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Spatial Spillover Effect of Public Infrastructure in Different GDP Sector Compositions: Spatial Panel Evidence in Eu-28 Regions

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Abstract

Spillovers have attracted wide attention in the areas of research in economics during the past decades. The reason for the interest in the topic lies in their important role in endogenous growth theory and the explanation of productivity growth. This paper investigates the spatial spillover of different types of public infrastructure on economic growth across EU-28 NUTS-II regions during 1995-2015. Particularly, we developed the previous studies by consedeing spillover in all types of the GDP sector composition including agriculture, industry, and services. The spatial Durbin panel data model is employed to consider spatial spillovers of both public infrastructure and economic growth. Empirical results show the positive spatial spillovers of communication infrastructure in all the sectors. The spillover effect of transport infrastructure is positive in the service and agricultural sector, whereas it is negative in the industry sector. Moreover, the spillover effect of local infrastructure is insignificant in all three sectors. Finally, we find significant evidence of positive geographical spillovers of economic growth implying spatially-growth dependency of regions to growth rate of neighboring regions.

Keywords: Infrastructure, Spillovers, Spatial Econometrics.
JEL Classification: H54, O47, C21

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Introduction

Public infrastructure is considered as one of the most important factors in the endogenous growth model (Barro, 1990; Futagami, Morita & Shibata, 1993), so that it increases the rate of return to private capital and thereby, simulates private investment expenditure (Aschauer, 1990). Many studies provide evidence in support of the large impact of public capital on private sector output and productivity (Aschauer, 1989; Holz-Eakin, 1988; Munell, 1992). Aschauer (1989) provided empirical evidence for the productive impact of public capital by expanding the conventional aggregate Cobb-Douglas production function to include the public capital stock. Munnell (1990a) confirmed Aschauer’s findings and developed the production function approach by using panel data (1990b). In turn, Bronzini and Piselli (2009) investigated the relationship between total factor productivity and public infrastructure in the long-run, while the estimated coefficient of public capital stock (0.15) appeared in line with the previous empirical result by Munell (1992) and Boarnet (1998). Infrastructure may affect the potential of an economy in two main ways: affecting output directly (as an additional factor of production) or indirectly by reducing transaction and other costs leading to increase in the productivity of private capital (Gramlich,1994; Romp & de Haan, 2007; Straub, 2008). Investment in public infrastructure increases resources and productivity of existing ones, for instance, a new highway construction which reduces transportation cost can lead to producing goods at a lower total cost (Munnell, 1992).

The idea of spatial spillovers from public infrastructure, which was first started with the Munnell’s works (1990a,b), have received increasing attention (Alvarez, Arias & Orea, 2006; Boarnet, 1998; Chandra & Thompson, 2000; Cohen & Paul, 2004; Ezcurra, Gil, Pascual & Rapún, 2005; Gutiérrez, Condeço-Melhorado & Martín, 2010; Hu & Liu, 2010; Kelejian & Robinson, 1997; Pereira & Roca-Sagalés, 2003; Pereira & Andraz, 2010; Yu, de Jong, Storm, & Mi ; 2013). The spatial dimension in infrastructure is an essential factor in the study of productivity (Moreno, López-Bazo & Artís, 2003). In public economics, some researchers show that region spending is influenced by the spending of neighboring states (see, for example, Case, Rosen, & Hines, 1993). The concept of spatial spillover of public capital formation is the situation that one region benefits from public infrastructures installed elsewhere (Pereira & Roca-Sagalés, 2003). For example, the new high way construction in one region can provide a better transportation network, leading to a decrease in transport cost for other firms located in near region (Pereira & Andraz, 2004). In fact, the redistribution of existing resources for production and finally impact on the proximate region’s economic growth (Cohen, 2007; Cohen & Paul, 2004; Jiwattanakulpaisarn, Noland, Graham & Polak, 2009; Pereira & Roca-Sagalés, 2003).

Although the important role of spatial spillover from public infrastructure has been emphasized in the economic literature, there is no clear consensus regarding public infrastructure spillover impact on output. These spillovers can be either positive (Cohen & Paul, 2004; Pereira & Roca-Sagalés, 2003) or negative (Alvarez et. al, 2006; Boarnet, 1988; Moreno et. al, 2003). Positive spillover is explained by connectivity characteristic of public capital that relates any piece of a network such as transport network to the entire network (Moreno et. al, 2003; Tong, YU, Chu, Jnson & Ugarte, 2013), while negative spillover would arise from factor migration such as labour and mobile capital. The negative spillover from public infrastructure is due to attracting mobile production factors from other locations, which is explained as the result of raising the comparative advantages that locate over the other's location (Boarnet, 1988; Alvarez et. al, 2006). In fact, negative output spillovers can result when mobile factors of production migrate to locations with the best infrastructure stocks (Boarnet, 1988).On the other hand, a different type of public infrastructure does not have similar effect on output[1] increase growth of the economy in the region which is located (Hu & Liu 2009), while other types of infrastructure like transport and communication infrastructure can produce both advantages in the regions which are located and transmit to other regions (Moreno & López-Bazo, 2007).

