Transportation infrastructure investment and economic growth at the MSA level; accounting for spillover effects

Eirini Kastrouni[a], Xiang He[b], Lei Zhang[c]

[a] ***Corresponding author***
Graduate Research Assistant
Civil & Environmental Engineering,
3109 Jeong H. Kim Engineering Building, University of Maryland, College Park, MD 20742, United States
Phone: 202-407-6430, E-mail: kast@umd.edu

[b] Graduate Research Assistant
Civil & Environmental Engineering,
3246 Jeong H. Kim Engineering Building, University of Maryland, College Park, MD 20742, United States
Phone: 301-233-6361, E-mail: xhe123@umd.edu

[c] Associate Professor
Civil & Environmental Engineering,
1179 Glenn Martin Hall, University of Maryland, College Park, MD 20742, United States
Phone: 301-405-2881, E-mail: lei@umd.edu

ABSTRACT
Past research has reached inconsistent conclusions regarding the magnitude of the effect of transportation investment on economic output, mainly due to different levels of geographic disaggregation which in some cases did not allow for unobserved heterogeneity to be captured by the model specifications. Using panel data at the MSA level for the period 1980-2008 for U.S., we estimate Gross Regional Product (GRP) elasticities of highway transportation investment using Cobb-Douglas and transcendental logarithmic production functions, to allow for comparison across different functional forms. The level of geographic analysis of our research and the transportation infrastructure's inherent network characteristics suggest the presence of spillover effects among neighboring MSAs. Using a Spatial Autoregressive Model, we revisit the model specifications by testing for and accounting for the presence of spillover effects among neighboring MSAs, for different neighboring criteria. The estimation results indicate significant output elasticity of the transportation infrastructure investment, and they support the hypothesis of interaction between neighboring areas, through productivity leakages and migration of production factors.

Keywords*:* Transportation investment; Gross Regional Product; Spillover effects

JEL Classification: H54, O18

1. INTRODUCTION

The empirical research on the linkage between transportation investment and economic growth has been carried out for several decades. At first, the studies focused on individual projects and tried to calculate all the benefits and costs of an individual project, so as to evaluate its economic impact. Aschauer *(1989a, b, c)* built a macro-econometric model to look at the impact of public infrastructure on economic growth at the national level. Since then, research followed this line with studies at different aggregation levels, exploring different questions associated with this topic. Most studies confirmed that there is positive correlation between public infrastructure investment and economic growth, while others found insignificant or even negative correlation. The majority of the literature deployed a production function to estimate the output elasticity with respect to public capital. In his pioneering paper, Aschauer *(1989a)* developed a production function with the ratio of private business output to private capital as the dependent variable. Using time series data for the time period 1949-1985, Aschauer estimated the output elasticity with respect to the public capital to be 0.39. With similar data set and modeling method, Munnell *(1990a)* confirmed Aschauer's findings and estimated an elasticity of 0.33. Munnell *(1990b)* further developed the production function approach by using panel data, and reported elasticities of 0.15 and 0.06 of output to public and highway capital respectively. Some other studies in this research line also found smaller positive effects with panel data *(Garcia-Mila and McGuire, 1992, Munnell, 1993; Moomaw and Williams, 1991)*. Some studies even found non-significant or negative public capital effects. *(Andrews and Swanson, 1995; Evans and Karras, 1994; Holtz-Eakin, 1994).*

Past research has reached inconsistent conclusions regarding the magnitude of the effect of transportation investment on economic output, mainly due to different levels of geographic disaggregation which in some cases did not allow for unobserved heterogeneity to be captured by the model specifications. Panel data offers greater variation in the dependent variable as well as the independent variables over time and space in the production function, thus avoiding the extraordinary large estimates reported by using time series data. However, as panel data usually covers smaller areas such as states or metropolitan areas, compared to national time series data, a problem called spillover effects may appear in these studies. Researchers argue that the economic impact of public infrastructure may not only lie in the region where the infrastructure investment occurs, but rather spillover into adjacent regions.

