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The spatial productivity of transportation infrastructure

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ABSTRACT

Transportation infrastructure services may cause an impact on the economy of the region in which they are located and, additionally, they are likely to have an impact on other regions. This effect has been labeled the spillover effect. In this study, the existence of direct and spillover effects of road, railway, airport and seaport infrastructure projects is tested by estimating a production function. Together with this primary objective, two common concerns in the literature are addressed: the lack of theoretical foundations for spatial econometrics models and the likely endogenous relationship between transport infrastructure and economic development. The estimated production function takes the form of a Spatial Durbin Model and is estimated using panel data from the 47 peninsular Spanish provinces by alternatively applying a Maximum Likelihood estimator and Instrumental Variables/Generalized Method of Moments estimators. According to the estimates, road transport infrastructure positively affects the output of the region in which the infrastructure is located and its neighboring provinces, while the remaining modes of transportation projects cause no significant impacts on average.

1. Introduction

The significant role that transportation infrastructure plays in the economy of a region is determined by the services that it provides. Improvements in transportation infrastructure services are expected to reduce generalized transportation costs as a result of shorter distances, lower congestion and higher speeds that reduce fuel, capital and labor costs (Forkenbrock and Foster, 1990). However, transportation projects create other significant spatial location services in addition to reducing travel and logistics costs (Rietveld, 1994; Beyzatlar et al., 2014). They may enlarge the market potential of businesses by enabling them to serve broader markets more economically. In addition, improvements to transportation systems can provide firms with a greater variety of specialized labor skills and input products, making them more productive. All of these consequences occur in the region in which the transport infrastructure is located, but they might also spread to its neighboring regions. Increasing connectivity provided by developments in transportation systems made certain researchers suspect the existence of these spillover effects (Cohen and Paul, 2004), which are also known as leakages.

Positive and negative spillovers have been detected and explained in the literature. Holtz-Eakin and Schwartz (1995) found positive and null impacts of highways on those regions in which they were located (direct effects) and positive, negative and insignificant spillover effects using different specifications of a panel data model applied to US states. Jiwattanakulpaisarn et al. (2012) also focused on the impacts of the development of highways on US states economies, obtaining positive direct and spillover effects in a dynamic panel data setting. Other scholars have studied the effects of

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all transport infrastructure projects located in a region including different mixes of road, railway, port and airport facilities. Kelejian and Robinson (1997) and Moreno and López-Bazo (2007) found positive direct effects and negative spillover effects using US states and Spanish Autonomous Communities, respectively.

The results shown by Boarnet (1998) indicate the existence of negative spillover effects of street and highway infrastructure among California counties. According to the author, if there was an increase in public capital in region A, there would be a rise in the price of labor and capital in the region, inducing resources to move from other regions to region A. This migration would yield a new output in region A, reducing the output in the remaining regions. Therefore, total output in one region would depend positively on its infrastructure stock and negatively on the infrastructure stock of other regions as a result of negative output spillovers. Delgado and Alvarez (2007), relying on a stochastic frontier approach, found a positive association between highways and economic output in Spanish regions where the infrastructure was built, while obtaining evidence of negative impacts in other regions. Analogous results were obtained by Jiwattanakulpaisarn et al. (2010) in a study of the effects of transportation on employment and in Ozbay et al. (2007), where the impact of highway investment on economic development was investigated. Sloboda and Yao (2008) measured the importance of public transport expenditure in the US, obtaining insignificant direct effects and some evidence of negative spillovers.

Conversely, the foundations of the existence of positive spillovers rely on the network characteristics of transportation infrastructure in which every piece is subordinate to the entire system (Moreno and López-Bazo, 2007). Network improvements in neighboring provinces might lead to a decrease in the transportation costs of moving inputs and final products for the economy of a particular province, which might translate into an increase in the demand for manufacturing goods and services. Congestion might also play a significant role when explaining positive spillovers; new transportation infrastructures in regions in which bottlenecks exist might improve the performance of the entire network. Positive direct and spillover effects of total transportation infrastructure have been found in China (Yu et al., 2013; Zhang, 2008), employing all US states (Tong et al., 2013) and the Northeast Corridor of that country (Chen and Haynes, 2013). Cantos et al. (2005) incorporated disaggregated information on transport infrastructure, obtaining positive direct and spillover effects of roads, ports and railways, while airport facilities were found to have no effect on economic performance of the private sector in Spanish regions. Positive spillover effects of maritime ports have been found in a study using regional data of 13 EU members (Bottasso et al., 2014) and Spanish provinces (Álvarez and Blázquez, 2014). In a recent study by Del Bo and Florio (2012) utilizing regions of 27 EU members, positive road infrastructure spillover effects were found, while the results demonstrated no highway and railway capacity spillover effects. Similarly, no effects on regions other than that in which the infrastructure is located were found in the Spanish case in the work of Álvarez et al. (2006).

A natural concern in the study of the relationship between transport development and the economic performance of a region is endogeneity. Most studies that have focused on the study of spillover effects have neglected the importance of determining causality between better transportation services and economic growth (Melo et al., 2013). In other cases, endogeneity has been addressed by the use of Instrumental Variable estimators (Cohen and Paul, 2004; Cantos et al., 2005; Del Bo and Florio, 2012; Chen and Haynes, 2013) and General Method of Moments (GMM) estimators (Jiwattanakulpaisarn et al., 2012; Bottasso et al., 2014). Employing both methods, all listed scholars have found no endogeneity issues in their applications. Other authors have studied the direction of causality by applying Granger analysis (Holtz-Eakin and Schwartz, 1995; Jiwattanakulpaisarn et al., 2010), with the results rejecting that causality runs from the economic environment to transport infrastructure accumulation. This issue is acknowledged in this paper, and Maximum Likelihood (ML) estimation and GMM estimates are compared, providing new insights into the endogeneity of transportation infrastructure.

