The Effects of Road Investments on Economic Output and Induced Travel Demand: Evidence for Urbanized Areas in the US

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ABSTRACT

The objective of this paper is to analyze the effects of road transportation investment on economic output and induced travel demand. Data for US urbanized areas are analyzed within a dynamic panel data VAR framework to test whether transportation induced economic growth effects and induced travel demand can be empirically validated. The results show that investment in road capacity increases average economic growth while simultaneously also inducing additional growth in traffic (vehicle miles travelled). Indeed, we find a general failure of investment to alleviate levels of congestion suggesting that productivity shifts are brought about due to a net increase in the scale of travel and associated interactions, rather than improved network performance as measured by travel times. The evidence also shows that congestion forms parts of the decision criterion used to allocate investments in road capacity. If improvements in network performance are to be achieved in a climate of travel demand growth, demand management techniques may be more effective than capacity expansion.

INTRODUCTION

Transportation investment is a high priority in the United States and forms a large portion of the nation's annual budget. In fact, it is considered so vital that on 6th September 2010, President Barack Obama announced a six year investment plan with an initial $50 billion infrastructure package to invest in roads, railways and airports [1]. Such policy statements are based on the principle that transportation and economic performance are positively linked, forming a key justification for the allocation of resources to the transportation sector. There has been extensive research examining the contribution of transportation infrastructure (and more generally public infrastructure) to economic output in the US. The quantification of these effects has been a source of much debate as there are difficult data and estimation issues complicating the analyses and the validity of their respective results. In their extensive survey of the literature, Banister and Berechman [2] conclude that whereas public capital investment can have positive impacts on economic growth, the magnitude and significance of the effects are far from conclusive. Nevertheless, there is ongoing support of a positive contribution of transportation investment to economic growth, as expressed by the abovementioned US DOT statements.

Critiques of transportation induced growth strategies are articulated in the literature on induced travel demand. This literature asserts that investments in additional road transportation capacity will induce additional road traffic growth, thus failing to ease congestion levels and achieve superior network performance [e.g. 3, 4-6]. Consequently, investments in road capacity are sometimes viewed as providing poor value for money since the cost of congestion to the economy may not be substantially reduced and could even worsen.

It is well understood that congestion has a negative impact on the delivery of goods, services, and people, eventually leading to a decline of economic growth. This is particularly important in the US, as unlike many other developed countries, the US relies more heavily on its road network. According to the Texas Transportation Institute (TTI), levels of traffic congestion have increased year on year since 1982. They further estimate that traffic congestion in the 439 urban areas in the US contributed to losses of about $87.2 billion in 2007 [7].

It is important to emphasize at the beginning that the objectives of this paper are not to produce new estimates of the output elasticity of transportation infrastructure nor elasticities of vehicle miles travelled (VMT) with respect to road lane miles. The objective of the study is to analyze the relationship between road transportation investment and economic output within an empirical framework that also allows for induced travel demand. The empirical work conducted in this paper is based on dynamic panel data VAR models applied to US urbanized areas. We perform bidirectional Granger causality tests to evaluate whether transportation induced economic growth effects and induced travel demand can be validated, and whether, and how, their potentially conflicting effects may be reconciled.

The results show that the hypotheses maintained both by advocates of induced transportation economic growth effects and induced travel demand appear to be valid for urbanized areas in the US. Investment in increased road capacity is found to increase economic output and vehicle miles travelled, while failing to alleviate congestion levels. We interpret this as showing that, far from being incompatible, transportation induced travel demand and transportation induced economic growth effects are consistent outcomes in the sense that by allowing for an increase in the scale of travel and associated interactions, investments have induced a positive shift in economic output. This positive effect can be interpreted as a form of external returns to scale, akin to the effect induced through urban agglomeration economies.

The results also show that although additional road capacity is not effective in lessening congestion, congestion does appears to influence the decision criteria used to allocate investment in road capacity. This implies that if improvements in network performance are to be achieved in a climate of travel demand growth, demand management techniques (e.g. road congestion pricing to achieve trip rescheduling and mode shift) may be more effective than capacity expansion.

This paper is structured as follows. Section two provides an overview of existing empirical evidence for the US on the relationship between transportation and economic performance and induced travel demand. Section three describes the data and empirical methodology. The main results are presented and discussed in Section four. Section five provides a summary of the main conclusions.

LITERATURE REVIEW

This section provides an overview of the two transportation-related literatures relevant for the analyses conducted in this study. The following sections summarise existing empirical evidence for the US on the relationship between transportation and economic performance and induced travel demand, respectively.

Transportation Investment and its Impact on Economic Output

The impact of transportation investment on economic performance has been the focus of extensive research over the past decades. Public investments in transportation infrastructure can increase economic performance both in direct and indirect ways. Transportation is an important input factor in the production process as it enables goods and passengers to be transferred between consumption and production centres. Improvements to transportation networks can also increase firms' output by reducing factor costs and thus allowing for scale effects (e.g. same output at lower cost or more output at same cost) [2, 8, 9].

Another important contribution of transportation to economic performance relates to what the literature generally calls 'transport-induced agglomeration effects'. Agglomeration economies occur when economic agents (firms, workers) benefit from being close to other economic agents. Transportation improvements can increase the strength of agglomeration economies to the extent that they increase connectivity within the spatial economy. By changing the way people and firms have access to economic activity, transportation bears an impact on the realization of agglomeration externalities and hence on the productivity effects derived from it [e.g. 10, 11].