The idea of spillover effects was first suggested by Munnell *(1990b)*. Spillovers can be found at smaller geographic areas but not in more aggregated levels of analysis. Spillover effects of transportation investment are attributed to the inherent network characteristics of transportation infrastructure, as opposed to other forms of public infrastructure investment with more local attributes (i.e. investments in the healthcare system, education system). The presence of spillover effects has been statistically supported both in the US and internationally for higher levels of geographic disaggregation. Holtz-Eakin *(1993, 1995)* and Álvarez et al. *(2007)* conclude that no significant spillover effects exist in their papers, while other studies confirmed the existence of spillovers *(Berechman, et al., 2006; Boarnet, 1998; Cohen & Paul, 2004; Delgado & Álvarez, 2007; Ezcurra et al., 2005; Hu & Liu, 2010; Kelejian & Robinson, 1997; Moreno & López-Bazo, 2007; , Owyong & Thangavelu, 2001; Pereira & Andraz, 2010; Yu, et al., 2013).*

The remainder of the paper is organized as follows: the data used in this study is thoroughly presented in Section 2; Section 3 describes the methodology deployed in this paper and Section 4 presents and discusses the estimation results. Finally, Section 5 summarizes the main findings of this analysis.

2. DATA DESCRIPTION

The level of geographic analysis of our research and the transportation infrastructure's inherent network characteristics suggest the presence of spillover effects among neighboring MSAs. A comprehensive dataset for the U.S. at the metropolitan level was collected for this study. This dataset includes information on both transportation investment and economic performance for 351 of the 367

Metropolitan Statistical Areas (MSAs) in the United States, and covers a long period from 1980 to 2008. A limited number of MSAs (16) were excluded from the dataset due to poor data availability in these areas.

This study utilizes two major measures as proxies for transportation infrastructure investment on the highway system. The first proxy variable summarizes the roadway lane miles for each MSA in each year. This measure indicates transportation supply, and can reflect the stock of highway infrastructure capital to some extent. However, roadways of any of the four functional classes are treated equally, and the differences in speed limit, pavement condition are neglected in this measure. The second proxy is total highway capacity for each MSA by year. This measure describes the amount of transportation service provided to the public, and takes into account the differences in service capability that roads of different levels can provide. The data source for computing both measures is Highway Performance Monitoring System (HPMS) raw data, which provides information regarding roadway attributes at segment level over the whole nation. In the HPMS, road segments are classified into 12 functional classes (rural interstate freeway, rural principal arterial – other freeways and expressways, rural principal arterial – other, rural minor arterial, rural major collector, rural minor collector, rural local roads, urban interstate freeway, urban principal arterial - other freeways and expressways, urban principal arterial - other, urban minor arterial, urban major collector, urban minor collector and urban local roads), and section length as well as number of lanes is provided for each segment. The total lane miles for each functional class for each MSA can thus be estimated. Moreover, according to the suggested capacity for different level of roads listed in the Highway Capacity Manual 2000 *(HCM 2000)*, the lane miles for each functional class are adjusted to derive capacity and then summed up to get the total capacity for each MSA.

Gross Regional Product (GRP) is the indicator for economic performance in this study. GRP at the MSA level is directly collected from a commercial database called The Complete Economic and Demographic Data Source (CEDDS), which is provided by Woods and Poole. In addition to the two key variables for transportation investment and economic growth, some control variables should be incorporated into the model. Information regarding important factors that would influence economic growth is also collected, including population, employment, retail sales and gas price. The data source for the first three variables is also CEDDS, while yearly average gas price at state level was collected from U.S. Energy Information Administration. Table 1 summarizes the statistics of the key variables that were used in the model development.

Table 1: Descriptive Statistics of Key Variables

Variables	Description	Mean	St.Dev.	Min	Max
GRP	Gross Regional Product, (millions of 2004 dollars)	21022.44	60876.28	366.50	1114002.86
Highway Capacity	Highway capacity, (thousand vehicle miles per hour)	9990.88	12477.04	496.50	119179.50
Population	Number of people, (thousand)	585.22	1405.55	26.49	19006.80
Retail Sales	Total retail sales, (Millions of 2004 dollars)	6828.94	16055.95	185.61	234675.60
Total Miles	Infrastructure Supply for Functional Classes: *Urban – Interstates, Urban – Other Principal Arterials, Rural – Interstates, Rural – Freeways and Expressways*	661.4241	874.4706	5.36	21967.45