The primary goal of this study is to estimate the contribution of transportation infrastructure to the economy by incorporating spillover effects and utilizing modern spatial econometrics techniques. The resulting model is applied to Spain, where transportation infrastructure projects have been promoted through the implementation of the Infrastructure and Transport Strategic Plan that raised the quality of Spain's transportation network to European standards in a short period of time. Most studies conducted on Spain to date have focused on the Nomenclature of Territorial Units for Statistics 2 (NUTS-2) regional level[1]; however, following the recommendations of Rephann and Isserman (1994), we build a more disaggregated database employing the NUTS-3 level, i.e., provinces in the Spanish Territorial classification. In this context, the objective of this study is to measure the output effects of transportation infrastructure projects in Spanish territories in the period between 1986 and 2006. In particular, we aim to account for the marginal productivity effects of transportation infrastructure services within a province and to document the existence of spillover effects outside of provincial boundaries through the use of spatial econometrics methodologies.

Our contribution to the existing literature is threefold. First, we estimate a Spatial Durbin Model using disaggregated information for Spanish provinces (NUTS-3) including transportation infrastructure as separate variables for roads, railways, airports and seaports. In this fashion, it is possible to retrieve spillover effects for each type of infrastructure project. The lack of a theoretical foundation is a frequent criticism of the application of spatial econometric models (Corrado and Fingleton, 2012; Gibbons and Overman, 2012). The second contribution is a theoretical justification for the use of Spatial Durbin Models in the context of regional production function studies. As is well-identified in the literature (for example, Melo et al., 2013), two main issues complicate this kind of analysis: reverse causality and the omission of relevant variables. The third

[1] Several studies have utilized regional data to study this issue in Spain (for exhaustive information, see the recent survey by la Fuente (2010)), whereas available papers using data on provinces are scarce, Álvarez et al. (2003), Delgado and Alvarez (2007) and Moreno and López-Bazo (2007).

contribution is managing these challenges simultaneously: Reverse causality is controlled using IV/GMM methods, and a more complete specification (the Spatial Durbin Model) together with the consideration of spatial fixed effects is utilized to reduce the potential bias caused by the omission of relevant variables.

The structure of this paper is as follows. In the next section, we review the methodological issues of production function approach and the treatment of the spillovers. In Section 3, we describe the data used and the source of the variables. In Section 4, the empirical models are discussed, along with the econometric issues. In Section 5, we present the estimation results. Finally, Section 6 contains some conclusions and policy recommendations.

2. Theoretical background

In this paper, we focus on the changes in productivity that result from increased infrastructural investments by employing a primal approach.[2] The main aim of this article consists of the estimation of the output elasticity of transport infrastructures while adequately incorporating the existence of spatial spillovers and controlling for endogeneity issues; to reach this objective, the production function methodology is more useful than the cost and profit function methodologies (Pfähler et al., 1996). We suppose that there is a conventional output production function that relates real physical output, Y, to the quantity of variable inputs, X, quasi-fixed private capital input, K, and external factors as different types of transportation infrastructure projects, G.

$$Y = f(X, K, G) \tag{1}$$

In a log-linear Cobb–Douglas specification:

$$\ln Y = \alpha_0 + \alpha_1 \ln X + \alpha_2 \ln K + \alpha_3 \ln G + \upsilon \tag{2}$$

where $\epsilon \sim \mathcal{N}(0, \sigma_\upsilon^2 I_n)$.

Different alternatives have been proposed in the literature to identify and estimate empirically spatial externalities. In recent years, most papers have chosen the techniques developed in the spatial econometric field. The specification option to test the existence of these spatial linkages is the introduction of the spatial lag of the dependent variable (the spatial lag model) and/or the spatial lag of the independent variables (the Spatial Durbin Model, SDM). The SDM is our preferred model, rather than the spatial lag model, following some ideas and results explained in the remainder of the paper.

In general terms, one of the main criticisms regarding the use of this type of model is the absence of a theoretical basis. In this sense, Corrado and Fingleton (2012) note that some model specifications have been driven by data-analytic considerations rather than having a firm foundation in economic theory. However, there are some exceptions in which the existence of spatial externalities is supported by the theory, such as models relying on New Economic Geography (NEG) (Fingleton, 2006; Gómez-Antonio and Fingleton, 2012a), neoclassical growth models (i.e., Fingleton, 2006; Ertur and Koch, 2007), dynamic models for regional labor markets (Patacchini and Zenou, 2007), and models in the field of tax interactions (Brueckner, 2003).

More closely related to the content of this paper, there are some studies in which the effect of infrastructure investment on economic performance including spatial externalities has been addressed using the Spatial Lag Model (SL) and/or the Spatial Durbin Model (SDM).[3] Recently, Yu et al. (2013) revised this literature, noting that these spatial spillovers between regions or states can be classified into one of two types, depending on how they are generated. On one hand, spatial spillovers are derived from network expenditures promoted by neighboring regions or planned by the national Government. On the other hand, spillover effects arise from factor migration, being positive for some regions and negative for others (Boarnet, 1998).

An additional argument that supports this kind of model is based on the variations in the capacity utilization rate. When inputs such as capital, K, enter the production function as a stock, unbiased comparative-static effects are computed on the assumption that changes in input services are proportional to changes in input stocks. However, in the presence of positive adjustment costs, this assumption may not hold for capital, K. The non-proportional changes in private capital stock, K, and its flow of services, K^*, are represented as variations in the capacity utilization rate, (CU). In particular, we consider the following expression: $CU = \frac{K^*}{K}$.[4]

The lack of provincial statistics for CU makes this variable an unobservable factor,[5] and as a consequence, the same happens to K^*. At this juncture, we suggest that CU depends on the economic performance (Gajanan and Malhotra, 2007) of each province and its neighborhood (spatial simultaneity), again suggesting a spatial autoregressive specification.