In previous studies, the effect of public infrastructure spillover on output according to different GDP sector compositions has not been taken into account. So, spatial spillover associated with public infrastructure has been assessed only in the agricultural sector (Tong et.al, 2013) or industry sector (Moreno et. al, 2003). In this context, we investigate the spatial spillover effect of transport, communication, and local infrastructure on agricultural, industrial and service output in EU-28 regions. By using the advantage of spatial econometric, we consider the spatial spillover of public infrastructure in the form of Spatial Durbin Model.

The paper is organized as follows. The econometric model and its estimation methods are discussed in Section 2. Section 3 presents the empirical results and a summary of data. The paper ends with conclusions and policy implications in Section 4.

Empirical Model

Model Specification

Following most of the previous studies, to estimate the effect of public infrastructure on output (Boarnet, 1996, 1998; Holtz-Eakin & Schwartz, 1995; Alvarz et.al, 2006), we use the Cobb Douglas production function:

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

where Y is the output, L is labor input, K is private sector capital stock, and G is public capital stock.

Following the ideas of Moreno et. al, (2003), it is assumed that the effect of infrastructure on output depends on the various types of public infrastructure. So, we consider transport infrastructure, communication infrastructure and local infrastructure in the basic specification model (1):

$$Y=f(L, K, Gtrans, Gcomun, Glocal) \tag{2}$$

$$\begin{aligned} \mathrm{LnY} &= \alpha + \beta_{\mathrm{L}}\mathrm{LnL} + \beta_{\mathrm{K}}\mathrm{LnK} \\ &+\beta_{Gtrans} LnGtrans \\ &\quad + \beta_{Gcomm} LnGcomun \\ &+\beta G_{local} LnGlocal + e \end{aligned} \tag{3}$$

The log specification of Eq. (2) becomes: Following LeSage & Pace (2009), the SDM, which denotes both the spatial effect from dependent and all the independent variables, is employed in this paper.

In order to consider the spatial interaction effect between the cross-sectional regions, the Spatial Durbin Model which accommodates the spatial interaction effect from dependent and all the explanatory variables is used (Elhorst, 2010). The Cobb-Douglas production function of Eq. (2), which is enlarged with spatially lagged independent and dependent variables in a SDM framework, as follows:

$$\begin{aligned} \mathrm{LnY_{It}} &= \alpha + \beta_{\mathrm{L}}\mathrm{LnL_{it}} + \beta_{\mathrm{K}}\mathrm{LnK_{it}} \\ &+\beta_{\mathrm{Gtrans}}\mathrm{LnGtran_{it}} \\ &+ \beta_{\mathrm{Gcomun}}\mathrm{LnGcomun_{it}} \\ &+\beta \mathrm{G_{local}}\mathrm{LnGlocalp} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{W_{itj}LnY_{jt}} \\ &+\gamma_{\mathrm{L}} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{W_{ij}LnL_{j}} + \gamma_{\mathrm{K}} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{W_{ij}LnL_{jt}} \\ &+\gamma_{\mathrm{Gtrans}} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{W_{ij}LnGtrans_{jt}} \\ &+\gamma_{\mathrm{Gcomun}} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{W_{ij}LnGomun_{jt}} \\ &+\gamma_{\mathrm{Glocal_{jt}}} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{W_{ij}LnGLocal_{jt}} + \mathrm{U_i} \\ &\quad + \lambda_{\mathrm{t}} + \mathrm{e_{it}} \end{aligned} \tag{4}$$

$$e_{it} \mid N + 0, \varpi^2,$$

here, Y_{it} is the economic output in region i at time t. δ is the constant term. W_{ij} Denotes the i , j th element of a positive $N \partial N$ spatial-

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[1]. There are various types of public infrastructure including local, transport, and communication infrastructures. Local infrastructure including water, sewage facilities, electricity, and urban structures is a type of infrastructure that creates benefit only for the place which is located. Whereas transport and communication infrastructures may produce both benefits in the area where they are located, and spillovers to other regions (Moreno et. al, 2003).