There has been substantial empirical work for the US with the aim of quantifying the relationship between transportation infrastructure and economic performance. The pioneering work of Aschauer [12] established a very strong contribution from public capital to private sector economic output, and provided an empirical platform for which much research has been conducted.

The most common empirical approach consists of estimating single-equation production and cost functions to estimate the output and cost elasticity of transportation investment respectively. Early studies using this approach at state level in the US provide evidence on strong positive effects of transportation to economic output (e.g. Costa et al. [13], Munnell [14], Garcia-Mila and McGuire [15], Williams and Mullen [16]). These studies were subject to criticisms on the grounds that they failed to account for major estimation issues notably that of unobserved individual heterogeneity and simultaneity bias between transportation and economic output. Latter studies made improvements on some of the key econometric issues and obtained lower and often statistically insignificant results (e.g. Evans and Karras [17], Baltagi and Pinnoi [18], Holtz-Eakin and Schwartz [19], and Garcia-Mila et al [20], Jiwattanakulpaisarn [21]).

As an alternative the single-equation models, various researchers have adopted a vector autoregressive (VAR) approach to identify the productivity effect of transportation investment. The most cited examples of such studies for the US include Pereira and Flores de Frutos [22] and Pereira [23]. Pereira and Flores de Frutos [22] find public capital to be productive, although considerably less than previously estimated by Aschauer [12]. They find evidence of reverse causality between economic output and public capital, and conclude that policy decisions on public capital investment depend positively on lagged values of output. Pereira [23] finds a positive effect from all types of public investment (highways and streets in particular) on economic output, and estimates that the magnitude of this effect in the long run equalled $4.46 of additional output for each one dollar spent in public investment. Demetriades and Mamuneas [24] offer an international perspective, and develop a dynamic model based on cross-country panel data. A system of equations is estimated on the returns of public capital in 12 OECD countries, which provides evidence in favour of a significant contribution of infrastructure to output. The long-run marginal products of capital obtained for the US are comparable to those obtained by Aschauer [12].

Despite the abundant research on the impact of transportation investment on economic output, there is very little empirical evidence on the effect of increasing road congestion on economic growth. Previous research by Boarnet [25] and Fernald [26], both using data for the US, suggests that there is indeed a negative impact on economic output, while Hymel [27] finds a negative impact of congestion on employment growth in large US metropolitan areas. The studies mentioned differ in the way they measure congestion. Hymel [27] is the only study using a direct measure of road congestion (travel delay), while Boarnet [25] and Fernald [26] use measures of road use (e.g. VMT). In this paper, we attempt to provide additional evidence on the relationship between road transportation infrastructure, road congestion, and economic output.

This brief overview of evidence for the US on the effects of transportation on economic growth suggests that existing empirical literature can be best described by the existence of mixed results, agreeing towards small, but statistically significant, positive effects. It also emphasise the lack of evidence on the effects of congestion on economic output.

Transportation Investment and Induced Travel Demand

Attempts to alleviate congestion by increasing road capacity heralds the well understood theory of induced travel demand (e.g. Leeming [28], Lee et al. [29], Noland [3], Cervero and Hansen[5]). There is an abundance of empirical studies on this topic. Cervero [4] carried out a meta-analysis and concluded that although empirical work confirms the hypothesis of induced travel demand, there is substantial variation in the magnitude of its effect.

Hansen et al [30] provide one of the first authoritative studies on induced travel demand at project level by focusing on 18 highway segments over a 20 year period in California. The study carried out regressions under two opposed scenarios: capacity increase versus no capacity expansion. The difference in predicted traffic under the two scenarios was assumed to be the traffic induced by expansion. The results show an increase in travel demand elasticities over the years (first 4 years 0.2-0.3, after 10 years 0.3-0.4, after 16 years 0.4-0.6). A more recent attempt includes Cervero [31], who looks at 24 freeway projects over a 15 year period in California. The study employed a path model to explore the causal links between freeway investments and the corresponding traffic increases. The results also confirmed the presence of induced demand increasing over time, while estimating much smaller elasticity values of 0.1 and 0.39 for short- to long-run respectively.

Considering the studies focusing on larger geographical areas, Hansen and Huang [32] analysed urban counties and metropolitan areas in California. The study used a panel data set and adopted several versions of a log-linear model including regional and time period fixed-effects. The results estimated elasticity values between 0.6-0.7 at county level, and 0.9 at the metropolitan level. Since then, more recent research has pointed out the issue of simultaneity bias. Fulton et al [33] applied fixed-effects panel data models and two-stage least squares procedures to data from Maryland, Virginia, North-Carolina, and Washington. Average elastiticity values were estimated to range between 0.2 and 0.6. Cervero and Hansen [5] considered urban counties in California. The study applied simultaneous models and proposed a comprehensive set of instrument variables to deal with simultaneity bias. The results indicate higher elasticities of 0.59 and 0.79 for short-term and medium-term respectively. Interestingly, both studies also included Granger causality tests. Fulton et al [33] used Granger causality tests to show lane miles precede growth in VMT, while Hansen [5] used Granger causality tests to cross-check the simultaneous estimations.

Examples of state level studies include Noland [3] and Hymel et al [6]. The former study adopted a fixed-effects panel data model and concluded that 25% of VMT growth could be attributed to lane mile additions. The latter study adopted simultaneous models on cross-sectional data, finding that congestion affects the demand for driving negatively, and an elasticity of induced demand of about 0.16.