From a theoretical point of view, shocks in the production of *neighbor* units might increase the demand for products in the region under study. In international macroeconomics, when an economic boom produces an increase in the output of a country such as the United States of America, simultaneous increases in outputs in other countries are observed. Open economy models frequently have difficulty in explaining why business cycles are so closely related among countries. According to

[2] Other papers have previously addressed this issue using a dual approach. Cost function models rely on duality theory and allow for a richer analysis through the estimation of the optimal input demand equation. However, one of the shortcomings of this type of model is that information on factor prices is required. Estimating a profit function is an alternative that permits the estimation of unconditional demand effects, but it is even more extensive than the cost function approach in terms of data requirements. The information required by the cost and profit function approaches is not available at the NUTS-3 level in Spain.

[3] The market potential concept is also widely used to capture the real spatial scope of infrastructure investments (Holl, 2011).

[4] Note that CU can also be expressed as the deviation of actual output from optimal output.

[5] Empirical regional measures of capacity utilization are described in Garofalo and Malhotra (2000).

Baxter and Farr (2005), the *CU* variable could explain why business cycles are so closely related among countries. Consequently, an alternative explanation would posit that the economic agents of one region might accommodate the utilization rate of capital to meet output increases in other regions (see Burnside and Eichenbaum, 1996).

Thus, we can formally express this concept using a spatial process as follows:

$$CU = \lambda + \phi WY + v \tag{3}$$

where λ is a constant term and v is distributed as a $\mathcal{N}(0, \sigma_v^2 I_n)$.

In Eq. (3), the n by n spatial weight matrix, W, reflects the connectivity of the provinces, and the scalar parameter, ϕ, reflects the strength of spatial dependence in Y. If the scalar dependence parameter, ϕ, is positive, then the *CU* rate in region i will be positively associated with the output of neighboring regions.

Substituting the spatial specification (3) in (2),

$$\begin{aligned}\ln Y &= \alpha_0 + \alpha_1 \ln X + \alpha_2(\ln CU + \ln K) + \alpha_3 \ln G + \upsilon = \alpha_0 + \alpha_2\lambda + \alpha_1 \ln X + \alpha_2\phi W \ln Y + \alpha_2 \ln K + \alpha_3 \ln G + \upsilon + \alpha_2 v \\ &= \mu + \alpha_1 \ln X + \beta W \ln Y + \alpha_2 \ln K + \alpha_3 \ln G + \epsilon \end{aligned} \tag{4}$$

where the intercept $\mu = \alpha_0 + \alpha_2\lambda$ and $\upsilon + \alpha_2 v = \epsilon \sim \mathcal{N}(0, \sigma^2 \epsilon I_n)$.

According to Manski (1993), the $W \ln Y$ variable in Eq. (4) denotes the endogenous interaction effects and $\beta = \alpha_2\phi$ is called the spatial autoregressive coefficient.

2.1. Treatment of spillovers

In Eq. (5), the provincial Cobb Douglas production function is augmented by including spillover effects using the spatial lags of the variable that contains information about inputs and transportation infrastructure projects, (G),

$$\ln Y = \mu + \beta W \ln Y + \alpha_1 \ln X + \alpha_2 \ln K + \alpha_3 \ln G + \theta_1 W \ln X + \theta_2 W \ln K + \theta_3 W \ln G + \epsilon \tag{5}$$

where Y is the output of province, X is a matrix containing variable inputs, K contains quasi-fixed input private capital, and G contains transportation infrastructure variables; $\alpha,\ \beta$ and θ are the parameters to be estimated. W is the row standardized N-by-N spatial weight matrix with $W_{ij} > 0$ when observation j is a spatial neighbor to observation i. To test for the consistency of the results, models are estimated using two different weighting matrices, W, which will be explained in the next section.

The specification of the Eq. (5) leads to what has been labeled the Spatial Durbin Model (*SDM*), which includes both the lagged dependent variable and lagged independent variables. The *SDM* can be simplified to the spatial lag model and the spatial error model because these models are special cases of *SDM*. Our approach approximates a general-to-specific selection strategy after the recent contributions about model specifications in spatial econometrics (LeSage and Pace, 2009; Elhorst, 2010). The most general model may include three different types of spatial interactions, which were identified by Manski (1993) as the following: endogenous interaction effects, exogenous interaction effects and correlated effects. Elhorst (2010) found that the parameter estimates of the endogenous and exogenous interaction effects are biased when all interaction types are considered. To solve this problem, LeSage and Pace (2009) proposes the exclusion of the spatially autocorrelated error term, taking *SDM* as a departure from the general model. The alternatives, the exclusion of, or leading to, an omitted relevant variable problem at the cost of ignoring spatial dependence in the disturbances will only cause a loss of efficiency. Furthermore, the *SDM* produces unbiased coefficient estimates when the true data-generation process is any spatial regression specification other than the Manski model.

Another advantage of the *SDM* is that it does not impose prior restrictions on the magnitude of indirect effects, e.g., the spatial spillovers; thus, this model is more appropriate for the aim of this study.[6]

3. Description of data and variables

In this section, we discuss the data employed in the estimation of the model. Spain is a decentralized country made up of two autonomous cities (Ceuta and Melilla) and 17 autonomous communities, each with its own heritage and government. These autonomous communities correspond to NUTS-2 in the European territorial unit classification and are composed of 47 mainland provinces and three island provinces (NUTS-3). Both Autonomous Communities and provinces may be considered regional economies nested within a national system. The main property of this system is interdependence among the Spanish provinces because the evolution of each region depends on the behavior of neighboring regions.[7]

We use a balanced panel dataset of 47 Spanish peninsular provinces covering the period from 1986 to 2006, which results in 987 observations, as shown in Table 1. The dependent variable, Gross Added Value, measured in thousands of 2000 Euros (Y), originated from the National Statistics Institute (INE). The source of the explanatory variables, labor force (L, as measured

[6] These spatial spillovers are set to zero in a non-spatial model and in the spatial error model. In the spatial lag model, the spatial spillover effects in relation to the direct effects are identical for each explanatory variable.

[7] Márquez and Hewings (2003) analyze the regional competition between Spanish regions (NUTS-2).

Table 1
Summary statistics of variables in logs.