weighting matrix, W that explains the spatial structure of the different regions. υ is the spatial autocorrelation coefficient that represents the interaction effect of the neighbor regions' economic output Y_{jt} with a given regions' economic output Y_{ti} at time t . These two elements present the spatial multiplier and the spillovers strength. Variable $\sum_{j\cong1}^{N} W_{ij} Y_{jt}$ is called a spatial lag in the dependent variable, which represents the spatially weighted average value of economic output from its neighboring region at time t, $\sum_{j\cong1}^{N} W_{ij} X_{jt}$ is called the spatial lag in the explanatory variables, and coefficient τ measures the effects of labour, private capital, communication, transport and local infrastructure of other regions on economic output of a particular region. e_{it} is a disturbance term with the zero mean and variance ϖ^2. We should use spatial specific effects (U_i) and time period specific effects (O_t) in order to remark spatial and temporal heterogeneity. Space-specific time-invariant variables are controlled by spatial specific effects, whereas time-specific space-invariant variables are controlled by time period specific effects (Elhorst, 2013). Specific effects behave as fixed effects or random effects. In the fixed effect model, the dummy variable for the spatial unit is used, whereas in the random model, we consider U_i and O_t like random variables distributed with a zero mean and variance ϖ^2 (Elhorst, 2013). Parameters ε_L, ε_K, ε_{Gtrans}, ε_{Gcomun} ε_{GLocal} denote the elasticity with respect to labor, physical capital, communication infrastructure, transport infrastructure, and local infrastructure, respectively.

Several specification tests such as Lagrange Multiplier (LM), Likelihood Ratio (LR) and Wald Test were conducted before applying SDM as the selected model. Lagrange Multiplier (LM) tests (Burridge, 1980; Anselin, 1988), as well as their robust version (Anselin, Florax & Yoon 1996), can be applied to examine the existence of spatial lag dependence or spatial error dependence. If the LM test results show the rejection of the spatial lag model or spatial error model, the SDM model will be recommended (Elhorst, 2010; Lesage & Pace, 2009).

To confirm further the appropriate model that best describes the data by applying the Likelihood Ratio (LR), Wald tests also is recommended (Elhorst, 2010). The Spatial Durbin Model can be simplified to the spatial lag model or spatial error model by testing the hypothesis $H_0 : \tau \cong 0$ and $H_0 : \tau .\ \upsilon\varepsilon \cong 0$, respectively (Burridge, 1980).[1] If both of the hypotheses are rejected, the Spatial Durbin Model will be adopted. Wald tests have advantages over LR test because of requiring fewer models to be estimated and more sensitivity to the parameterization of non-linear constraint (Hayashi, 2000). It is notable that where the results of LR/Wald tests contradict LM results tests, the preferred spatial model will be Spatial Durbin Model since it is the general form of other spatial models like Spatial Error Model and Spatial Lag Model (Elhorst, 2010).

We can use different types of contiguity matrix W that will demonstrate the various form of infrastructure spillover to examine spillovers' sign and magnitude. The basis of the definition of the weighting matrix is that geography plays a fundamental role in the interaction among areas.

In the first type of contiguity matrix, which is called a binary matrix, its value elements would be 1 if two regions are close to each other and 0 otherwise. The second type which relies on Power Distance Weights will include the inverse of the distance or the square inverse of the distance. These weights are based on geographical criteria, such as contiguity (sharing a common border) or distance, including the nearest neighbor distance (Cliff & Ord, 1981; Anselin, 1988). The spatial weights determination is an

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[1] Both of these tests follow a chi-square distribution with k degrees of freedom.

important point in spatial interpretation. However, there is no consensus over its association with the selection of the appropriate weight matrix in spatial analysis (Anselin, 1988) so that their specification is usually ad hoc, unless a formal theoretical model for specific interaction determines the weights (Cho, Roberts & Kim, 2011; Anselin, Le & Jayet, 2008). In this study, the weights in terms of the inverse of distance between each pair of spatial unit, are used (Alvarez, Shi, Wilson, & Skeath, 2003), more precisely the great-circle as a geographic distance is used for elements of weighting matrix[1]