Regardless of the scale of analysis, it appears that induced travel demand is persistently significant in previous research, although its magnitude varies across studies. Interestingly, Cervero [4] reminds us that perhaps too much emphasis has been placed on measuring induced travel demand, and that regardless of the elasticity of VMT with respect to road investment, there should be more focus on the potential contributions of travel demand management strategies.

DATA AND METHODOLOGY

Data

The data used in this study relates to the 100 urbanized areas included in TTI Annual Urban Mobility Reports. Transportation infrastructure data and congestion data have been compiled and updated annually by the TTI as part of their series of Annual Urban Mobility Reports. The TTI Urban Mobility database is therefore used as the main source of data for the analyses conducted in the paper as it offers an integrated record of both road infrastructure and road congestion measures for a relatively long period (1982 to 2010). The same database has been previously used to study congestion in the US [e.g. 6, 27].

Two road types are considered, freeways and arterial streets. Freeways can be defined as express routes with limited access, while arterial streets essentially consist of major thoroughfares that serve traffic in urban areas. Under the DOT, the Federal Highway Administration (FHWA) [34] provide functional classification guidelines for which streets and highways are grouped into classes, or systems. In general, it is acknowledged that freeway commuters tend to travel longer distances. On the other hand, arterial streets are designed to be high capacity while tending to involve shorter commutes. An example includes Denver City [35], where their arterial street system is described as interconnecting *"major urban elements such as the Central Business District, industrial facilities, large urban and suburban commercial centers, major residential areas, and other key activity centers".*

As a measure of road supply, lane miles (LM) are available for each urbanized area and year between 1982 and 2009. As a measure for travel demand, the database provides daily vehicle miles of travel (VMT) for freeways and arterial streets, which consists of the average daily traffic on a road section multiplied by its length. To represent congestion, we use the TTI measure hours of delay per peak period traveller is used (TD), which provides an approximation of the total annual amount of time lost because of congestion. Appendix A of the TTI Urban Mobility Report provides a description of the methodology from which these measures have been calculated, as well as a discussion of its main limitations.

Economic data for real Gross Domestic Product (GDP) per capita were obtained from the US Department of Commerce, Bureau of Economic Analysis (BEA), but are restricted to the period 2001 to 2009 for the Metropolitan Statistical Areas (MSA). The TTI data for lane miles, vehicle miles travelled, and delay are at the level of Urban Areas (UA), whereas data for economic output are available only at the MSA level. We therefore attributed real GDP per capita data to UA based on the respective MSA to which the UA belongs; we use this measure as a proxy for each UA's production. While, we acknowledge that this may give rise to some measurement error, this was thought to be a reasonable way to derive economic data for UA.

Table 1 describes the variables used in our analyses, their sources, and provides some basic descriptive statistics. Figure 1 shows the evolution in vehicle miles travel, lane miles, and annual delay per peak period traveller between 1982 and 2009 for freeways and arterial streets. We computed Compound Annual Growth Rates (CAGR) to analyse the growth in these variables.

Over the period 1982-2009 VMT has grown by an average annual rate of 2.2% for arterials and 3.13% on freeways. Note that between 2007 and 2009 the number of VMT dropped (-0.98% for arterials and -1.17% for freeways) and this can be attributed to the global financial crisis. When we compare the average annual increase in VMT to that of network lane miles over the same period, which is 1.71% and 1.63% for freeway and arterial roads respectively, it is clear that the rate of increase in demand is far greater than the rate of increased capacity. In fact the growth of freeway and arterial street lane miles has been very steady over the period (even during the recent recession period the CAGR for arterials and freeways was positive and equal to 0.31% and 0.24% respectively), but has lagged rates of VMT growth (see Figure 1). Consequently, congestion has also increased. In particular, total delay per peak period traveller is observed to have increased according to a CAGR equal to 3.21% between 1982 and 2007, while it reduced by -3.88% between 2007 and 2009 (see Figure 1).

Methodology

We develop a dynamic panel VAR model to examine the presence of Granger causality by testing whether past values of a given variables (e.g. X) help predict future values of another variable (e.g. Y). The first application of VAR models using panel data was presented by Holtz-Eakin et al [36]. Recent approaches have drawn from this, and relevant examples include Jiwattanakulpaisarn [21] and Graham el al [37]. These papers are especially relevant as the models used in this paper follow the same empirical procedure.

The empirical model underlying our analyses can be described as follows:

$$\mathrm{lnX_{it}} = \propto + \sum_{p=1}^{m} \beta_p \mathrm{lnX_{i,t-p}} + \sum_{p=1}^{m} \gamma_p \mathrm{lnY_{i,t-p}} + \mathrm{f_i} + \eta_t + \varepsilon_{it} \quad (1)$$

$$\mathrm{lnY_{it}} = \delta + \sum_{p=1}^{m} \Phi_p \mathrm{lnY_{i,t-p}} + \sum_{p=1}^{m} \psi_p \mathrm{lnX_{i,t-p}} + \zeta_i + \xi_t + \nu_{it} \quad (2)$$

where the subscripts *i* (*i*=1,…,N) and *t* (*t*=1,…,T) index the various urbanized areas and time periods respectively. The terms ε_{it} and ν_{it} denote white noise residuals, while η_t and ξ_t account for unobserved shocks that are common to all urbanized areas but vary across time, and f_i and ζ_i represent unobserved individual time-invariant heterogeneity. The number of time lags is *m*, which is specified to be identical for all variables.