	Mean	Std. dev.	Min.	Max.
y	15.61	0.9	13.76	18.63
k	16.3	0.85	14.44	19.31
l	5.21	0.86	3.39	8.00
kh	−1.96	0.34	−3.14	−1.14
road	14.39	0.63	12.77	16.22
rail	12.94	0.979	10.5	16.54
air	6.52	5.45	0	15.78
port	5.48	6.39	0	14.52

in thousands of workers, and human capital (*HK*), as measured by the share of total employment with higher-level education (secondary school, technical college and university degrees), are INE and BBVA Foundation-Ivie, respectively.

The latest series of capital stock for the Spanish economy were also obtained from BBVA Foundation-Ivie (see Ivars et al., 2012), where net wealth and productive capital stock data are available for both public and private capital (*K*). Productive capital stock at constant pricing is a quantity factor that takes into account loss of efficiency as assets age and is the relevant component of productivity analysis.[8] Transportation infrastructure projects, such as roads and highways, ports, airports and railways are measured following this methodology. The *road* variable includes high-capacity road networks as well as other road networks.

Since the 1970s, there has been substantial development of road transportation infrastructure in Spain; during the 1990s, in particular, the implementation of the Infrastructure and Transport Strategic Plan caused a significant boost in investment into High Capacity Networks.[9] Fig. 1 represents the national stock of infrastructure for the different transportation modes for the period of 1986–2006. Fig. 2 presents the compound annual growth rates of regional output at the provincial level during that same period. Neighboring provinces share similar growth rates for this variable that display an uneven distribution that is far from a random spatial process.

4. Econometric model and estimation issues

4.1. Model specification

The empirical model we estimate is based on the log-linear Cobb–Douglas production function. Following the previous discussion about different spatial econometric models, we estimate a Spatial Durbin Model:

$$\begin{aligned} y_{it} = {} & \mu_i + \beta W y_{it} + \alpha_1 l_{it} + \alpha_2 hk_{it} + \alpha_3 k_{it} + \alpha_4 road_{it} + \alpha_5 rail_{it} + \alpha_6 air_{it} + \alpha_7 port_{it} + \theta_1 Wl_{it} + \theta_2 Wkh_{it} + \theta_3 Wk_{it} \\ & + \theta_4 Wroad_{it} + \theta_5 Wrail_{it} + \theta_6 Wair_{it} + \theta_7 Wport_{it} + \epsilon \end{aligned} \quad (6)$$

where variables on both sides of the equations are in logarithms, ϵ is a well-behaved error term, and subscripts *i* and *t* denote provinces and time periods, respectively. Compared to Eq. (5), this equation also includes human capital, *hk*, and public capital, *G*, separated into four variables: road transportation infrastructure, *road*; railways, *rail*; airports *air*; and ports, *port*. Moreover, as discussed above, these equations include the spatial lag of the dependent variable and the spatial lag of the explanatory variables. Two different criteria have been used to build *W*.[10] *Wn* stands for a physical contiguity matrix, in which its values would be 1 for two bordering provinces and 0 for all others. *Wd*150 is another binary weighting matrix with elements valued at 1 for those provinces within a radius of 150 km from the centroid of the province of reference and 0 for provinces beyond that distance. These matrices treat physical proximity as the main driver of the presence of spillovers. Finally, spatial fixed effects, μ_i, are introduced into the model to control for all province-specific time-invariant variables whose omission could bias the estimates. These fixed effects capture pure spatial heterogeneity.

It is necessary to evaluate whether spatial and/or time effects should be considered as fixed or random, which affects the estimation procedure. From a theoretical point of view, the use of random effects in the literature is not sufficiently justified (Elhorst, 2012). In any case, Beenstock and Felsenstein (2007) and Nerlove and Balestra (1996), among others, note that spatial and/or time-fixed effects may be adopted when the values of the variables in each spatial unit are not obtained randomly. Thus, random effects do not appear to be adequate when the data used refer to all Spanish provinces.

From an estimation point of view, the consideration of spatial fixed effects is easily managed by demeaning. Two problems have been identified in the literature to estimate this kind of spatial model: (i) the endogeneity of the spatial lag of the

[8] The computations of the productivity of capital stock are obtained by employing a new methodology applied to Spanish capital stock estimates that is based on two OECD manuals (Schreyer, 2001; Schreyer et al., 2003).

[9] Holl (2007) analyzes the improvements in terms of accessibility from 1980 to 2000 using municipal data.

[10] The weighting matrices have been row normalized following standard practice in the spatial econometrics literature. After transformation, the sum of all elements in each row equals one. Note that the row elements of a spatial weighting matrix demonstrate the effect on a particular unit of all other units.

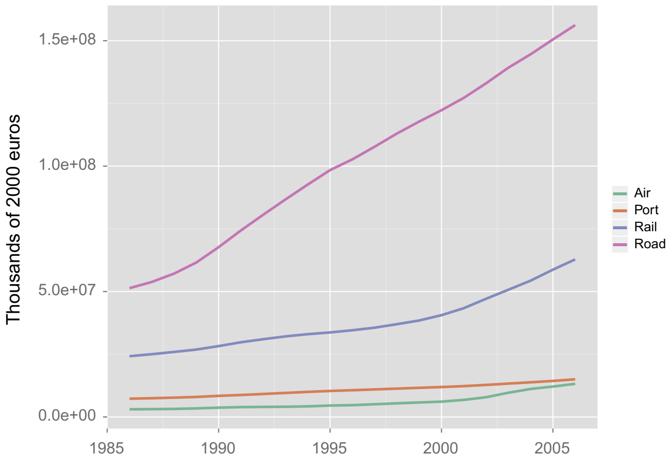

Fig. 1. Stock of transportation infrastructure aggregated at national level.