In addition, LeSage &Pace (2009) provide some evidence for the use of the Spatial Durbin Model: First, the model produces unbiased estimation in comparison with other spatial data modeling processes. Second, it separates the impact of the change in explanatory variables into direct and indirect. In the SDM which consists of spatial lag in both dependent and independent variables, the interpretation of marginal effects would be more complicated. It explains these decomposed effects into direct and indirect. Particularly, the direct effect includes the initial effect of a change in a level of one independent variable in a single region on a dependent variable. Moreover, the spillover feedback from dependent variables of other neighboring regions is considered, if the weight matrix has a higher degree of order than one. The indirect effect (spillover effect) can be interpreted in two ways: the impact of a change in the explanatory variable in all regions on the dependent variable in a particular region or the impact of the change in an independent variable of a particular region on a dependent variable in all other regions. Moreover, this model (4) further nests the spatial lag and the spatial error model, i.e. models involving dependence in the error term and in the dependent variable. Spatial econometric model that includes a spatially lagged dependent variable or a spatially autoregressive process in the error term, is known as the Spatial Lag Model (SLM) and Spatial Error Model (SEM), respectively. The Spatial Durbin Model proposed by Lesage and pace (2009).

In our spatial analysis, by using spatial lag of the explanatory and dependent variables spatial lag, 'direct impact' would be explained as the effect of the change in a single independent variable on a particular region as well an 'indirect effect' on all other regions. These results are created due to the spatial connection that is included in spatial regression analysis.

Using Ordinary Least Squares (OLS) method to estimate spatial models, which incorporates spatial effects, lead to unbiased and inconsistent results[2] (Elhorst, 2003). To solve this problem, the maximum likelihood estimation method based on the conditional log-likelihood function of the model was employed (Anselin, 1988).

Direct and Indirect (Spillover) Effects

LeSage and Pace (2009) point out that the interpretation of the parameters in models which include a spatial lag of the dependent variable $\left(\sum_{j=1}^{N} W_{ij} Y_{jt}\right.$, and independent variable $\left[\sum_{j=1}^{N} W_{ij} X_{jt}\right]$ becomes richer and more complicated. In order to better interpret the estimation of SDM, we should consider the direct, indirect, and the total impact (Lesage & pace, 2009). Particularly, the direct effect represents the change of the dependent variable in one particular region due to a change in an explanatory variable in a specific region and the feedback effect from dependent variables of other neighboring regions. When a change occurs in one region, its effect passes through the neighboring regions and backs to the origin region, which is called feedback

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[1] When creating spatial weights, we can apply uses either the straight-line (crow-fly) Euclidean distance or the Great Circle distance depending on whether the latitudes and longitudes supplied in variable list are projected or not. In this paper, Spwmatrix command in Stata produced weighting matrix by using latitude and longitude data. According to the data, selection measure for distance is Great Circle. The great-circle or orthodromic distance is the shortest distance between two points on the surface of a sphere.

[2] In the case that spatial model is consist of a spatially lagged dependent variable, the OLS estimator of the response parameters not only be unbiased but also is inconsistent. (Elhorst,2003)

effect. The indirect effect which is known as the spillover effect measures the effect of a change in a dependent variable in the specific region on a dependent variable in all other regions.

In order to better explain the derivation of the marginal effects of explanatory variables in a spatial panel data setting, Eq. (4) can be rewritten in the vector form (Elhorst, 2014):

$$\mathrm{Y} \cong (\mathrm{I}\,0\,\rho\mathrm{W})^{01}(\mathrm{X}\beta\,.\ \mathrm{W}\mathrm{X}\theta\mathrm{X}\ \ \mathrm{R} \qquad (5)$$

$$\mathrm{R} \cong (\mathrm{I}\,0\,\rho\mathrm{W})^{01}\alpha\mathrm{I}_{\mathrm{N}}\ .\ \ (\mathrm{I}\,0\,\rho\mathrm{W})^{01}\varepsilon \qquad (6)$$

Where the identity matrix is presented by I, I_N is a $n\partial 1$vector of ones, η denotes e_{it}, and time period fixed effects and/or possible spatial and R contains the intercept and error terms.