For equation (1), Y is said to Granger-cause X if we can reject the joint null hypothesis that the parameters $\gamma_1 = \gamma_2 \ldots . = \gamma_p$ are equal to zero. Similarly for equation (2), X is said to Granger-cause Y if we can reject the null hypothesis that the parameters $\psi_1 = \psi_2 \ldots = \psi_p$ are equal to zero. Essentially, the criterion being tested is whether the lagged independent variable provides statistically significant information that helps to predict contemporary values of the dependent variable.

Because the VAR model above includes autoregressive terms that are correlated with the time-invariant individual effects, standard panel data estimators will produce inconsistent parameter estimates. The Generalised Method of Moments (GMM) can offer a means of obtaining consistent parameter estimates in the context of dynamic panel models [e.g. 38, 39].

Essentially, the idea is to construct a set of valid instruments based on the time series nature of the dataset, which are correlated with the covariates but uncorrelated with the error term.

We will consider two dynamic GMM estimators. The difference-GMM estimator [38] involves taking first differences of the model, to eliminate individual effects, and using time lags from periods *t-2* and earlier ($t \geq 3$) as instruments. However, the difference-GMM has been shown to perform rather poorly when highly persistent data (i.e. little variation aver time) are used [e.g. 40]. This is because of the weak correlation between the lagged levels of the variables and their first-differences, which gives rise to the well documented issue of weak instrument bias [39]. In this context, the system-GMM [39, 41], which proceeds by estimating regressions in differences and in levels simultaneously, has been shown to be a preferable alternative to the difference-GMM as it can offer substantial increases in efficiency and less finite sample bias [e.g. 40].

In carrying out the Granger causality tests, there are a number of issues to contend with. Firstly, we must consider the appropriate lag order of the models to be estimated. To select the most appropriate lag structure, we adopt a sequential general-to-particular approach, where a joint significance test is used to evaluate the statistical importance of successive time lags of the variables in the model. The maximum number of lags was limited to three. This approach is consistent with Graham [37], who notes that the inclusion of further lags does not provide additional information and can introduce strong multicollinearity in the estimation in a context of highly persistent data.

Consistency of the dynamic GMM estimator depends on two crucial assumptions: no first order serial-autocorrelation in the error term of the levels equation, and instrument exogeneity. To evaluate these assumptions, we consider the Arellano and Bond autocorrelation tests and the Sargen/Hansen tests. The Arellano and Bond [38] tests for serial autocorrelation evaluate the hypothesis that there is no second-order serial correlation in the first differenced residuals, which in turn implies that the errors from the levels equations are serially uncorrelated [37]. If there is serial correlation then the instruments used are not valid and there is need for another set of instruments starting with deeper time lags. The Sargan/Hansen test of overidentifying restrictions is the standard test for the validity of the instrument [37].

The relevance of instruments used in the difference and system GMM can be determined by performing Wald tests. Similarly to [37], these are obtained by regressions on the identifying instruments. We consider two tests. The Wald test (FD) shows the results for the regression of first differences on past levels of the endogenous variable, corresponding to the moment conditions of the difference GMM estimator. The Wald test (Levels) shows the results for the regression of the current levels on first differences, corresponding to the additional moment conditions contained in the system GMM estimator.

Similarly to any general IV estimation, the appropriateness of the dynamic GMM estimators also depends on the quality of the instruments used. To evaluate instrument relevance in the context of dynamic GMM, we estimate auxiliary regressions, for both the difference- and system GMM, of the lagged dependent variable on its corresponding instruments. We then conduct a test for the joint significance of the instruments in order to assess which of the difference and system GMM estimators appears to provide better instruments. A similar approach is used by Jiwattanakulpaisarn [21] and Graham el al [37].

As explained in Jiwattanakulpaisarn [21] and Graham el al [37], the individual parameters of Granger causality models are difficult to interpret when considered alone; as a result we compute long run elasticity estimates related to respective Granger causality results. Considering equation (1) above, the long run coefficient for Y - γ_{LR} - is calculated as follows:

$$\gamma_{LR} = \frac{(\gamma_1+\gamma_2+\cdots+\gamma_m)}{(1-(\beta_1+\beta_2+\cdots+\beta_p))} \tag{3}$$

where γ_p and β_p are the coefficients of variables Y and X lagged mth periods, respectively. All other long-run coefficients were calculated in a similar manner.

RESULTS

Full GMM estimates from the VAR models are presented in Table 2. There are 20 columns of estimates in the table, comprising 10 for freeways and arterial streets respectively. The long run elasticity estimates relating to the statistically significant Granger causality tests are reported in Table 3 and are also illustrated in Figure 2.

We first consider the results in Table 2 and the validity of the assumptions underlying the model specification. The following tests are to be considered. There is one test for the lag order of the VAR model – Wald test (Order) -, and three tests concerning the validity of the dynamic GMM estimators: tests for serial autocorrelation - AB AR(1) and AB AR(2) -, tests for instrument exogeneity - Hansen test -, and tests for instrument quality - Wald test (FD) and Wald test (Levels).

We select the lag structure using a Wald test and a sequential general-to-particular approach as explained in section three of the paper. All the models shown in Table 2 pass the Arellano-Bond tests (AB AR(1) and AB AR(2)) of serial autocorrelation in the error term of the levels equation. The Hansen test fails to reject the null hypothesis of instrument exogeneity in all of the models, suggesting that the set of instruments used is valid.