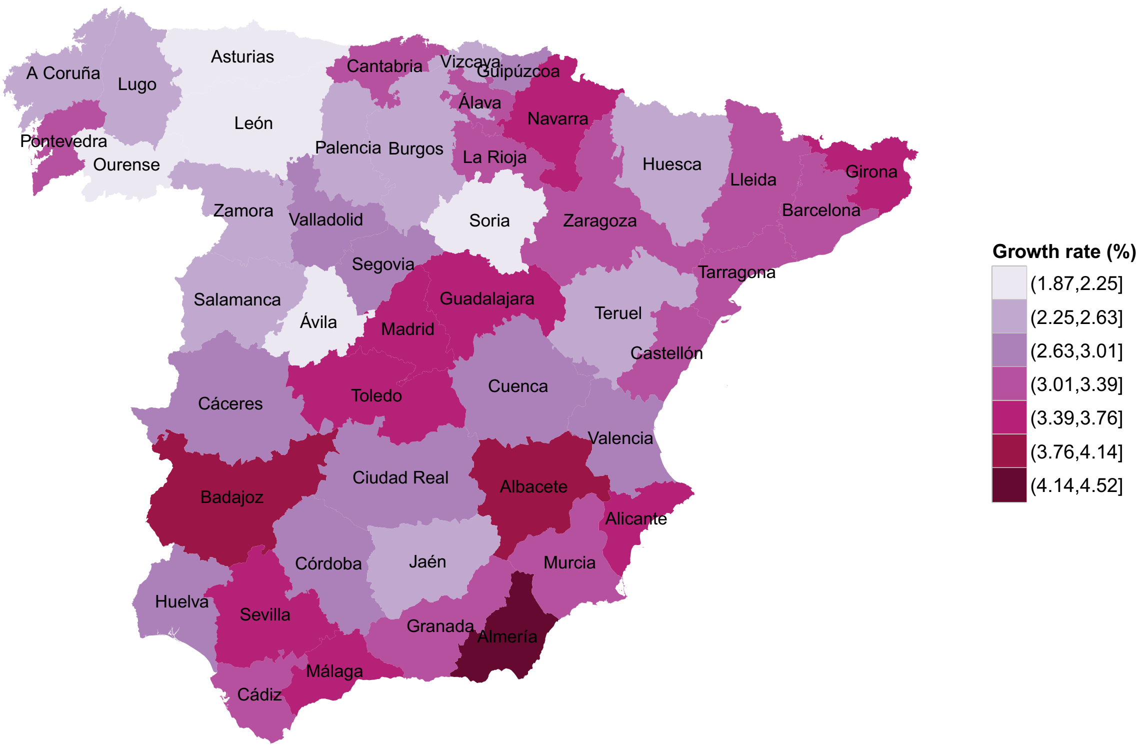

Fig. 2. Compound annual growth rate of GDP of Spanish provinces in the period of 1986–2006.

dependent variable and (ii) the effect of the spatial dependence on the fixed-effects estimates (see Anselin et al., 2008). Elhorst (2003) derives the ML estimator for the spatial lag model (which is easily amplified for the SDM including the spatial lag of the explanatory variables). Lee and Yu (2010) note that Elhorst (2003)s proposal produces inconsistent estimates of the variance parameter when N is large and T is small, and they propose a correction bias solution. Following these authors, we employ this corrected Maximum Likelihood procedure to obtain the parameter estimates.

So far, we have assumed that transportation infrastructure stock variables might be considered exogenous to the economic environment. The exogeneity assumption should be taken with caution given that stock variables might be endogenous due to reverse causality. From an economic point of view, we consider that this problem does not affect our results because the effect of any infrastructure investment on the economic behavior is not immediate. Additionally, there may be some omitted variables that simultaneously affect regional productivity and the infrastructure stocks, but in this case, the consideration of spatial fixed effects solves this issue.

The ML procedure solved the issue associated with the endogeneity of the spatial lag of the dependent variable. Another challenge is how to control the possible endogeneity of additional explanatory variables in a spatial autoregressive specification; i.e., it is necessary to simultaneously consider a simultaneous spatial interaction and the common presence of endogenous variables in applied works. These problems as a whole had not been analyzed in depth until the contribution by Fingleton and Le Gallo (2008), who proposed a three-stage procedure on the basis of the feasible generalized spatial two-stage least squares estimators developed by Kelejian and Prucha (2010) utilizing a cross-section framework. This method may be understood as a combination of Instrumental Variables (IV) and Generalized Method of Moments (GMM).

Regarding panel data frameworks, Kapoor et al. (2007) propose a GM method for spatial panel data with the assumption of random effects, which is extended by Fingleton (2008) including, among other technical considerations, the existence of a spatially lagged dependent variable, whereas a pure IV approach is recovered by Mutl and Pfaffermayr (2011) considering fixed or random effects. Recently, Piras (2013) extended this method following more closely the fixed- and between-effects two-stage least squares estimator proposed by Baltagi and Liu (2011).

In this case, we applied this IV-GMM setting to estimate the proposed model, allowing for an additional endogenous variable (infrastructure investments), and we compared the parameter estimates with the results obtained using ML.[11] A similar strategy is applied by Gómez-Antonio and Fingleton (2012b). Bottasso et al. (2014) analyzed this issue in a cross-section environment, while Chen and Haynes (2013) apparently neglected the lag of the dependent variable.

4.2. Endogeneity discussion

In addition to comparing ML estimates to the GMM results, we test the potential endogeneity of the infrastructure variables in order to guarantee the validity of the different estimated effects, particularly the spatial spillover effects. Then, IV panel data models have been estimated so that the instrumental variables must have a time dimension. In this paper, we choose two types of instrumental variables. First, we consider the most classical option, which is the use of the lagged valued of the endogenous variables: lagged values are less likely to be influenced by current shocks, which is a guarantee of non-correlation with the error term. It is expected that there is a delay between the implementation of policy measures aimed at improving innovation and their impact on economic growth. Following this reasoning, we consider as instruments the possible endogenous variables lagged by one period and two periods, following Rodríguez-Pose and Peralta (2014). Recently, Bottasso et al. (2014) employ the lagged value of ports to control for reverse causality between GDP and this variable.

