Departamento de Economía Aplicada
Universidad de Oviedo

DPAE/11/02

Discussion Papers on Applied Economics.

Department of Applied Economics. University of Oviedo.

Public infrastructure spillovers: revisiting Boarnet with entropy econometrics

Esteban Fernández-Vázquez (University of Oviedo)

Abstract:

The contribution of the stock of public capital to the economic growth has been a topic that has generated some debate in the recent literature. The usual way of obtaining empirical evidence of the productivity of public infrastructures is by estimating an aggregate production function, as suggested by Aschauer (1989). In his work he found some evidence that public infrastructure investments enhanced private productivity. This result was later either confirmed or rejected in other subsequent papers (see Sturm et al. 1998, for a survey). The work of Boarnet (1998) triggered even more the discussion to the field. His results showed that productivity gains realized by infrastructure investment were partially offset by productivity losses in neighboring locations. The argument given was that public infrastructure investment in one location can draw resources (and therefore production) away from other locations since «it enhances the comparative advantage of that location relative to other places». Our argument is that the estimates obtained from a production function could be seriously affected by the presence of multicollinearity. Several authors (Ai and Cassou, 1997; Vijverberg, Vijverberg and Gamble,1997) have shown that regional aggregate data are characterized by strong multicollinearity. Entropy Econometrics (EE) provides a rigorous but operationally simple method to deal with samples affected by collinearity problems. The objective of the present paper is to compare the results of a standard Least Squares estimation with fixed regional effects with an EE approach when estimating public infrastructure spillovers in the presence of strong multicollinearity in the data. We do this in the framework of a Cobb-Douglas production function using a panel dataset of Spanish provinces for the period 1995-2006.

Keywords: Infrastructures, spillovers, multicollinearity, ill-conditioned data, Entropy Econometrics.

1. Introduction

The present paper deals with the quantification of spatial spillovers from public transport infrastructures, which has received much attention in the literature since is a crucial issue for the policy makers. Infrastructures productivity is usually measured by specifying an aggregate production function where the endowment of public capital is considered as an input. The production function approach was first used by Aschauer (1989), being the Cobb-Douglas function a very common functional form, where functions like the following are specified at an aggregate level:

$$Y_{it} = A_{it} L_{it}^{\theta_L} K_{it}^{\theta_K} G_{it}^{\theta_G} \quad (1)$$

in which y stands for value added, A is a measure of total factor productivity, K indicates the stock of physical capital, L denotes employment, G is the stock of public infrastructures, t is the time index and i is the unit index. The potential effects of some type spatial spillovers were also considered in previous studies, and the previous function is extended by including as additional factor the stock of infrastructures in other locations. The previous production function is transformed into:

$$Y_{it} = A_{it} L_{it}^{\theta_L} K_{it}^{\theta_K} G_{it}^{\theta_G} IG_{it}^{\theta_{IG}} \quad (2)$$

where IG stands for the stock of “indirect” public infrastructures in other regions.

Although policy makers usually expect from public infrastructure to increase productivity and foster economic growth, finding empirical evidence of these positive effects has proven to be a difficult task. Aschauer’s (1989) original results suggested that public investment in infrastructure increases private productivity. This hypothesis was later confirmed by some authors, but rejected by others (see a survey in Sturm et al., 1998).

There has been a great deal of discussion about the role played by the spatial spillovers generated by public infrastructures. This topic was addressed in Holtz-Eakin and Schwartz (1995), Kelejian and Robinson (1997), and Cohen and Morrison (2002) for the case of road infrastructure in the United States. Some of these studies found that the spillover effects were not important. The paper by Boarnet (1998) went a step beyond finding that they were significantly negative.

In the theoretical model that Boarnet develops, productivity gains realized by infrastructure investment can be potentially offset by losses in neighboring locations. Losses arise because public infrastructure investment in one location can draw resources (and therefore production) away from other locations since «it enhances the comparative advantage of that location relative to other places». He tested his model with data from Californian counties from 1969 to 1988 under different criteria to define the set of neighbor locations. Although the results depend to some extent on this criterion, he found in general significantly negative spillovers.