3. METHODOLOGY

3.1. Production function specification

Traditionally, past research has mainly deployed a Cobb-Douglas production function in order to capture the effect of transportation infrastructure investment on economic growth. In generic total production (Y), labor (L), capital (K), and total factor productivity (A) terms, the Cobb-Douglas production function specification receives the following forms:

$$Y = A * L^{\beta} * K^{\alpha} \tag{1}$$

$$lnY = lnA + \beta lnL + a lnK \tag{2}$$

Limited research has deployed a transcendental logarithmic production function approach, despite its flexible specification that allows capturing of second-order and interaction terms of the variables of interest:

$$lnY = \alpha_L lnL + \alpha_K lnK + \beta_{LL}(lnL)^2 + \beta_{KK}(lnK)^2 + \beta_{LK} lnL * lnK \tag{3}$$

In the current analysis, the authors deploy both production function specifications, in a bid to identify similarities and differences in the model development, and how these differences affect policymaking. More particularly, a random-effects panel data approach is used to account for correlated error terms within each MSA.

At the temporal level, due to the panel nature of the dataset, the authors test for first-order autocorrelation (AR(1)) in the disturbance terms:

$$\varepsilon_t = \rho \varepsilon_{t-1} + u_t \tag{4}$$

Woolridge's test allows for detecting first-order autocorrelation in the error terms in a panel data set, under the following null hypothesis:

$$H_0: var(\varepsilon_t, \varepsilon_s) = 0, \forall\, t \neq s$$

3.2. Detecting and accounting for spillover effects

At the spatial level, Moran's *I* statistic allows for detecting spatial autocorrelation in the dataset, for neighboring MSAs. Limited past research has used this statistic as a preliminary step in detecting spillover effects *(Berechman et al., 2006; Hu & Liu, 2010; Yu et al., 2013)*. The estimated *I* statistic is compared with the expected value E(*I*) under the null hypothesis of no spatial autocorrelation in the data, based on Equations (5) and (6):

$$E(I) = -\frac{1}{N-1} \tag{5}$$

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \tag{6}$$

The *I* statistic is estimated for each distinct variable of interest, for each year.

Evidence of spatial autocorrelation provided by the estimation of Moran's *I* statistic supports the use of a spatial autoregressive model that is able to capture these spatial relationships across the data. For a given variable *X*, the *effective variable X* for MSA *i* also includes a weighted portion of the variable for each neighboring MSA *j*, based on Equation (8) *(Hu & Liu, 2010; Álvarez et al., 2006; Moreno & López-Bazo;2007)* :

$$X_i^{eff} = X_i + \theta \sum_{j=1}^{N} w_{ij} X_j \quad (8)$$

The nature of the dataset (at the MSA level) does not allow for deploying the most common weighting matrix, which is a binary matrix based on adjacency *(1: adjacent; 0: non-adjacent).* Thus, in this research, the authors deploy two distinct sets of weighting matrices that fit the MSA-level study. The results of the two different matrices are presented and compared further in Section 4.

Although comprehensive information is available for each MSA, spillovers can be assumed and supported by theory for a limited number of variables; these include *Highway Capacity* and *Infrastructure Supply by Functional Class.* For the latter one, in particular, it is assumed that only specific functional classes of the transportation network contribute in spillovers; U*rban – Interstates, Urban – Other Principal Arterials, Rural – Interstates, Rural – Freeways and Expressways.* The sum of the infrastructure supply for these four functional classes is denoted as Total Miles in the remainder of the paper. The theory behind assuming spillovers for this set of variables entails the idea that mobile factors that boost economic development move on the transportation network, using the supplied level of transportation infrastructure of neighboring MSAs.

The use of weighting matrices is essential when estimating the *effective* levels of the variables for which spillover effects are assumed. A distance-based weighting matrix accounts for the distance between any given pair of MSAs. The form of the W_{dist} matrix implies the decrease of the magnitude effect between two MSAs as distance increases. Each non-diagonal element of the matrix is a row-standardized element of the following form:

$$W_{dist} = \begin{bmatrix} 0 & \left\{\frac{1}{\left(\Delta dist_{1,2}\right)^2}\right\}_{stand.} & \cdots & \left\{\frac{1}{\left(\Delta dist_{1,351}\right)^2}\right\}_{stand.} \\ \left\{\frac{1}{\left(\Delta dist_{2,1}\right)^2}\right\}_{stand.} & 0 & \cdots & \left\{\frac{1}{\left(\Delta dist_{2,351}\right)^2}\right\}_{stand.} \\ \vdots & \vdots & \ddots & \vdots \\ \left\{\frac{1}{(\Delta dist_{351.1})^2}\right\}_{stand.} & \left\{\frac{1}{(\Delta dist_{351.2})^2}\right\}_{stand.} & \cdots & 0 \end{bmatrix}$$