In the second setting, we build four instrumental variables for roads, railways, airports and ports based on the shift-share decomposition. The shift-share decomposition distinguishes three effects: national, sectorial and regional or competitive effects, so we calculate the national effect for each year of the period 1986–2006 to consider each potential endogenous variable as an instrument (roads, railways, airports, ports):

$$Inst_{it} = End_{it-1}(1 + g_{t,t-1}) \tag{7}$$

where $g_{t,t-1}$ is the rate of growth of the investments in infrastructure for the whole nation, End_{it-1} is the value of the endogenous variable for each location, and $Inst_{it}$ represent the values of the instrument variable in province i. The use of these values (national effect) introduces a major grade of independence, and consequently, the correlation caused by regional shocks should be addressed. A similar approach is applied by Luthi and Schmidheiny (2014) using the sectoral growth rates in Germany instead of the registered values in Switzerland. The instrumental variables should verify two conditions to be reliable: exogeneity and relevance. Then, they must be non-correlated with the error term simultaneously showing correlation with the endogenous explanatory variable.

Employing the first group of instruments, we found that they are strong when attending to the weak instrument test. The value of Kleibergen and Paap (2006) Wald rank F-statistic robust to clustering and heteroskedasticity is 307.69, rejecting the null hypothesis of weak instruments. Additionally, the first-stage F-statistics and Angrist–Pischke F tests for the relevance and validity of excluded instruments are included in Table 2. We further used a Hansen-J overidentification test to check whether the instruments are uncorrelated with the error term so the instruments can be considered valid. The orthogonality conditions have been satisfied according to the corresponding p-value (0.101). The statistic value for the endogeneity test is 2.161. This test follows a χ^2_4, which has a $p - value$ equal to 0.706, so the null hypothesis of the exogeneity of these variables is not rejected. Additionally, a bootstrap Hausman test has been computed, offering the same results (only in the case of roads, the null hypothesis is rejected at 1%). Summing up all of the empirical evidence, we may conclude that there is no significant variation between the two sets of estimates, and consequently, the ML estimation results displayed in Table 3 could be considered unbiased and consistent.

Employing the second group of instruments, Kleibergen and Paap (2006) Wald rank F-statistic is small, so the null hypothesis of weak instruments is not rejected. However, considering the results of the Anderson–Rubin Wald test ($\chi^2_4 = 75.10$), the inference could be considered valid when utilizing these instruments, and the conclusion of the endogeneity test is the same as presented in the table.

[11] This method is available in the splm package of R (Millo and Piras, 2012).

Table 2
Test for validity of instruments and endogeneity test.

	AP under	AP weak	Underidentification	Weak-identification	Over-identification	Endogeneity
Group I			5.15 ($p = 0.076$)	307.69	2.687 ($p = 0.101$)	2.161 ($p = 0.706$)
lroad	4618.00	2177.20				
lrail	2232.06	1052.33				
lair	1720.76	811.27				
lport	3517.06	1658.15				
Group II			1.93 ($p = 0.382$)	1.22	0.00 ($p = 0.992$)	7.173 ($p = 0.127$)
lroad	28.77	13.60				
lrail	2.03	0.96				
lair	36.90	17.44				
lport	8.22	3.89				

Significance code: $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Table 3
Spatial durbin model with spatial fixed effects.

	MLE				IV-GMM			
	W_n		W_{d150}		W_n		W_{d150}	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
K	0.169***	8.32	0.187***	9.12	0.151***	7.35	0.169***	8.08
L	0.319***	17.75	0.325***	18.04	0.329***	18.40	0.335***	18.68
HK	0.023**	2.30	0.025**	2.42	0.020**	2.04	0.023**	2.22
Road	0.069***	6.01	0.067***	5.65	0.041***	3.40	0.042***	3.42
Rail	0.001	0.09	0.003	0.57	−0.005	−0.98	−0.002	−0.47
Air	0.001	0.59	0.001	0.85	0.001	0.38	0.001	0.57
Port	−0.039***	−3.81	−0.043***	−4.20	−0.035***	−3.40	−0.037***	−3.59
$W * K$	0.046	1.30	0.017	0.45	0.065*	1.80	0.041	1.06
$W * L$	−0.077***	−2.60	−0.053*	−1.82	−0.070**	−2.33	−0.046	−1.57
$W * HK$	0.022	1.23	0.031*	1.75	0.042**	2.29	0.044**	2.48
$W *$ Road	0.033	1.16	0.021	1.16	0.017	0.94	0.036*	1.88
$W *$ Rail	−0.007	−0.81	−0.006	−0.67	−0.002	−0.19	−0.002	−0.21
$W *$ Air	0.001	0.14	−0.001	−0.61	0.001	0.67	0.001	0.08
$W *$ Port	0.018	1.04	0.011	0.58	0.026	1.38	0.015	0.75
$W * Y$	0.306***	7.60	0.254***	6.27	0.267***	6.32	0.227***	5.20
Corrected R^2	0.966		0.965		0.965		0.964	
Log-likelihood	2003.03		1987.47		1949.79		1935.42	
Wald test spatial lag	18.56	$p = 0.009$	18.45	$p = 0.010$	29.83	$p = 0.000$	29.01	$p = 0.000$
LR spatial lag	19.35	$p = 0.007$	19.27	$p = 0.008$	30.75	$p = 0.000$	29.86	$p = 0.000$
Wald test spatial error	68.69	$p = 0.000$	55.06	$p = 0.000$	84.12	$p = 0.000$	69.58	$p = 0.000$
LR spatial error	80.50	$p = 0.000$	61.80	$p = 0.000$	96.70	$p = 0.000$	75.65	$p = 0.000$

Spatial fixed effects are not displayed, but are available under request.
* Significance code: $p < .1$.
** Significance code: $p < .05$.
*** Significance code: $p < .01$.