The purpose of this paper is to check is this result could be determined by ill-conditioned data set, with high collinearity between the explanatory variables. Several authors (Ai and Cassou, 1997; Vijverberg, et al., 1997) have shown that regional aggregate data are characterized by strong multicollinearity, which usually increases the variability of the parameter estimates. In this paper, with a real data set of Spanish provinces, we reproduced the model estimated by Boarnet for the Californian counties using two different estimation strategies. One is the one employed by Boarnet himself and the other is a Generalized Maximum Entropy (GME) estimator. This alternative estimator provides a rigorous but operationally simple method to deal with prior information (Marsh and Mittelhammer, 2004) that alleviates the collinearity problems.

The paper is organized in four more sections. In section 2 we describe the data set used for the analysis and the results obtained by applying the same estimation strategy as in Boarnet (1998). Section 3 introduces the general basis of the GME estimation technique, whereas Section 4 compares the results of the proposed GME estimator with the previous ones. Finally, section 5 concludes.

2. Estimating productivity of transport infrastructures for the Spanish provinces (1995-2006)

The main objective of this section will be to apply the same estimation strategy as in the paper by Boarnet (1998) to the set of 47 Spanish inland provinces (we exclude the Canary and Balearic Island in our analysis). The regression model to be estimated is a transformation of (2) into logarithms like:

$$\ln(Y_{it}) = \ln(A_{it}) + \theta_L \ln(L_{it}) + \theta_K \ln(K_{it}) + \theta_G \ln(G_{it}) + \theta_{IG} \ln(IG_{it}) \qquad 3$$

The dependent variable in the regression will be the annual data on GDP at province level available from the National Statistical Spanish Institute (INE) from 1995 to 2006. For this same period, the Valencian Institute of Economic Research (IVIE) constructed series of labor (L), physical private capital (K) and stock of public infrastructures for transport (G) for the Spanish provinces.[1]

The stock of public capital in other regions (IG_{it}) is obtained as a weighted average of the stock of public infrastructure in other locations,

[1] See http://www.ivie.es/banco/banco.php?idioma=EN for details. These transport infrastructures are composed basically by roads, highways ad railways.

$$IG_{it} = \sum_{j \neq i}^{N} w_{ij} G_{jt} \qquad 4$$

In the original paper by Boarnet, different alternatives for the weighting matrix W are specified. In this paper we only focus in those that try to capture the similarities between locations, giving larger weights to regions that are more similar. The general definition of these weights is:

$$w_{ij} = \frac{|x_i - x_j|^{-1}}{\sum_{j=1}^{N}[|x_i - x_j|^{-1}]}$$

Depending on the specific characteristic included in variable x_i, the specification of the weighting matrix will be different. In the same fashion as Boarnet, the regional indicators chosen with this purpose were:

x_i=population density in 2000 (people by km^2)	$\boldsymbol{W^{pop}}$
x_i=income per capita in 2000 (thousands of Euros)	$\boldsymbol{W^{inc}}$
x_i= proportion of workers in construction in 2000	$\boldsymbol{W^{con}}$
x_i=proportion of workers in services with an university degree in 2000	$\boldsymbol{W^{ser}}$

The matrices defined as above try to replicate the same ideas as in Boarnet. For example, $W^{pop}$and W^{inc} are identically specified. However, in the definition of W^{con} we account for the great weight that the construction industry had in Spain in the period under study.[2] Furthermore, due to the lack of appropriate data, matrix W^{ser} is only a proxy of the original definition, which was based in the proportion of workers in finance, insurance and real estate industries.