Following the same concept, a GRP-based weighting matrix assigns a higher weight on MSAs with dissimilar level of economic development, assuming that richer MSAs will affect their less-developed counterparts in a more intense pattern. In this case, the W_{GRP} weighting matrix is a block diagonal matrix of the following form:

$$W_{GRP} = \begin{bmatrix} W_{GRP,t=1} & 0 & \cdots & 0 \\ 0 & W_{GRP,t=2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & W_{GRP,t=29} \end{bmatrix}$$

For a random time period t, the $W_{GRP,t}$ element of the block-diagonal W_{GRP} matrix is row-standardized and receives the following form:

$$W_{GRP,t} = \begin{bmatrix} 0 & \left\{\frac{\left(\Delta GRP_{1,2}\right)_t}{\left(\Delta dist_{1,2}\right)^2}\right\}_{stand.} & \cdots & \left\{\frac{\left(\Delta GRP_{1,351}\right)_t}{\left(\Delta dist_{1,351}\right)^2}\right\}_{stand.} \\ \left\{\frac{\left(\Delta GRP_{2,1}\right)_t}{\left(\Delta dist_{2,1}\right)^2}\right\}_{stand.} & 0 & \cdots & \left\{\frac{\Delta GRP}{\left(\Delta dist_{2,351}\right)^2}\right\}_{stand.} \\ \vdots & \vdots & \ddots & \vdots \\ \left\{\frac{\left(\Delta GRP_{351,1}\right)_t}{\left(\Delta dist_{351.1}\right)^2}\right\}_{stand.} & \left\{\frac{\left(\Delta GRP_{351,2}\right)_t}{\left(\Delta dist_{351.2}\right)^2}\right\}_{stand.} & \cdots & 0 \end{bmatrix}$$

4. ANALYSIS RESULTS

In the current section, the estimation results are presented and discussed, following the methodology of Section 3.

4.1. Testing for AR(1) and spillover effects

At the temporal level, the authors test for AR(1) disturbances. The results of Woolridge's test for first order autocorrelation statistically support the existence of AR(1) disturbances in our panel dataset at 99.9% level of significance:

Table 2: Woolridge test for first order autocorrelation in panel data

$H_0: var(\varepsilon_t, \varepsilon_s) = 0, \forall\, t \neq s$			
$F_{(1,350)}$	p-value	$F_{(1,350),critical}$	Conclusion
593.468	0.0000	11.013	Reject H_o at 99.9%

At the spatial level, Moran's *I* statistic for detecting spatial autocorrelation is a cumulative statistic which is estimated for consecutive spatial bands (range: 0-100; step: 10), for variables with spillover attributes and for each distinct year of the study period. Table 3 presents the results for a single variable (Total Miles) for a single year (1992); similar results are available for the remainder of the study period, for the *Total Miles* and *Highway Capacity* variables, upon request.

Table 3: Moran's I cumulative statistic for Total Miles for 1992

Distance bands	I	p-value
(0-10]	0.007	0.081
(0-20]	-0.008	0.087
(0-30]	-0.003	0.437
(0-40]	-0.005	0.128
(0-50]	-0.003	0.394
(0-60]	-0.003	0.452
(0-70]	-0.003	0.348
(0-80]	-0.003	0.487
(0-90]	-0.003	0.31

Distance bands	I	p-value
(0-100]	-0.003	0.274
E(I) = -0.003		

The results of Moran's *I* statistic suggest that spillover effects decrease as distance from the investment location increases, supporting the use of weighting matrices that apply reduced weights between MSAs located further away, as those were presented in Section 3.2.

4.2. Production function model specification

Based on the statistical evidence of the existence of AR(1) disturbances and spatial autocorrelation, the authors account for these issues in the model specification. In this paper, the authors develop both a Cobb-Douglas (Table 4) and a transcendental logarithmic (Table 5) production function. For each specification, three (3) cases are examined; *(i)* assuming ***no spillover effects*** among neighboring MSAs, *(ii)* assuming spillover effects – use of $\boldsymbol{W_{dist}}$, (iii) assuming spillover effects – use of $\boldsymbol{W_{dist}}$. The presentation of the 3 cases for each model specification allows for validating and quantifying the existence of spillovers, as well as comparing the performance of the two distinct weighting matrices.