The rows ‘Wald test (FD)’ and ‘Wald test (Levels)’ inform about instrument quality and refer to the regressions of the instruments used in the difference- and system-GMM respectively. The tests show that the system-GMM provides an improvement of instrument relevance, compared to the difference-GMM. This is as expected, as the system-GMM estimator provides more efficient estimates as it combines moment conditions obtained from equations in first-differences with additional moment conditions exploited from equations in levels.

In order to interpret the results, it is important to remember that the criterion being used to establish Granger causality is whether the lagged independent variables provide statistically significant information that helps us to predict contemporary values of the dependent variable. As explained previously, we must also take into account the long run coefficients, as the individual parameters of Granger causality models are difficult to interpret when considered alone. We report the long run elasticities relating to the statistically significant Granger causality tests in Table 3; these relationships are also illustrated in Figure 2.

We first consider the evidence relating transportation investment to economic growth. We find evidence that investment in both freeways and arterial streets Granger causes economic growth in urbanized areas. This result is in line with the theory proposing that public infrastructure has positive effects on economic performance levels. There is, however, no evidence of reverse causality from economic growth to road transportation infrastructure. Although perhaps unexpected, this result is consistent with the remaining findings emerging from our analysis, as we discuss below.

The second main finding relates to induced travel demand. We find evidence supporting the presence of induced travel demand in urbanized areas. This result is in accordance with the induced travel demand argument that additional road capacity is 'absorbed' by increases in traffic volumes, leading to the worsening of congestion and its eventual return to initial levels. The following Granger causality relationships underpin this result. Investment in additional arterial streets' lane miles is found to Granger cause traffic volumes (VMT), which in turn are also found to Granger cause congestion levels (hours of delay per peak traveller). As a result, adding more capacity to road leads to the building-up of increased traffic and the subsequent deterioration of road performance levels and travel time reliability, both reflected in increased hours of delay.

Turning to the evidence for reverse causality, we find that congestion Granger causes arterial lane miles, whereas there is no evidence of Granger causality from arterial VMT to arterial lane miles. This result suggests that road supply investment decisions may be based on congestion levels, that is, investment in additional road capacity is allocated both spatially and temporally according to road performance levels. Moreover, this result may also help understand the failure to observe Granger causation running from productivity to road transportation supply, as it seems that the latter responds to road performance levels instead.

It is interesting to notice that the relationships discussed above, between road supply, road traffic, and road congestion, are only identified for arterial streets, not for freeways. There is no evidence of Granger causality links between freeway lane miles and induced travel demand or congestion. To help understand this result, we consider the following reasons. Whereas arterial streets relate essentially to urban interactions, freeways are more likely to connect different urban areas. As a result, we would expect freeways' road supply to be a function of the degree of economic interaction and size of *neighbouring* urban areas, rather the size of the own-urban area size. Given their inter-urban nature, relationships involving freeways are likely to be better characterised according to gravity type models. The results obtained in the Granger causality context developed in this paper may therefore result, at least partially, from the inability of our models to appropriately capture the effects described above.

So far, we have found evidence supportive of the assertions defended by both the transportation- productivity literature and the induced travel demand literature. Both claims appear to be confirmed by our empirical analyses using data for urbanized areas in the US. To reconcile what may appear to be a conflicting result, that is, the fact that investment in additional road capacity should not be pursued by decision makers on the grounds that it only achieves, at best, initial congestion levels, we now consider the final set of results. We find evidence that VMT in both freeways and arterial streets Granger cause economic output. This means that even though congestion levels are not alleviated by additional road capacity, the increase in the scale of interactions promoted by increased road capacity gives rise to a form of increased returns to scale, which similarly to urban agglomeration economies, have a positive impact on economic performance. Compared to the studies conducted by Boarnet [25] and Fernald [26], we find weaker evidence of a negative impact of road congestion on economic output growth. We believe this is because we also allow for a scale effect captured by the additional economic interactions (represented by VMT) enabled by additional road capacity.

Four key findings emerge from these results. First, the results unambiguously suggest that investment in road transportation networks helps predict future levels of economic output, a result consistent with the causality proposed by theory. The second important finding is that we also find evidence in favour of the theory of induced travel demand: increases in arterials' road capacity induce additional growth in traffic volumes, raising road congestion levels. The third important finding is that in spite of the inability of additional road capacity to alleviate congestion, the evidence supports the existence of positive returns to scale resulting from the increase in interactions made possible by investments in additional road capacity.

Finally, and although the aforementioned scale effect appears to still outweigh the negative impacts from congestion, it is also evident from our analysis that improvements to road performance levels should not be pursued solely on the grounds of additional road capacity, but rather include demand management measures which may be more effective in influencing the different components of additional travel demand (e.g. mode shifts, time-of-day shifts, etc.). As a result, these measures may also allow for efficiency improvements resultant from a selection process that favours more productive trips/interactions over less productive ones.

CONCLUSION

This paper conducted empirical work based on dynamic panel data VAR models to analyze the relationship between road transportation investment and economic output within a framework that also accounts for the role of induced travel demand.

The results of the analyses confirm that the claims maintained both by advocates of induced transportation economic growth effects and induced travel demand appear to be valid for urbanized areas in the US. Increased road capacity is found to increase economic output in urbanized areas. Similarly, increased road capacity is also found to increase traffic volumes (vehicle miles travelled), without alleviating congestion levels. We interpret this as showing that, far from being incompatible, transportation induced travel demand and transportation induced economic growth are consistent outcomes in the sense that by allowing for an increase in the scale of travel and associated interactions, investments have induced a positive shift in economic performance. This positive effect can be interpreted as a form of external returns to scale, akin to the effect induced through urban agglomeration economies.