Following Holtz-Eakin and Schwartz (1995), equation **¡Error! No se encuentra el origen de la referencia.** is transformed into an equation in differences to the initial year in order to capture the long-term relationships between the variables, provided that period t is sufficiently far from the initial period. In the papers by Holtz-Eakin and Schwartz (1995) and Boarnet (1998), a span of 6 years is considered as a sufficiently long difference. Consequently, differences in our analysis are formed by subtracting the initial year 1995 to all the periods from 2000 to 2006. The final equation to be estimated is:

[2] In the original paper the proportion of workers in the manufacturing sector was used instead.

$$\ln(\dot{Y}_{it}) = \gamma_t + \theta_L\, ln(\dot{L}_{it}) + \theta_K\, ln(\dot{K}_{it}) + \theta_G\, ln(\dot{G}_{it}) + \theta_{IG}\, ln(\dot{IG}_{it}) \quad 5$$

where the dots denote differences to the initial period and the γ_t are year-specific dummies for each t=2000,…,2006. A suggested in Holtz-Eakin and Schwartz (1995) this equation is estimated by generalized least squares (GLS) to correct for autocorrelation in the disturbances. The following table summarizes the results obtained:

Table 1. GLS estimates for the Spanish provinces under different W matrices

	(A)	(B)	(C)	(D)
Variable	W^{pop}	W^{inc}	W^{con}	W^{ser}
Labor (L)	0.496**	0.479**	0.498**	0.496**
Private capital stock (K)	0.106**	0.116**	0.104**	0.105**
Public infrastructures stock (G)	0.140**	0.163**	0.138**	0.137**
Transport infrastructures stock in neighbor regions (IG)	0.027	-0.159**	-0.041	0.030
N	329	329	329	329
R^2	0.914	0.917	0.915	0.914

** indicates that the estimates are significant at 5% level.

The results in Table 1 are in line with the estimates reported in Boarnet (1998). In brief, we hardly find evidence of any positive spillover from transport infrastructures in other regions. Under the different specification of the weighting matrix in columns A, C, and D; we found positive but insignificant spillovers of transport infrastructure. In column B, on the other hand, we found a significant result but negative, which would be an indication of the effect of infrastructures on regions with similar characteristics (income): it enhances competitive advantage on some location, which turns it into a more attractive destination for mobile factors, which draws resources away from other regions and reduces their productivity.

Even when this could be a plausible explanation for these empirical evidences, we question about if these results could be largely conditioned by the data set. Samples affected by collinearity problems lead to high variability in the estimates, as pointed out in Ai and Cassou (1997) or Vijverberg et al. (1997). This could be the case of our specific data set, which would mean that the estimates are misleading. In order to explore this possibility, several indicators of collinearity between the stock of infrastructures in other regions and the rest of inputs have been computed. Table 2 summarizes the figures obtained:

Table 2. Indicators of collinearity between IG with the other inputs

	Linear correlation of (IG) with:			VIF_{IG}	η
Specification of W	**L**	**K**	**G**		
W^{pop}	0.337	0.432	0.544	15.505	30.093
W^{inc}	0.168	0.450	0.676	10.308	22.695
W^{con}	0.370	0.490	0.472	10.701	24.949
W^{ser}	0.327	0.467	0.595	10.530	23.226

The first three columns show the linear correlation coefficient between factor IG with the rest of the inputs, which are in general larger for the cases of K and G. Even when they are moderate, they are not a proper diagnostics of collinearity problems. There are two standard ways of detecting if the sample is affected by collinearity. One is the Variance Inflation Vectors (VIF), which aims to quantify how much the variance of an estimated regression coefficient is increased because of collinearity. Usually a cut-off value of 10 is taken as a signal of collinearity problems affecting the estimate of this regressor. In the fourth column of Table 2 we can see that under all the specification of matrix W considered this is the case.

Additionally, the fifth column in Table 2 reports the Condition Number (η) as a global indicator (affecting all the explanatory variables) of collinearity problems. The condition number was proposed by Belsley, Kuh and Welsch (1980) and is defined as the squared root of the maximum and minimum eigenvalue of the matrix has been obtained as:

$$\eta = \sqrt{\frac{\psi_{max}}{\psi_{min}}}$$

Usually, condition numbers larger than 20 are considered as a clear signal of huge collinearity. In the dataset analyzed the condition number is again higher than these reference values.

Since the estimates of the coefficient of IG could be potentially affected by multicollinearity in the sample, the next step will be to estimate equation (5) using an alternative estimator that provides a solution to this ill-conditioned sample. The estimator proposed in this paper is the Generalized Maximum Entropy (GME) estimator, which is briefly described in the next section. More extensive introductions can be found in Kapur and Kesavan (1993) and Golan et al. (1996).

