). To test for cointegration, the Engle–Granger cointegration test is applied, which uses an augmented Dickey–Fuller test on the residuals of a regression featuring two possibly cointegrated variables. For instance, if all variables are $I(1)$ and a linear combination of the two creates an $I(0)$ time series, the two variables are defined as cointegrated.

Selection of Lag Length

The lag length selection for the VAR model is made through the several tests found in the varsoc command in the STATA 11.1 (64-bit) Data Analysis and Statistical Software Program. Since Pozdena (*6*) uses lags of 4 years, that lag is used as the maximum lag length although prior studies on GDP consistently have found a need for only 1- or 2-year lags for this type of VAR (*18*). Five test statistics are used to help determine the longest lag that continues to contribute to the explanation of a VAR. So, if 3 years is found to be the appropriate lag length, lags of 1, 2, and 3 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, Akaike's information criterion, Schwarz's Bayesian information criterion, the Hannan and Quinn information criterion (HQIC), and the likelihood ratio. Ivanov and Kilian further describe these tests (*19*). In situations where all tests do not agree on lag length, Akaike's information criterion always selects the largest order, Schwarz's Bayesian information criterion always selects the smallest, and HQIC is somewhere in between (*20*). When this lack of agreement occurs, HQIC is selected in this analysis.

DATA

National Data, 1929 to 2009

The Bureau of Economic Analysis (*21*) provides annual U.S. GDP and PI data from 1929 to the present. Both GDP and PI are expressed throughout this study in terms of real 2005 dollars in order to control for inflation. FHWA publishes annual estimates of U.S. national VMT over the same time period (*22*). 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 gives general summary statistics for the national data, providing mean, standard deviation, minimum, maximum, and percent annual growth from 1929 to 2009. The same data were used by Pozdena for the 1949 to 2007 subperiod.

Urban and Metropolitan Data, 1982 to 2009

The data for urban areas have been collected and published by TTI since 1982 for their annual Urban Mobility Report (*23*). From this data set, average daily VMT on freeways and principal arterial roads is used as the urban-area VMT for this study. These VMT estimates are compiled by TTI from the Highway Performance Monitoring System database and other local transportation data sources and are put into per capita form by using population estimates from the U.S. Census Bureau.

Since urban-area GDP data are unavailable, metropolitan statistical area (MSA) PI data for the MSA that coincides with the TTI urban areas were used. At the national level the correlation between PI and GDP of .999 makes PI a good proxy for GDP. Definitions of urban area and metropolitan statistical area are given by the U.S. Census Bureau (*24*) and the Office of Management and Budget (*25*). PI, in real 2005 dollars, is from the Bureau of Economic Analysis (*21*).

TTI collects detailed data on 100 individual U.S. urban areas and categorizes these urban areas into four population-size groupings: very large (vlg), large (lrg), medium (med), and small (sml); TTI (*26*) gives categorical definitions and a list of areas in each group. Only 98 of these 100 urban areas were included in this study because two are not core urban areas inside an MSA and without this distinction PI data are not available. Very large urban areas are major generators of transportation emissions and thus may be targeted for VMT reduction policies although factors such as the aggressiveness of local transportation planning will ultimately determine implementation. Explored here is whether the size of an urban area, all else being equal, affects the causal relationship between VMT and economic activity.

Table 2 provides summary average annual statistics for VMT, income, and population variables in the TTI urban areas for the period 1982 to 2009. Although PI per capita has grown in all urban

TABLE 1 National Data Summary Statistics, 1929–2009

Variable	Mean	SD	Minimum	Maximum	% Annual Growth
Daily VMT (millions)	3,540	2,600	542	8,350	3.64
Daily VMTPC	15.21	8.03	4.16	27.94	2.45
Annual VMT (millions)	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 (millions)	$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 (millions)	$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 (millions)	203	57.1	122	308	1.16

NOTE: SD = standard deviation.