While our results suggest that investment in road capacity may not offer an effective congestion mitigation strategy, the evidence indicates that congestion has been used as a decision rule to allocate investment in road capacity. If improvements to road performance and travel time reliability are desired, investments which are not restricted to the physical capacity of road networks, but rather include demand management techniques may be more effective by targeting the various components of induced travel demand individually (e.g. road congestion pricing to achieve trip rescheduling and mode shift).

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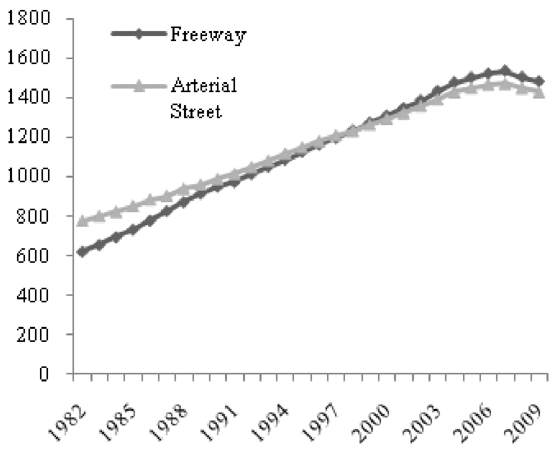
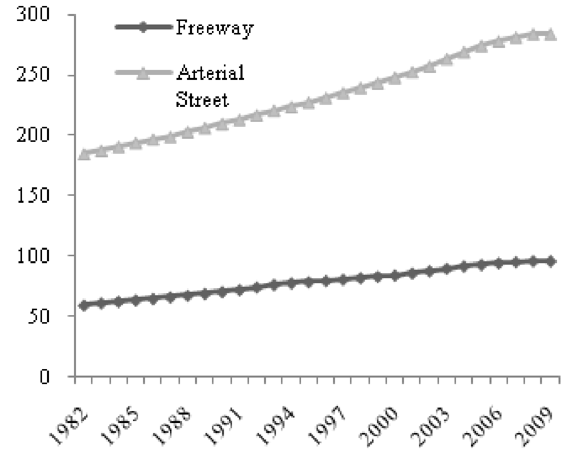
LIST OF TABLES AND FIGURES



(a)



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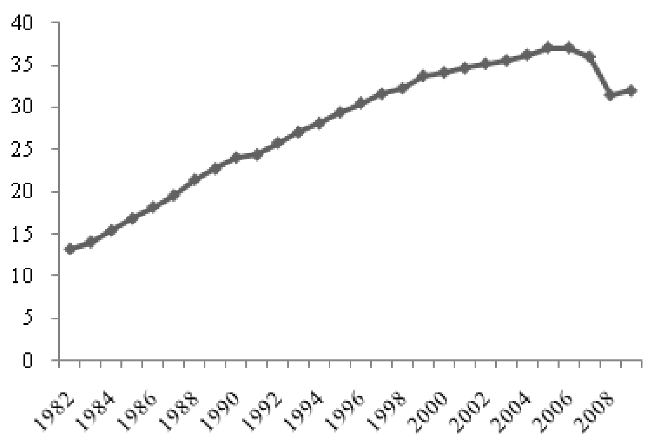

(c)

FIGURE 1 (a) Vehicle Miles of Travel (millions); (b) Lane Miles (thousands); (c) Average Annual Delay per Peak Period Traveller. Data are for TTI 100 Urban Areas, 1982-2009.

TABLE 1 Description of Variables, Data Source, and Descriptive Statistics

Variables	Code	Years	Count	Mean	Standard Deviations		
					Overall	Between	Within
Freeway Lane Miles[a]	LM	1982-2009	2,800	790.18	970.36	959.81	171.08
Arterial Street Lane Miles[a]	LM	1982-2009	2,800	2,328.48	3,016.61	2,994.31	469.65
Freeway Vehicle Miles of Travel[a] (000s)	VMT	1982-2009	2,800	11,311.73	17,294.76	16,742.29	4,637.71
Arterial Street Vehicle Miles of Travel[a] (000s)	VMT	1982-2009	2,800	11,535.38	16,030.47	15,688.91	3,634.33
Annual Hours of Delay per Peak Period Traveller[a]	TD	1982-2009	2,800	27.76	17.44	14.68	9.52
Gross Domestic Product per Capita[b]	GDP	2001-2009	900	42,732.85	11,316.88	11,138.3	2,261.41

[a] Texas Transportation Institute (TTI), as part of 2009 Annual Urban Mobility Report, http://mobility.tamu.edu/ums/
[b] US Department of Commerce, Bureau of Economic Analysis - http://www.bea.gov/. Real GDP data are for Metropolitan Statistical Areas and are in millions of chained 2005 dollars.