3. The Maximum Entropy approach and the GME estimator: an introduction

The essential property of the ME principle is that it chooses the 'most uncertain', 'most uniform' or 'least information-requiring' distribution for the estimate of a parameter, provided that it agrees with the data observed. This is fundamentally different from a more classical estimation approach, in which several assumptions on the distribution of the error term must be taken for granted. The main idea is that a random variable (such as an estimator) can take on different M possible values with unknown probabilities. The final objective will be to estimate this target probability distribution p. Following the formulation proposed by Shannon (1948), the entropy of this distribution, E(p), is:

$$\underset{\boldsymbol{p}}{\text{Max}}\, E(\boldsymbol{p}) = -\sum_{m=1}^{M} p_m\, ln(p_m) \qquad 6$$

The entropy function E measures the 'uncertainty' of the outcomes of the event. This function reaches its maximum when p has a uniform distribution. On the other extreme, this function takes a value of zero (no uncertainty) when the probability of one of the outcomes goes to one. If some information about the variable (for example, observations on the dependent and independent variables) is available, it can be used as constraints in a linear programming model aimed at maximizing (6). Each piece of information will lead to an update of p, similarly to the Bayesian approach. In the linear regression framework, the estimator of a coefficient is found by computing its expected value given p. In situations in which the number of observations is not large enough to apply classical econometrics or, alternatively, the sample is ill-conditioned by problems such collinearity, this approach can be used to obtain robust estimates of unknown parameters. Standard errors (required to judge the statistical significance of the point estimates) can be obtained as well.

The underlying idea of the ME methodology can be applied for estimating the parameters of general linear models, which leads us to the so-called Generalized Maximum Entropy (GME). Let us suppose a variable y that depends on H explanatory variables x_h:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\epsilon} \qquad 7$$

Where y is a (T × 1) vector of observations for y, X is a (T × H) matrix of observations for the x_h variables, β is the (H × 1) vector of unknown parameters $\beta = (\beta_1, \dots, \beta_H)$ to be estimated, and ϵ is a (T × 1) vector with the random term of the linear model. Each β_h is assumed to be a discrete random variable. We assume that there is some information about its $M \geq 2$ possible realizations. This information is included for the estimation by means of a support vector $b' = (b_1, \dots, b_M)$ with corresponding probabilities $p'_h = (p_{h1}, \dots, p_{hM})$. The vector b is based on the researcher's a priori belief about the likely values of the parameter.[3] For the sake of convenient exposition, it will be assumed that the M values are the same for every parameter, although this assumption can easily be relaxed. Now, vector β can be written as:

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_H \end{bmatrix} = \boldsymbol{BP} = \begin{bmatrix} \boldsymbol{b}' & 0 & \cdots & 0 \\ 0 & \boldsymbol{b}' & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{b}' \end{bmatrix} \begin{bmatrix} \boldsymbol{p_1} \\ \boldsymbol{p_2} \\ \vdots \\ \boldsymbol{p_H} \end{bmatrix} \qquad 8$$

Where B and P have dimensions (H × HM) and (HM × 1) respectively. Now, the value of each parameter β_h is given by the following expression:

$$\beta_h = \boldsymbol{b}' \boldsymbol{p_h} = \sum_{m=1}^{M} b_m \, p_{hm}; \ \forall h = 1, \dots, H \qquad 9$$