In the Cobb-Douglas production function approach, the model specification in the ***no-spillovers*** case receives the following form:

$$\ln(GRP_{it}) = constant + \ln(Tot.Miles_{it}) + \ln(Retail\ Sales_{it}) + \ln(Capacity_{it}) + Population_{it} + (v_i + \eta_{it})$$

Accounting for spillover effects, the authors revised the previous model specification, including the *effective* variables:

$$\ln(GRP_{it}) = constant + \ln(Tot.Miles_{it}^{eff}) + \ln(Retail\ Sales_{it}) + \ln\left(Capacity_{it}^{eff}\right) + Population_{it} + (v_i + \eta_{it})$$

The estimation results for the 3 cases of the Cobb-Douglas production function are presented in Table 4:

Table 4: Random Effects Cobb-Douglas production function results – correcting for AR(1) disturbances

		(i) No spillovers		*(ii)* W_{dist}		*(iii)* W_{GRP}	
Y: *GRP*		**Coeff.**	**p-value**	**Coeff.**	**p-value**	**Coeff.**	**p-value**
Total Miles	**No spillovers**	0.104	0.007	n/a	n/a	n/a	n/a
	Effective	n/a	n/a	0.032	0.0000	0.008	0.0120
Retail Sales		1.000	0.0000	0.970	0.0000	1.003	0.0000
Capacity	**No spillovers**	0.031	0.000	n/a	n/a	n/a	n/a
	Effective	n/a	n/a	0.094	0.0000	0.026	0.0000
Population		0.006	0.0000	0.005	0.0000	0.006	0.0000
Constant		2.882	0.0000	2.488	0.0000	2.904	0.0000
R-sq. Within		0.9267		0.9272		0.9267	

	(i) No spillovers		*(ii)* W_{dist}		*(iii)* W_{GRP}	
Y: *GRP*	**Coeff.**	**p-value**	**Coeff.**	**p-value**	**Coeff.**	**p-value**
R-sq. Between	0.9713		0.9720		0.9712	
R-sq. Overall	0.9690		0.9697		0.9689	
No. of obs.	10,179					
No. of groups	351					

Note: Italic font indicates the variable is logged.

The model fit in all three cases is highly satisfactory, with an overall R squared of approximately 97%. All variables have the expected sign, and are statistically significant at a 99.9% level of significance. Transportation infrastructure supply has a positive effect on GRP, ranging from 0.008 to 0.104, depending on the assumption about spillovers and the weights deployed. More particularly, in case *(i),* the effect of transportation infrastructure on GRP is higher than cases *(ii),* and *(iii)*, suggesting that, under the evidence of spillovers, there is interaction in the use of transportation infrastructure among neighboring MSAs. In elasticity terms, 1% increase in transportation supply *(miles)* would lead to a 0.104%, 0.032%, and 0.008% increase in GRP for cases *(i), (ii), (iii)* respectively. For the *Highway Capacity* variable, the coefficient estimates for the 3 cases do not follow the same pattern as *Total Miles;* case *(ii)* overestimates the coefficient whereas cases (*i),* and *(ii)* provide similar-level results. Finally, the estimated coefficients of the remainder of the variables are of similar magnitude across all 3 cases.

In a similar pattern, the transcendental logarithmic production function specification under the ***no spillovers*** assumption is:

$$\ln(GRP_{it}) = constant + \ln(Tot.Miles_{it}) + \ln(Retail\ Sales_{it}) + Population_{it} + (Population_{it})^2 + \ln(Tot.Miles_{it}) * Population_{it} + (v_i + \eta_{it})$$

The revised specification which accounts for spillover effects is:

$$\ln(GRP_{it}) = constant + \ln(Tot.Miles_{it}^{\boldsymbol{eff}}) + \ln(Retail\ Sales_{it}) + Population_{it} + (Population_{it})^2 + \ln(Tot.Miles_{it}^{\boldsymbol{eff}}) * Population_{it} + (v_i + \eta_{it})$$

The estimation results are presented in Table 5:

Table 5: Random Effects Transcendental logarithmic production function analysis results – correcting for AR(1) disturbances