TABLE 2 GMM Estimates from Granger Causality Tests

Freeway	LM – TD		LM - GDP		LM – VMT		VMT – TD		VMT - GDP	
	1	2	3	4	5	6	7	8	9	10
	$\ln(LM)_t$	$\ln(TD)_t$	$\ln(LM)_t$	$\ln(GDP)_t$	$\ln(LM)_t$	$\ln(VMT)_t$	$\ln(VMT)_t$	$\ln(TD)_t$	$\ln(VMT)_t$	$\ln(GDP)_t$
$\ln(LM)_{t-1}$	1.395***	0.005	1.134***	-0.036	1.450***	0.066	-	-	-	-
	(0.049)	(0.008)	(0.280)	(0.123)	(0.255)	(0.085)	-	-	-	-
$\ln(LM)_{t-2}$	-0.187**	-	-0.221	0.088	-0.749***	0.039	-	-	-	-
	(0.074)	-	(0.152)	(0.137)	(0.178)	(0.143)	-	-	-	-
$\ln(LM)_{t-3}$	-0.209***	-	-	-	-	-0.064	-	-	-	-
	(0.036)	-	-	-	-	(0.128)	-	-	-	-
$\ln(VMT)_{t-1}$	-	-	-	-	0.110	1.321***	1.530***	0.003	1.012***	-0.098
	-	-	-	-	(0.115)	(0.144)	(0.104)	(0.008)	(0.243)	(0.087)
$\ln(VMT)_{t-2}$	-	-	-	-	0.143*	-0.142	-0.460***	-	-0.145	0.142
	-	-	-	-	(0.078)	(0.325)	(0.126)	-	(0.128)	(0.095)
$\ln(VMT)_{t-3}$	-	-	-	-	-	-0.218	-0.084**	-	-	-
	-	-	-	-	-	(0.249)	(0.042)	-	-	-
$\ln(TD)_{t-1}$	0.002	0.997***	-	-	-	-	-0.028*	0.996***	-	-
	(0.008)	(0.023)	-	-	-	-	(0.016)	(0.024)	-	-
$\ln(TD)_{t-2}$	0.002	-	-	-	-	-	0.022	-	-	-
	(0.005)	-	-	-	-	-	(0.015)	-	-	-
$\ln(TD)_{t-3}$	-0.002	-	-	-	-	-	0.016**	-	-	-
	(0.004)	-	-	-	-	-	(0.007)	-	-	-
$\ln(GDP)_{t-1}$	-	-	0.037	0.951***	-	-	-	-	0.211	0.969***
	-	-	(0.092)	(0.131)	-	-	-	-	(0.156)	(0.130)
$\ln(GDP)_{t-2}$	-	-	0.119	-0.329***	-	-	-	-	0.063	-0.336***
	-	-	(0.172)	(0.073)	-	-	-	-	(0.133)	(0.076)
$\ln(GDP)_{t-3}$	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
AB AR(1)	0.000	0.002	0.029	0.002	0.000	0.019	0.000	0.002	0.027	0.002
AB AR(2)	0.678	0.280	0.508	0.304	0.010	0.968	0.044	0.280	0.584	0.341
Hansen test	0.153	0.477	0.192	0.438	0.124	0.174	0.156	0.480	0.064	0.360
No. instruments	55	55	17	17	54	53	54	55	17	17
IV lags	t-1	t-1	t-1	t-1	t-2	t-3	t-2	t-1	t-1	t-1
Wald test (Order)	m=3	m=1	m=2	m=2	m=2	m=3	m=3	m=1	m=2	m=2
Wald (FD)	79.68	837.40	58.19	65.11	132.53	297.34	231.89	841.53	98.91	69.83
Wald (Levels)	3570.31	5149.06	703.77	783.03	20603.27	35305.20	8798.20	5481.62	823.68	809.90
Observations	2500	2700	700	700	2600	2500	2500	2700	700	700

Notes: Significance at 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

TABLE 2 GMM Estimates from Granger Causality Tests (*continued*)

Arterial Streets	LM – TD		LM - GDP		LM – VMT		VMT – TD		VMT - GDP	
	11	12	13	14	15	16	17	18	19	20
	$\ln(LM)_t$	$\ln(TD)_t$	$\ln(LM)_t$	$\ln(GDP)_t$	$\ln(LM)_t$	$\ln(VMT)_t$	$\ln(VMT)_t$	$\ln(TD)_t$	$\ln(VMT)_t$	$\ln(GDP)_t$
$\ln(LM)_{t-1}$	0.872***	0.003	1.480***	-0.377*	1.287***	0.079	-	-	-	-
	(0.092)	(0.010)	(0.141)	(0.225)	(0.065)	(0.131)	-	-	-	-
$\ln(LM)_{t-2}$	-	-	-0.545***	0.423*	-0.109	-0.217**	-	-	-	-
	-	-	(0.104)	(0.233)	(0.068)	(0.097)	-	-	-	-
$\ln(LM)_{t-3}$	-	-	-	-	-0.165***	-	-	-	-	-
	-	-	-	-	(0.058)	-	-	-	-	-
$\ln(VMT)_{t-1}$	-	-	-	-	0.003	0.903***	0.849***	-0.313***	1.041***	-0.136
	-	-	-	-	(0.016)	(0.142)	(0.133)	(0.110)	(0.143)	(0.117)
$\ln(VMT)_{t-2}$	-	-	-	-	-0.002	0.236**	-	0.148***	-0.197**	0.186
	-	-	-	-	(0.008)	(0.118)	-	(0.055)	(0.070)	(0.128)
$\ln(VMT)_{t-3}$	-	-	-	-	-0.014	-	-	0.165*	-	-
	-	-	-	-	(0.015)	-	-	(0.096)	-	-
$\ln(TD)_{t-1}$	0.072*	0.998***	-	-	-	-	0.101	1.072***	-	-
	(0.043)	(0.024)	-	-	-	-	(0.094)	(0.046)	-	-
$\ln(TD)_{t-2}$	-	-	-	-	-	-	-	0.001	-	-
	-	-	-	-	-	-	-	(0.046)	-	-
$\ln(TD)_{t-3}$	-	-	-	-	-	-	-	-0.082***	-	-
	-	-	-	-	-	-	-	(0.030)	-	-
$\ln(GDP)_{t-1}$	-	-	0.055	0.936***	-	-	-	-	0.080	0.911***
	-	-	(0.041)	(0.139)	-	-	-	-	(0.064)	(0.156)
$\ln(GDP)_{t-2}$	-	-	0.033	-0.304***	-	-	-	-	0.169	-0.300***
	-	-	(0.084)	(0.069)	-	-	-	-	(0.158)	(0.065)
$\ln(GDP)_{t-3}$	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
AB AR(1)	0.038	0.002	0.000	0.002	0.022	0.098	0.110	0.000	0.000	0.002
AB AR(2)	0.661	0.279	0.282	0.546	0.776	0.424	0.169	0.797	0.719	0.390
Hansen test	0.215	0.482	0.533	0.458	0.356	0.386	0.217	0.419	0.731	0.419
No. instruments	55	55	17	17	55	55	55	55	17	17
IV lags	t-1	t-1	t-1	t-1	t-1	t-1	t-1	t-1	t-1	t-1
Wald test (Order)	m=1	m=1	m=2	m=2	m=3	m=2	m=1	m=3	m=2	m=2
Wald (FD)	1208.91	820.71	58.78	64.63	180.65	156.09	463.41	166.34	41.78	64.85
Wald (Levels)	6814.14	5587.50	950.03	810.26	10027.47	14782.88	13074.36	6957.59	644.95	818.95
Observations	2700	2700	700	700	2500	2600	2700	2500	700	700