For the random term, a similar approach is followed. Oppositely to other estimation techniques, GME does not require rigid assumptions about a specific probability distribution function of the stochastic component, but it still is necessary to make some assumptions. ϵ is assumed to have mean $E[\epsilon] = 0$ and a finite covariance matrix. Basically, we represent our uncertainty about the realizations of vector ϵ treating each element ϵ_t as a discrete random variable with $J \geq 2$ possible outcomes contained in a convex set $v' = \{v_1, \dots, v_J\}$, which for the sake of simplicity is assumed as common for all the ϵ_t. We also assume that these possible realizations are symmetric around zero ($-v_1 = v_J$). The traditional way of fixing the upper and lower limits of this set is to apply the three-sigma rule (see Pukelsheim, 1994). Under these conditions, vector ϵ can be defined as:

$$\boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_T \end{bmatrix} = \boldsymbol{VU} = \begin{bmatrix} \boldsymbol{v}' & 0 & \cdots & 0 \\ 0 & \boldsymbol{v}' & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{v}' \end{bmatrix} \begin{bmatrix} \boldsymbol{u_1} \\ \boldsymbol{u_2} \\ \vdots \\ \boldsymbol{u_T} \end{bmatrix} \qquad 10$$

and the value of the random term for an observation t equals:

$$\epsilon_t = \boldsymbol{v}' \boldsymbol{u_t} = \sum_{j=1}^{J} v_j \, u_{tj}; \ \forall t = 1, \dots, T \qquad 11$$

---

[3] Golan, Judge and Miller (1996, chapter 8) pay attention to the consequences of choices concerning the elements of the vector **b**.

Consequently, model (7) can be transformed into:

$$\boldsymbol{y} = \boldsymbol{XBp} + \boldsymbol{Vu}$$

So we need also to estimate the elements of matrix U (denoted by $\tilde{u}_{tj}$) and the estimation problem for the general linear model (7) is transformed into the estimation of H + T probability distributions. For this estimation, the GME problem is written in the following terms:

$$\underset{\boldsymbol{P},\boldsymbol{U}}{\text{Max}}\, E(\boldsymbol{P},\boldsymbol{U}) = -\sum_{h=1}^{H}\sum_{m=1}^{M} p_{hm}\, ln(p_{hm}) - \sum_{t=1}^{T}\sum_{j=1}^{J} u_{tj}\, ln(u_{tj}) \qquad 12$$

subject to:

$$y_t = \sum_{h=1}^{H}\sum_{m=1}^{M} b_m p_{hm}\, x_h + \sum_{j=1}^{J} v_j\, u_{tj};\ \ \forall t = 1, \dots, T \qquad 13$$

$$\sum_{m=1}^{M} p_{hm} = 1\,;\ \forall h = 1, \dots, H \qquad 14$$

$$\sum_{j=1}^{J} u_{tj} = 1\,;\ \forall t = 1, \dots, T \qquad 15$$

The restrictions in (13) ensure that the posterior probability distributions of the estimates and the errors are compatible with the observations. The equations in (14) and (15) are just normalization constraints.[4]

The large sample properties of the GME estimators are analyzed in Golan, Judge and Miller (1996; chapter 6). GME estimators are shown to be consistent and asymptotically normal. These authors analyze also the small sample properties using Monte Carlo simulation. They compare numerically the GME estimators to traditional least squares and maximum likelihood estimators. Their results show a good performance in terms of the accuracy of the estimates.

[4] This GME estimation procedure can be seen as a particular case of the r Generalized Cross Entropy (GCE) principle (or alternatively the GCE can be considered as generalization of the GME procedure). The GCE approach uses as point of departure a non-necessarily uniform probability distribution $\boldsymbol{q}$, and the target is to minimize the Kullback-Leibler divergence between $\boldsymbol{p}$ and $\boldsymbol{q}$. The solutions of both approaches are the same when the a priori probability distribution contained in $\boldsymbol{q}$ is uniform. In other words, the ME solutions are obtained by minimizing the Kullback-Leibler divergence between the unknown p_{hm} and the a priori $q_{hm} = \frac{1}{M}\ \forall m = 1, .., M$.