TABLE 2 Sample Urban-Area Daily VMT Summary Statistics, 1982–2009

Variable Name	Mean	SD	Minimum	Maximum	% 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 (millions)	$59,700	$95,300	$136,000	$959,000	2.70
PI (vlg) (millions)	$209,000	$45,700	$134,000	$282,000	2.67
PI (lrg) (millions)	$54,800	$12,900	$34,500	$74,700	2.83
PI (med) (millions)	$25,100	$5,030	$16,900	$33,100	2.48
PI (sml) (millions)	$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

NOTE: SD = standard deviation; UA = urban area; MSA = metropolitan statistical area; pop. = population.

areas, the growth has been fastest in the largest areas and slowest in the small urban areas.

RESULTS

Results are presented in four subsections. First, U.S. national VMT, GDP, and PI data are analyzed for 1929 to 2009 and then for the 1949 to 2007 time period for comparison with Pozdena's results (*6*). 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.

National Results

The augmented Dickey–Fuller test was used for the stationarity of logged variables from aggregate national 1929 to 2009 data. Results indicate that all six national variables are integrated of Order 1, $I(1)$, and thus are stationary as logged first differences. The Engle–Granger cointegration test provided the MacKinnon approximate p-value for the augmented Dickey–Fuller test statistic and indicated no evidence of cointegration between any of the relevant variable pairs. Thus, a standard reduced-form VAR model may be applied to this national data set.

Finally, the results of all five tests for lag structure were analyzed. Although not all test statistics agree on lag length, the HQIC test indicated a 2-year lag length in every regression at the national level. Thus a 2-year lag is used here, a choice consistent with past GDP time series studies (*18*). Because of space limitations, detailed results for all of these specification tests are not shown but are available from the authors upon request.

The Granger causality results shown in Table 3 indicate that economy activity consistently Granger-caused VMT but no statistically significant reverse causation from VMT to economic activity

TABLE 3 Granger Causality: National Data, 1929–2009

	Probability > Chi-Square	
Regression Name	VMT Causes Economy	Economy Causes VMT
VMT-GDP	0.138	0.034[a]
VMTPC-GDPPC	0.158	0.028[a]
VMT-GDPPC	0.147	0.026[a]
VMTPC-GDP	0.148	0.037[a]
VMT-PI	0.109	0.010[a]
VMTPC-PIPC	0.181	0.013[a]
VMT-PIPC	0.167	0.011[a]
VMTPC-PI	0.119	0.011[a]

[a]Represents statistical significance at 5% level.

TABLE 4 Granger Causality: National Data for Four Periods

	Probability > Chi-Square	
Regression Name	VMT Causes Economy	Economy Causes VMT
National Data (1949–2007)		
VMT-GDP	0.000[a]	0.000[a]
VMTPC-GDPPC	0.000[a]	0.000[a]
VMT-PI	0.000[a]	0.000[a]
VMTPC-PIPC	0.000[a]	0.005[a]
National Data (1949–1981)		
VMT-GDP	0.002[a]	0.000[a]
VMTPC-GDPPC	0.000[a]	0.001[a]
VMT-PI	0.001[a]	0.001[a]
VMTPC-PIPC	0.001[a]	0.014[a]
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
National Data (1982–2009)		
VMT-GDP	0.002[a]	0.120
VMTPC-GDPPC	0.005[a]	0.216
VMT-PI	0.002[a]	0.120
VMTPC-PIPC	0.005[a]	0.216

[a]Represents statistical significance at 5% level.

for the 1929 to 2009 time span. These results are significant at the 5% level and robust across alternative measures of economic activity (GDP, GDPPC, PI, and PIPC). This finding supports the hypothesis that VMT is a normal good and that consumers drive more as a result of higher incomes associated with increased economic activity. This finding does not support the contention that exogenous policy reductions in VMT would cause a significantly negative impact on economic activity as measured by either GDP or PI.

For direct comparison with Pozdena, Granger causality results for the 1949 to 2007 period are shown in the first section of Table 4. When Pozdena's subperiod is used, the bidirectional results that he reports are found here as well. Thus, it appears that the Granger causality results may be somewhat dependent on the specific time period considered. Possible reasons for this difference in results are explored in the next section.