Notes: Significance at 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

TABLE 3 Summary of Significant GMM Granger Causality Tests

	Long Run (γ_{LR})
Freeways	
LM → GDP	0.137**
VMT → GDP	0.122*
Arterial Streets	
LM → GDP	0.125**
VMT → GDP	0.129*
LM → VMT	0.989*
VMT → TD	0.031**
TD → LM	0.559*

Notes: Significance at 10% and 5% levels is indicated by * and ** respectively.

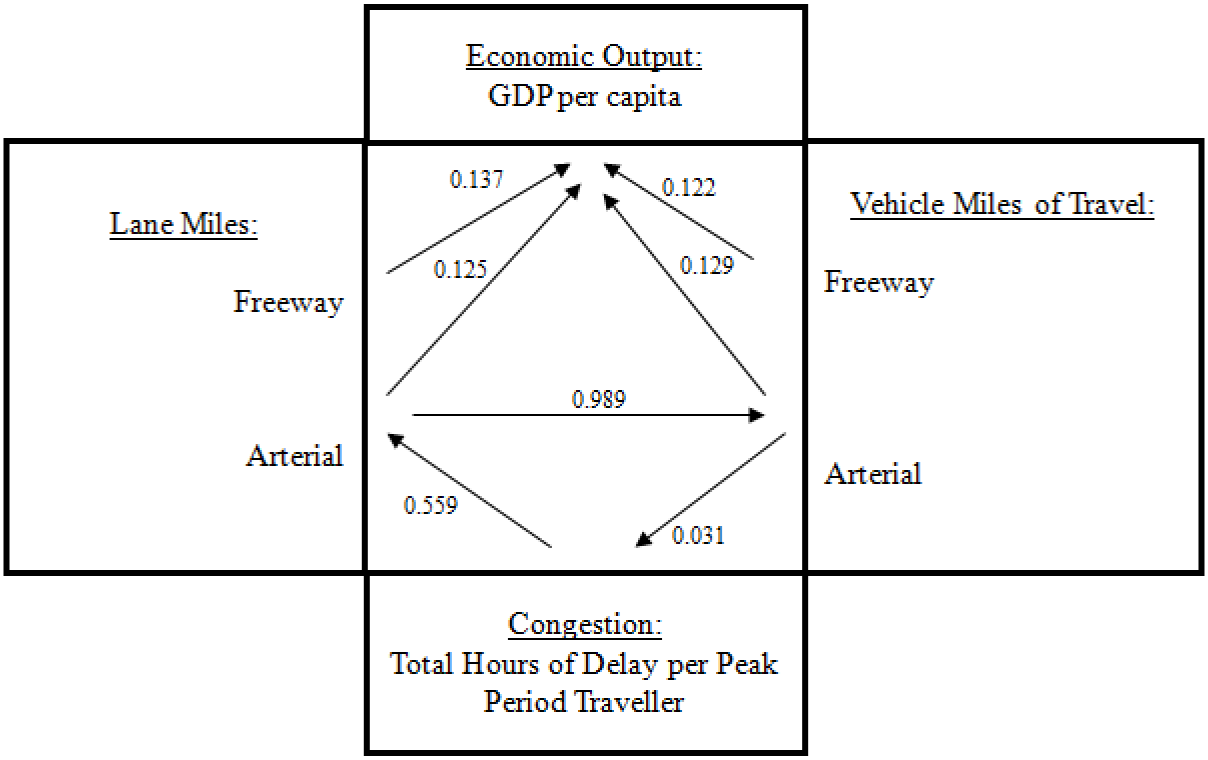

FIGURE 2 Illustration of Significant GMM Granger Causality Tests and Corresponding Long Run Coefficients.