5. Results

5.1. Comments on the results

Before discussing the results, it is worth noting that the coefficient estimates must be interpreted carefully because the model specification and, consequently, the spatial connectivity relationships determine the final effect of changes in the explanatory variables. For example, if the estimated model had the form of the Spatial Error Model (*SEM*), the coefficient estimates in log form could be directly interpreted as elasticities. However, utilizing a *SDM*, the effect of a change in a single explanatory variable related to a certain province i has no straightforward interpretation. In this framework, it is necessary to decompose the results of taking partial derivatives into direct and indirect effects.

LeSage and Pace (2009) shows that the partial derivatives take the form of an N-by-N matrix for each k regressor and comments on their fundamental properties. For instance, the partial derivatives matrix corresponding to the road regressor (*road*) from Eq. (6) would have the following form,

$$\frac{\delta y_t}{\delta road_t} = (I_N - \beta W)^{-1}(\alpha_4 I_N + \theta_4 W) \tag{8}$$

The direct effect measures the effect that a change in an independent variable in province *i* has on the dependent variable in this province. Direct effects, which appear in the main diagonal of the matrix shown in Eq. (8), are their own partial derivatives, which includes feedback effects, i.e., those effects that pass through neighboring units and back to the unit that instigated the change. The cross-partial derivatives are named indirect effects, and they measure the effect of a change in an independent variable in province *i* on the dependent variable in all the other provinces. Thus, indirect effects are understood as spillover effects in this study.

LeSage and Pace (2009) propose scalar summary averages to increase the ease of reporting the effects associated with the regressors; the direct effect is summarized using the average of the elements of the main diagonal in Eq. (8), whereas the indirect effects appear as off-diagonal elements and are summarized as row sum averages. Finally, total effects are computed as the sum of direct and indirect effects.

The results obtained through the estimation process are presented in Table 3, which contains the point estimates of the production function model using two alternative spatial weight matrices, as discussed above. In Table 4, direct, indirect and total effects computations are reported for the SDM.[12]

Overall, the parameter estimates associated with the explanatory variables are consistent with other production function studies, and the estimates of the spatial lag parameters confirm the existence of significant spatial processes working through the dependent variable. As discussed below, there are certain results shared by all of the estimated models. All of the specifications of the model yield similar results regarding the output point estimates of the coefficients that accompany the regressors. It is worth underlining the positive and highly significant effects of the spatial lag of the dependent variable that demonstrate values of 0.306 and 0.254 depending on the W specification adopted. This result indicates that the weighted average of the output of neighbor provinces positively affects production in the geographic unit under analysis. According to the theoretical model that we developed in Section 2, changes in the business cycle in other provinces would significantly affect productivity in a particular province. In this case, because the sign of the parameter that accompanies the spatial lag of the dependent variable is positive, economic agents in that province would increase the capacity utilization of quasi-fixed inputs when output in other provinces grows, and they would decrease this utilization when output falls.

The Wald and Likelihood Ratio (LR) tests permit the determination of the validity of the hypothesis positing that the Spatial Durbin Model can be simplified to the Spatial Lag Model. The MLE results reported using the Wald test (18.56 for the contiguity matrix and 18.45 for the W_{d150} matrix) or utilizing the LR test (19.35, and 19.27) indicate that the hypothesis must be rejected. Similarly, the hypothesis that the SDM can be simplified to the Spatial Error model must be rejected according to the Wald tests (68.69 and 55.06, when the spatial weight matrix is W_{d150}) and the LR tests (80.50 and 61.80). To investigate the null hypothesis that the spatial fixed effects are jointly insignificant, an LR test may be conducted. The results (3248.95, $p < 0.01$ and 3233.27, $p < 0.01$, both with 47 degrees of freedom) indicate that this hypothesis must be rejected and justify the extension of the model with spatial fixed effects. Test results for the GMM models led to analogous conclusions.

As discussed above, inferences must be made about the effect of independent variables on the productivity of a province with regard to the direct, indirect and total effects displayed in Table 4. According to these results, the direct effects of labor and private capital on the aggregated output of a particular province are positive and significant. Moreover, these elasticities are very stable. The elasticities of labor (approximately 0.33), human capital (close to 0.025) and private capital (between 0.16 and 0.19 are positive and significant in all of the models.[13] These coefficients are similar to those obtained in some of the most recent applied studies in Spain (Márquez et al., 2010). Estimations of the direct effects of railway and airport infrastructure are also insignificant, regardless of the empirical specification. Seaport infrastructure appears to impose negative impacts on the economy of those provinces in which the ports are located. At first sight, this could be considered an unexpected result, but we have found that some previous studies have obtained similar estimates. In Cantos et al. (2005), both positive and negative direct effects of port infrastructure are estimated depending on the model specification and the sectoral output under study. However, these authors do not provide any potential justification of this result. A plausible explanation is that whereas positive effects of new port investments could be spread across the nation, the direct and indirect costs (pollution and congestion) are assumed by the local authority and consequently by the province (Bottasso et al., 2014). It is also important to note that the estimated effects in Table 4 are computed as national average effects using the whole set of geographical units. Thus, the estimated effects for a particular province (or a particular port) might be different from those results reported in Table 4. In any case, the negative direct impacts of port infrastructure might require a more profound examination of its contribution to the Spanish economy, including insular provinces and breaking the output-dependent variable into sectoral output. The estimated coefficients that accompany the variable related to road infrastructure are positive and highly significant, and their sizes show little variation. On average, a 100% increase of the road infrastructure of a certain province causes an increase in its productivity that ranges from 4.3% to 7%.

[12] In our results, if we incorrectly interpreted the coefficient associated to *Wroad* as the indirect impact, we would conclude that its effect is 0.023 (on average) and is statistically insignificant, whereas the true indirect effect is statistically significant and higher, with values between 0.032 and 0.055.

[13] Elhorst (2010) emphasize that empirical studies usually find significant differences among the coefficient estimates from models with and without spatial fixed effects. Models that include spatial fixed effects use time-series variations of the data, whereas models without controlling for spatial fixed effects utilize cross-sectional components of the data. Models of the first type tend to give short-term estimates, and models without controls for spatial fixed effects tend to give long-term estimates (Baltagi, 2008).

Table 4
Direct, indirect and total effects.