		(i) No spillovers		*(ii)* W_{dist}		*(iii)* W_{GRP}	
Y: *GRP*		**Coeff.**	**p-value**	**Coeff.**	**p-value**	**Coeff.**	**p-value**
Total Miles	**No spillovers**	0.014	0.0000	n/a	n/a	n/a	n/a
	Effective	n/a	n/a	0.011	0.0010	0.042	0.0000
Retail Sales		0.995	0.0000	0.996	0.0000	0.990	0.0000
Population		0.0185	0.0000	0.0171	0.0000	0.014	0.0010
(Population)^2		-0.00004	0.0000	-0.00005	0.0000	-0.00004	0.0000
***Total Miles* * Population**	**No spillovers**	-0.0007	0.035	n/a	n/a	n/a	n/a
	Effective	n/a	n/a	-0.0005	0.1100	-0.0002	0.6680
Constant		3.169	0.0000	3.176	0.0000	3.042	0.0000

	(i) **No spillovers**		*(ii)* $\mathbf{W_{dist}}$		*(iii)* $\mathbf{W_{GRP}}$	
Y: ***GRP***	**Coeff.**	**p-value**	**Coeff.**	**p-value**	**Coeff.**	**p-value**
R-sq. Within	0.9267		0.9267		0.9269	
R-sq. Between	0.9723		0.9723		0.9726	
R-sq. Overall	0.9698		0.9699		0.9702	
No. of obs.			10,179			
No. of groups			351			

Note: Italic font indicates the variable is logged.

The model fit in all three cases is highly satisfactory, with an overall R squared of approximately 97%. All variables have the expected sign; the negative sign of the second-order term of *Population* is of particular interest, suggesting a non-linear relationship between MSA size and economic growth (in GRP terms). More precisely, the estimated coefficients suggest that the relationship between *Population* and GRP is not monotonic, providing evidence that overpopulated areas may not have the expected economic growth. This result may be of high significance to policymakers regarding the emerging policy topic of optimal city size. Regarding the level of significance of the model variables, all variables, except for the interaction term, are statistically significant at 99.9%. The interaction term suggests that in larger MSAs, the level of infrastructure supply is not as important as in smaller MSAs (in population terms). Transportation infrastructure supply has a positive effect on GRP, ranging from 0.011 to 0.014, depending on the assumption about spillovers and the weights deployed. More particularly, in case *(iii),* the effect of transportation infrastructure on GRP is higher than cases *(i),* and *(ii),* suggesting that, under the evidence of spillovers between MSAs of dissimilar levels of economic development, there is interaction in the use of transportation infrastructure. In elasticity terms, 1% increase in transportation supply *(miles)* would lead to a 0.014%, 0.011%, and 0.042% increase in GRP for cases *(i), (ii), (iii)* respectively. Finally, the estimated coefficients of the remainder of the variables are of similar magnitude across all 3 cases.

5. CONCLUSIONS

The estimation results indicate significant output elasticity of the transportation infrastructure investment, and they support the hypothesis of interaction between neighboring areas, through productivity leakages and migration of production factors.

The contribution of this study is two-fold. First, it tests for and corrects for spatial correlation and spillover effects at the MSA level, whereas past research in this area has mainly focused on national-, state- or county-level analysis. Additionally, this paper identifies and discusses the results that different methodological approaches yield, and how these results may support different policies. The key findings can be summarized as follows:

- The use of panel data suggests testing for and correcting for AR(1) disturbances, if necessary.
- At the MSA level, spatial autocorrelation exists and spillover effects should be accounted for when exploring the relationship between transportation supply and economic growth.
- The Cobb-Douglas production function yields more consistent results, regarding variable selection and expected signs.
- The Transcendental logarithmic production function, despite its flexible form, does not provide a good fit for our data, as it fails to include all the second-order and interaction terms, based on the generic Transcendental logarithmic model specification.
- The level of infrastructure supply is not as important as in smaller MSAs (in population terms).

- The relationship between *Population* and GRP is not monotonic, providing evidence that overpopulated areas may not have the expected economic growth, raising questions regarding the issue of optimal city size.
- The effect of transportation infrastructure on GRP suggests that, under the evidence of spillovers, there is interaction in the use of transportation infrastructure among neighboring MSAs

The analysis results and the conclusions drawn from them are particularly helpful for policymakers in the process of identifying the impact level of the own and the neighboring MSA transportation infrastructure supply on GRP.