Testing for Structural Break in Data Set

In the early part of the 20th century, the highway system was in its infancy. Following World War II, highway building accelerated, especially after the initiation of the Interstate Highway System in 1956 and its completion in the 1970s. The 1949 to 2007 sample period was divided into two subperiods, 1949 to 1981 and 1982 to 2007, for two reasons. First, it is reasonable to 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 before and after 1982 it can be seen that public road mileage grew at an annual percentage rate of 0.50% during the 1949 to 1981 time period but at a rate of only 0.19% between 1982 and 2007. The higher rate of growth in road miles 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 policy making, 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 in this study to explore the relationship in urban areas were only available on an annual basis from 1982 to the present.

A Chow test [discussed by Hamilton (*16*)] was used for a structural break in the post–World War II national data with 1949 to 1981 and 1982 to 2007 as the subperiods. The resulting F-statistic (2, 55) of 74.0667 suggests a significant improvement in the model's fit by splitting the sample at the year 1982 rather than pooling the data from 1949 to 2007 (*27*). This finding confirms the hypothesis of a structural change in the relationship between VMT and GDP at the national level in 1982.

Granger causality results for the before- and after-1982 periods are reported in the second and third sections of Table 4. As noted earlier, bidirectional causality is found between VMT and GDP for all of the period 1949 to 2007. However, when the sample is split into the before- and after-1982 subperiods, bidirectional results are found for 1949 to 1982 only. There is no significant relationship in either direction for the after-1982 period. This significant change in causality results suggests that factors other than VMT are the major determinants of GDP or PI and that exogenous policy decreases in VMT would not negatively affect economic activity.

Impact of Business Cycle on Relationship of VMT and Economic Activity

The results reported earlier are sensitive to the years included in the study. When the data set 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 to 2009 period there is significant Granger causation flowing from VMT to economic activity (fourth section in Table 4). Typically the addition of only 2 years would not be expected to completely change the significance of the Granger causation, but the 2 years added were both in the heart of an economic recession (known to be caused by a 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 dating for peaks and troughs in the business cycle between 1929 and 2009 from the National Bureau of Economic Research (*28*) 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 as upturns if they occur during the time between a trough and a peak. Now the analysis shows that during economic downturns VMT Granger-causes economic activity (or bidirectional causation is seen), but during economic upturns economic activity Granger-causes VMT (see Table 5). This finding explains why the addition of the data for 2008 and 2009, two economic downturn years, completely changed the output. Changes in VMT are often used by macroeconomic forecasters as one indicator of turning points in the business cycle, although every large macroeconomic cycle that has occurred in this time span has generally accepted causes other than exogenous reductions in VMT.

TABLE 5 Granger Causality: National Data Structural Breakdown with Economic Downturns, 1929–2009

Regression Name	Probability > Chi-Square: VMT Causes Economy	Economy Causes VMT
National Data: During Economic Downturn (*n* = 16 of years 1929–2009)		
VMT-GDP	0.002[a]	0.159
VMTPC-GDPPC	0.005[a]	0.183
VMT-PI	0.007[a]	0.003[a]
VMTPC-PIPC	0.003[a]	0.026[a]
National Data: During Economic Upturn (*n* = 62 of years 1929–2009)		
VMT-GDP	0.113	0.000[a]
VMTPC-GDPPC	0.140	0.000[a]
VMT-PI	0.064	0.001[a]
VMTPC-PIPC	0.217	0.002[a]

[a]Represents statistical significance at 5% level.

TABLE 6 Granger Causality for 98 Urban Areas

Regression Name	Probability > Chi-Square: VMT Causes Economy	Economy Causes VMT
Urban Area Data (1982–2009)		
VMT-PI	0.524	0.357
VMTPC-PIPC	0.116	0.101
VMT-PIPC	0.151	0.454
VMTPC-PI	0.111	0.002[a]
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[a]	0.462
Urban Area Data (1982–2007)		
VMT-PI	0.805	0.320
VMTPC-PIPC	0.782	0.037[a]
VMT-PIPC	0.932	0.647
VMTPC-PI	0.796	0.941
VMTPC(vlg)-PIPC(vlg)	0.929	0.359
VMTPC(lrg)-PIPC(lrg)	0.170	0.046[a]
VMTPC(med)-PIPC(med)	0.900	0.381
VMTPC(sml)-PIPC(sml)	0.778	0.148

[a]Represents statistical significance at 5% level.