	MLE				IV-GMM			
	W_n		W_{d150}		W_n		W_{d150}	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Direct effects								
K	0.176***	9.09	0.191***	9.58	0.158***	8.09	0.173***	8.18
L	0.320***	18.59	0.327***	18.05	0.330***	18.74	0.336***	19.29
HK	0.024**	2.43	0.027**	2.63	0.023**	2.35	0.026**	2.54
Road	0.069***	6.02	0.070***	6.12	0.043***	3.63	0.045***	3.80
Rail	−0.001	−0.02	0.002	0.49	−0.001	−1.01	−0.002	−0.58
Air	0.001	0.56	0.001	0.77	0.001	0.42	0.001	0.47
Port	−0.038***	−3.83	−0.042***	−4.13	−0.034***	−3.37	−0.036***	−3.68
Indirect effects								
K	0.132***	3.14	0.081*	1.89	0.135***	3.26	0.095**	2.22
L	0.028	0.86	0.037	1.24	0.026	0.86	0.033	1.16
HK	0.040*	1.70	0.049**	2.34	0.062**	2.68	0.060***	2.85
Road	0.032**	2.53	0.049**	2.33	0.037*	1.73	0.055**	2.49
Rail	−0.010	−0.86	−0.006	−0.58	−0.004	−0.33	−0.003	−0.32
Air	0.001	0.22	−0.001	−0.50	0.002	0.65	0.001	0.10
Port	0.008	0.38	−0.001	−0.02	0.021	0.95	0.008	0.41
Total effects								
K	0.311***	7.27	0.272***	6.07	0.292***	6.99	0.270***	6.19
L	0.348***	11.41	0.365***	12.37	0.356***	12.16	0.370***	13.35
HK	0.064**	2.50	0.075***	3.31	0.085***	3.36	0.085***	3.73
Road	0.101***	4.96	0.119***	5.80	0.080***	3.77	0.099***	4.53
Rail	−0.009	−0.82	−0.004	−0.34	−0.008	−0.72	−0.005	−0.56
Air	0.001	0.35	−0.001	−0.17	0.002	0.65	0.001	0.29
Port	−0.030	−1.43	−0.043*	−1.98	−0.012	−0.058	−0.028	1.28

* Significance code: $p < .1$
** Significance code: $p < .05$.
*** Significance code: $p < .01$.

In the SDM, the indirect effects influence the existence and size of effects across boundaries. We find evidence of positive spatial spillovers for the *road* variable with estimates between 0.032 and 0.055 depending on the W matrix employed to define neighbors and the estimation method. According to these results, increases in the road infrastructure of a province would yield positive effects on the productivity of its neighbor of up to 5.5%. For the remaining modes of transportation, we found no clear evidence of spillovers. Following the indirect effects interpretations presented above, developing road infrastructure in one province would cause positive spillovers to other provinces by raising the quality of the road transportation network as a whole. Conversely, increased investment in ports, airports and railway infrastructure projects in a province would not cause spillover effects through the migration of productive factors to those regions with the larger levels of public capital investment.

These results offer evidence of spatial spillovers for the different types of transportation infrastructure projects, consistent with most of the literature utilizing Spanish provincial data. For instance, employing a stochastic frontier approach, Delgado and Alvarez (2007) found positive and negative spillovers depending on the sector of the economy under review and the definition of the weighting matrix. Utilizing a production function, Moreno and López-Bazo (2007) found the existence of negative spatial spillovers for transportation infrastructure development. By contrast, utilizing Spanish provincial data, Álvarez et al. (2006) replicated the models used by Holtz-Eakin and Schwartz (1995) and Mas et al. (1996) and found neither positive nor negative spillovers.

Finally, we obtain the total effects of the variables in the productivity of a province by adding direct and indirect effects. We find that variables of labor, capital, human capital and road infrastructure are significant with the expected signs. As discussed above, the average total effect of road transportation infrastructure is positive and significant (ranging from 0.08 to 0.119). Conversely, the average total effect of investment in other modes of transport infrastructure appears to have no impact on the productivity of Spanish provinces.

6. Conclusions

In this paper, we attempt to find the correct specifications for an aggregated production function to measure the effects of transport infrastructure on the economy of Spain. The main contribution of the work is twofold. The empirical models include spatial lags of the independent variables and of the dependent variable, which is not common in the literature. We empirically and theoretically justify the inclusion of the spatial lag as an explanatory variable. Primarily, we accommodate the private capital grade of utilization in the business cycles contained in the geographical units. In this fashion, we attempt to capture the underlying spatial processes at work. According to the theoretical framework presented and the model estimates, the business cycle in a province directly affects the economic performance of its neighboring provinces. Second, we offer further evidence on endogeneity issues in a model devoted to account for the direct and indirect effects of transportation infrastructure projects. Statistical tests and comparisons between Maximum Likelihood and Instrumental Variables procedures indicate that in this case, there is no evidence of the endogeneity of transport infrastructure investment and economic development.

As our main empirical result, we find strong evidence of the positive effects of road infrastructure projects on the private economy of a province. Spillovers caused by investment in transportation infrastructure (i.e., the effects on one province of changes in the flows of road services in other provinces) are approximately one-half the size of the direct effects of such investments. Improvements in the road infrastructure of one spatial unit increases productivity in neighboring units by approximately one-half the amount of the improvement in the spatial unit in which the infrastructure is located. Additionally, we have also found negative output effects associated to seaport projects in those provinces in which they are located. The latter result appears to be consistent with some of the literature studying the economic contribution of ports to the Spanish economy. Another interesting result is the lack of any impact at the macro level of the infrastructure associated with railways and airport services.

According to the outcome of this model, the importance of spillover effects in particular appears to support the idea that the effects of road transport infrastructure investment are not confined to the territory in which an infrastructure project is located. In the Spanish political context, this conclusion can have major consequences because both regional and provincial governments share decision-making responsibilities with the national government about where to allocate infrastructure investments. These results support the notion of designing the transport system, especially road infrastructure, as a whole.

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