In order to do inference in the GME approach, the procedure suggested in Fraser (2000) or Golan, Perloff and Shen (2001) can be followed. Under some assumptions on the behavior of model $y = X\beta + \epsilon$ that guarantee the consistency and asymptotical normality of the estimator, the distribution of the estimates follows $\hat{\beta} \rightarrow N[\beta, \hat{\sigma}^2(X'X)^{-1}]$, where $\hat{\sigma}^2$ is a diagonal matrix with a typical element:

$$\hat{\boldsymbol{\sigma}}^{\boldsymbol{2}}{}_{\boldsymbol{h}} = \sigma_e^2 \left(\frac{\sigma_b^2}{\sigma_b^2 + \sigma_v^2} \right), \forall h = 1, \ldots, H; \qquad 16$$

where $\sigma_e^2 = \left[\frac{1}{T-H}\right] \sum_{t=1}^{T} \hat{e}_t^2$; being $\hat{e}_t = \sum_{j=1}^{J} v_j \tilde{u}_{tj}$ and:

$$\sigma_b^2 = \sum_{m=1}^{M} b_{hm}^2 \tilde{p}_{hm} - \left(\sum_{m=1}^{M} b_{hm} \tilde{p}_{hm} \right)^2 \qquad 17a$$

$$\sigma_v^2 = \sum_{t=1}^{T} \sum_{j=1}^{J} v_j^2 \tilde{u}_{tj} - \left(\sum_{t=1}^{T} \sum_{j=1}^{J} v_j \tilde{u}_{tj} \right)^2 \qquad 18b$$

Hence, it is possible to estimate the variance of GME estimators and obtain the t-ratios as $\frac{\hat{\beta}}{\sqrt{\hat{Var}(\hat{\beta})}}$. Note that the structure of the variance of the estimators lead to smaller variances than in the case of LS regression, given that (18b) includes the term σ_v^2 which is always non-negative.

4. Re-estimating productivity of public infrastructure with GME

In this section, equation (5) is estimated again for the case of the Spanish provinces between 1995 and 2006, but now applying the GME estimator. If we get the same results as in Table 1, this would be a signal of non-significantly positive or eventually negative contributions of regional spillovers from transport infrastructures. Oppositely, if the GME estimates are different from those obtained previously, this would indicate that cast some doubts on the previous conclusions.

The application of the entropy-based estimation procedure proposed in this paper requires specifying some supports for the set of parameters and for the errors. Given that we estimate elasticities, the bound of 1 in absolute value seems natural. For all the parameters of the model we have considered the same support vector b with 3 points $(-1, 0, 1)$. Note that this imply we are assuming that, in principle, all the elasticities are expected to be zero (if we had no observations at all in the sample this would be the solution). Moreover, the inclusion of negative values in the supporting vectors allows negative estimates. The usual three-sigma rule applies for specifying the supporting vectors for the error terms in all the cases.

The following table summarizes the results obtained by the GME approach under the same different specifications of the weighting matrix:

Table 3. GME estimates for the Spanish provinces under different W matrices

	(A)	(B)	(C)	(D)
Variable	W^{pop}	W^{inc}	W^{con}	W^{ser}
Labor (L)	0.476**	0.488**	0.481**	0.478**
Private capital stock (K)	0.133**	0.125**	0.125**	0.124**
Public infrastructures stock (G)	0.169**	0.178**	0.176**	0.156**
Transport infrastructures stock in neighbor regions (IG)	0.195**	0.018**	0.115**	0.162**
N	329	329	329	329
Pseudo-R^2	0.911	0.911	0.910	0.909

** indicates that the estimates are significant at 5% level. The pseudo-R^2 is obtained from the variance of the errors of the model as suggested in Arnd et al. (2002).

The GME estimator used above highlight the differences between classical econometrics and the application of the ME principle. If the sample is affected by collinearity, the estimates tend to present high variability and are less precise. Goldberger (1991, p. 246) discusses the similarities between collinearity in regression analysis with small sample problems in a univariate population. In other words, he sees multicollinearity as a problem of lack of enough information in the sample to estimate the parameters of a model. The ME approach can alleviate this problem by introducing additional information (contained, for example, in the supporting vectors of the parameters).

This could be the case of the results on Table 1, where a standard GLS estimator was applied. The GME estimates in Table 3 tell a completely different story compared with those in Table 1, suggesting now that there is no evidence of negative spillovers under any of the possible specifications of matrix W. On the contrary, these estimates indicate the presence of significant positive spatial spillovers from transport infrastructure for the case of the Spanish provinces.