Urban-Area Results

The same methodology that was applied to the national-level data set is used again for the urban-area data set. Data are first aggregated over all 98 urban areas in the study and Granger results are presented. The urban areas are then divided into the TTI urban size subgroups to determine whether there is a difference in the relationship observed between VMT and economic activity depending on urban-area size.

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

Since the VMT variables are stationary and do not share the same order of integration as the PI variables, they cannot be cointegrated. Hence, the standard reduced-form VAR model can be applied to the urban-area data, as it was to the national data.

The urban-area VAR tests indicate a 2-year lag length in every regression except VMTPC-PI, for which a 3-year lag length was indicated and thus used. As before, when not all five lag tests agree on lag length, the HQIC result was chosen.

Granger causation at the aggregated urban-area level for the 98 urban areas in this sample indicates no significant causation in either direction for most VMT–income definitions for both the 1982 to 2007 and the 1982 to 2009 sample periods (Table 6). In the two cases in which there is significant causation (VMTPC-PI for the 1982 to 2009 period and VMTPC-PIPC for the 1982 to 2007 period) it is from economic activity to VMT. Although the national data show no significant causation for the 1982 to 2007 sample, reverse causation from VMT to economic activity was found for all VMT–income definitions (see Table 4) in the national data. Thus, there appears to be some difference in results for the urban areas and the nation as a whole.

Although reverse causation for the national data was earlier shown to be related to downturns in the business cycle, the researchers were unable to test the causal relationship for aggregated urban areas over the business cycle because of an insufficient number of downturns in the after-1982 period to allow STATA 11.1 to produce statistically meaningful results.

Overall the results for the four different-size urban areas show there to be little evidence of significant causation in either direction for either time period. For large areas, economic activity leads to VMT when per capita definitions are used with the 1982 to 2007 data set but not for the data set that goes through 2009. The small urban-area group shows reverse causation for 1982 to 2009, but the 1982 to 2007 result shows no significant causation in either direction.

CONCLUSIONS

The relationship between VMT growth and growth in economic activity is complex. This study uses time series techniques and Granger causality to provide some insight into the causal relationships. Earlier studies that found bidirectional causation are shown to be valid only for the before-1982 period but not for 1982 to the present, which is the time period that should be of interest for prospective policy making.

Results showing that changes in VMT lead to economic activity seem to be very sensitive to the exact time period selected. In the national data set the addition of 2 years of economic downturn, 2008 and 2009, to the 1982 to 2007 data set resulted in a finding of reverse causation or VMT leading to economic activity. Further analysis showed the causal relationship between VMT and GDP to be dependent on the macroeconomy and the stage of the business cycle. In macroeconomic upturns, which represent almost 80% of the years in the current sample, GDP growth was found to unidirectionally Granger-cause VMT growth. VMT was found to lead to economic activity only in downturns. However, this finding does not necessarily mean that reductions in VMT caused the economic downturns since there is little theory to support this finding at the national level. Rather, this is a statistical finding that supports the practice of using VMT changes as an indicator of a turning point in the macroeconomic business cycle.

Further, virtually no significant causal relationship was found between VMT and economic activity in urban areas, and when significant Granger causation was found, it suggested that changes in economic activity lead to changes in VMT. Only for small urban areas with the 1982 to 2009 sample period was some reverse causation found, a result that turned insignificant when the 1982 to 2007 period was used instead.

These findings suggest that policies designed to reduce VMT may be used without the threat of compromising national economic activity since the results from this study indicate either that economic activity "causes" VMT or that there is no clear significant causation in either direction.

The results for the U.S. urban areas show little significant causal relationship between economic activity and VMT. However, care should be taken to further explore the determinants of VMT in urban areas before VMT reduction policies are implemented across the board. This stipulation is especially true for small urban areas, where the causal results were mixed. For instance, it is possible that smaller urban areas lack the transit alternatives available in larger areas that help mitigate negative impacts from exogenous reductions in VMT. Thus future research is needed to explore the relationship between VMT and economic activity on a more microeconomic level in urban areas to determine where potential adverse impacts might arise and how policy could be formulated to mitigate those impacts.

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