6. REFERENCES

Álvarez, A., Arias, C., Orea, L. (2006), Econometric Testing of Spatial Productivity Spillovers from Public Capital, Hacienda Pública Española/Revista de Economía Pública, 178, 9-21.

Andrews, K. and Swanson, J. (1995), Does Public Infrastructure Affect Regional Performance" Growth and Change, Vol. 26, No. 2, pp. 204-216.

Aschauer, D. A. (1989a), Is Public Expenditure Productive? Journal of Monetary Economics, 23, 177-200.

Aschauer, D. A. (1989b), Does Public Capital Crowd Out Private Capital? Journal of Monetary Economics, 24, 171-188.

Aschauer, D. A. (1989c), Public Investment and Productivity Growth in the Group of Seven, Economic Perspectives, 13(5), 17-25.

Berechman, J., Ozmen, D., and Ozbay, K. (2006), Empirical Analysis of Transportation Investment and Economic Development at State, County, and Municipality Levels, Transportation, 33, 537-551.

Boarnet, M. G. (1998), Spillovers and the Locational Effects of Public Infrastructure, Journal of Regional Science, Vol. 38, pp. 381-400.

Cohen, J. and Paul, C. (2004), Public Infrastructure Investment, Interstate Spatial Spillovers and Manufacturing Costs, The Review of Economics and Statistics, Vol. 86, No. 2, pp. 551-560.

Delgado, M. J., and Álvarez, I. (2007), Network Infrastructure Spillover in Private Productive Sectors: Evidence from Spanish High Capacity Roads, Applied Economics, 39(12), 1583-1597.

Evans, P. and Karras, G. (1994), Are Government Activities Productive? Evidence from A Panel of U.S. States, The Review of Economics and Statistics, Vol. 76, No. 1, pp. 1-11.

Ezcurra, R., Gil, C., Pascual, P. and Rapún, M. (2005), Public Capital, Regional Productivity, and Spatial Spillovers, The Annals of Regional Science, 39, 471-494.

Garcia-Mila, T. and T. J. McGuire (1992), The Contribution of Publicly Provided Inputs to States' Economies, Regional Sciences and Urban Economics, 22, 29-242.

Holtz-Eakin, D. (1993), Public investment in infrastructure, Journal of Economic Perspectives, Vol. 7, No. 4, pp. 231-234.

Holtz-Eakin, D. (1994), Public Sector Capital and the Productivity Puzzle, The Review of Economics and Statistics, Vol. 76, pp. 12-21.

Hu, A. and Liu, S. (2010), Transportation, Economic Growth and Spillover Effects: the Conclusion Based on the Spatial Econometric Model, Frontiers of Economics in China, 5(2), 169-186.

Kelejian, H. H., and Robinson, D. P. (1997), Infrastructure Productivity Estimation and its Underlying Econometric Specifications: a Sensitivity Analysis, Papers in Regional Science: The Journal of the RSAI, 76 (1), 115-131.

Moomaw R. and Williams, M. (1991), Total Factor Productivity Growth in Manufacturing: Further Evidence from the States, Journal of Regional Science, Vol. 31, No. 1, pp. 17-34.

Moreno, R., and López-Bazo, E. (2007), Returns to Local and Transport Infrastructure under Regional Spillovers, International Regional Science Review, 30-47.

Munnell, A. H. (1990a), Why has Productivity Declined? Productivity and Public Investment, New England Economic Review, Jan./Feb., 3-22.

Munnell, A. H. (1990b), How does Public Infrastructure Affect Regional Economic Performance, New England Economic Review, Sep./Oct., 11-32.

Munnell, A. H. (1993), An Assessment of Trends and Economic Impacts of Infrastructure Investment, in Infrastructure Policies for the 1990s, Paris: OECD, Chapter 2, pp. 21-54.

Owyong, D. T. and Thangavelu, S. M. (2001), An Empirical Study on Public Capital Spillovers from the USA to Canada, Applied Economics, 33(11), 1493-1499.

Pereira, A. and Andraz, J. (2010), On the Regional Incidence of Highway Investments in the USA, Annals of Regional Science.

Yu, N., de Jong, M., Storm, S., Mi, J. (2013), Spatial Spillover Effects of Transport Infrastructure: Evidence from Chinese Regions, Journal of Transport Geography, 28, 56-66.