5. Conclusions

In this paper, we have explored the use of maximum entropy estimation for empirical analysis when multicollinearity is an issue. This problem is relatively common when estimating Cobb-Douglas production functions with aggregate data in which public capital is included as an input. The key element of the estimation by maximum entropy is the introduction of prior information on parameter values. From data of the Spanish provinces between 1995 and 2006, we replicate the estimation strategy followed in the paper by Boarnet (1998), finding no evidence of positive regional spillovers from public infrastructure. In the sample we detected the presence of collinearity problems that could be ill-conditioning the dataset and affecting the estimates.

Although the results obtained with the GME estimation need a detailed analysis of sensitivity, the methodology appears as a useful procedure to gather empirical evidence when the use of more common econometric methods is impeded or precluded by multicollinearity. Due to multicollinearity, standard estimators fail to provide evidence of positive spillovers from public capital while estimating the model by GME suggests quite strong evidence of this positive effect.

References

AI, C. AND CASSOU, S., (1997): "On public capital analysis with state data", Economics Letters, Vol. 57, 209-212.

ASCHAUER, D.A., (1989): "Is public expenditure productive?", *Journal of Monetary Economics*, 23(2), 177-200.

BALTAGI, B.H. AND N. PINNOI, (1995): "Public Capital Stock and State Productivity Growth: Further Evidence from an Error Components Model", *Empirical Economics*, Vol. 20, 351-359.

BOARNET, M. G. (1998): "Spillovers and the locational effects of public infrastructure", *Journal of Regional Science* 38: 381–400.

COHEN, J. P., AND C. J. MORRISON (2002): "Public infrastructure investment, inter-state spatial spillovers, and manufacturing costs". Mimeo, Department of Agricultural & Resources Economics, UC Davis.

FRASER, I., (2000): "An application of maximum entropy estimation: the demand for meat in the United Kingdom", *Applied Economics*, Vol. 32(1), 45-59.

KELEJIAN, H. H, AND D. P. MORRISON (1997): "Infrastructure productivity: a razor's edge". Working paper, University of Maryland.

GARDEBROEK, C. AND A. OUDE LANSINK, (2004): "Farm-specific Adjustment Costs in Dutch Pig Farming", *Journal of Agricultural Economics*, Vol. 55(1), 3-24.

GOLAN, A., JUDGE, G. AND D. MILLER, (1996): *Maximum Entropy Econometrics: Robust Estimation with Limited Data*, New York, John Wiley & Sons.

GOLAN, A., PERLOFF, J.M. AND E.Z. SHEN, (2001): "Estimating a Demand System with Nonnegativity Constraints: Mexican Meat Demand", *The Review of Economics and Statistics*, Vol. 83(3), 541-550.

GOLDBERGER, A.S., (1991): *A Course in Econometrics*, Cambridge-USA, Harvard University Press.

HOLTZ-EAKIN, D., AND A. SCHWARTZ (1995): "Spatial productivity spillovers from public infrastructure: Evidence from state highways". International Tax and Public Finance 2: 459–68.

INE, (2009): *Contabilidad Regional de España. Base 1995*, Madrid.

MARSH, T.L. AND C. MITTELHAMMER, (2004): *Generalized Maximum Entropy Estimation of a First Order Spatial Autoregressive Model*, Advances in Econometrics, Vol.18, 199-234, Elsevier.

PUKELSHEIM, F., (1994): "The three sigma rule", *The American Statiscian*, Vol. 48(4), 88-91.

SHANNON, C.E., (1948): "A Mathematical Theory of Communication", *Bell System Technical Journal*, Vol. 27, 379-423.

STURM, J .E., G. H. KUPER, AND J. DE HAAN (1998): "Modelling government investment and economic growth on a macro level: A review". In Market behaviour and macroeconomic modelling, 359–406. New York: St. Martin's Press; London: Macmillan Press.

VIJVERBERG, W.P.M., VIJVERBERG, C.P.C., AND J.L. GAMBLE, (1997): "Public capital and private productivity", *The Review of Economics and Statistics*, Vol. 79(2), 267-278.