Taking a partial derivative of the expected value of Y with respect to the explanatory value of X from unit 1 to unit N in time, we obtain the following matrix $N\partial N$ that shows the marginal effect:

$$\cong \begin{bmatrix} \frac{\div \mathrm{E(Y)}}{\div \mathrm{X}_{1\mathrm{k}}} & . & \frac{\div \mathrm{E(Y)}}{\div \mathrm{X}_{\mathrm{Nk}}} \end{bmatrix} \cong \begin{bmatrix} \frac{\div \mathrm{E(Y_1)}}{\div \mathrm{X}_{1\mathrm{k}}} & \frac{\div \mathrm{E(Y_1)}}{\div \mathrm{X}_{\mathrm{Nk}}} \\ \frac{\div \mathrm{E(Y_N)}}{\div \mathrm{X}_{1\mathrm{k}}} & \frac{\div \mathrm{E(Y_N)}}{\div \mathrm{X}_{\mathrm{Nk}}} \end{bmatrix} \cong (\mathrm{I}0\ \upsilon\,\mathrm{W})^{01} \begin{bmatrix} \varepsilon_{\mathrm{k}} & \mathrm{w}_{12}\tau_{\mathrm{k}} & . & \mathrm{w}_{1\mathrm{N}}\theta_{\mathrm{k}} \\ \mathrm{w}_{21}\tau_{\mathrm{k}} & \varepsilon_{\mathrm{k}} & . & \mathrm{w}_{2\mathrm{N}}\tau_{\mathrm{k}} \\ . & . & . & . \\ \mathrm{w}_{\mathrm{N}1}\tau_{\mathrm{k}} & \mathrm{w}_{\mathrm{N}2}\theta_{\mathrm{k}} & . & \varepsilon_{\mathrm{k}} \end{bmatrix} \qquad (7)$$

where ε_k and τ_k are the coefficient estimates associated with the kth explanatory variables

where I is the identity matrix, I_N is a $N\partial 1$vector of ones, e is error term.

This $N\partial N$ matrix denotes that one unit change of a particular explanatory variable in a particular unit, not only will affect a dependent variable in that unit but also the dependent variable of all units.

In the above matrix, diagonal elements show a direct effect, while off-diagonal elements include an indirect effect. In different units, direct and indirect effects are different, so K different $N\partial N$ matrices of direct and indirect effects are extracted that make the interpretation of results difficult. To overcome this problem, LeSage and Pace (2009) suggest a summery indicator including the direct and indirect effect on the basis of diagonal element average and the row sums average or the column sums average of the off-diagonal elements, respectively.

In the SDM, the estimation of the variable (ε_k) represents the direct effect, while indirect effect is shown by the coefficient estimate of its spatial lagged value (τ_k) (Elhorest, 2014)

Data and Empirical Results:

Data

The sample is carried out of NUTS-II regions from 1995 to 2015 period. We used Cambridge Econometrics dataset, collected from Eurostat's REGIO database, the annual macroeconomic database of the European Commission's (AMECO) database and the data were collected by Eurostat. The nuts classifications include NUTS-I, NUTS-II, and NUTS-III. Because the lack of the data for NUTS-III, we choose between NUTS-I and NUTS-II level. Although there is no obvious reason for this choice, this level usually is selected as the appropriate level in the regional context analysis because of the consideration of the NUTS-II level in the regional policy by the Member States. The final units of observation are 266 NUTS-II regions belonging to eighteen countries of the former EU28. Whereas we focus on regional rather than national differences, our choices would contain the countries with one or two NUTS-II regions including Cyprus, Ireland, Latvia, Estonia, Luxemburg, Malta and Slovenia are not taken into account[1]. Following Hall and

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[1] In this case, regions behave like the countries so that our analysis in regional context may be changed to the national context.

Jones (1999), the stock of physical capital is derived from the gross fixed capital formation series by applying perpetual inventory calculation, where a linear yearly depreciation rate of 6% is considered (Bernanke & Gurkaynak, 2001). Public capital can be calculated in two ways: by applying the perpetual inventory method to the flows of public investment (terms of money) (Bronzini & Piselli, 2009; Fernald, 1999) or the measurement of the physical amount of public infrastructure (terms of infrastructure such as km of railway or number of internet user). Investments in public capital may not always be productive (Canning, 1999; Pritchett, 1999; Easterly, Levine & Roodman, 2004). The amount of physically existing public infrastructure may differ from accumulated money created by the government due to corruption such as fraud, embezzlement, waste, and mismanagement (Golden & Picci, 2005). In other words, the value of public infrastructure and the cost of public works can significantly differ because of the inefficiency of the public administration, mismanagement, waste, or even corruption (Bronzini & Piselli, 2009; Golden & Picci, 2005). In this study, we quantify the stock of public capital infrastructure by physical measures such as the length of railway (transport infrastructure), electricity production (local infrastructure) and internet users' telecommunication infrastructure. The definitions of variables are summarized in Table 1.

Table 1. Definition of Variables

variable	Definition	Unit of measure
GDP	Gross domestic product at the current price	Million Euro
Labour Force	Total labour force comprises people aged 15 and older. They, according to EU LFS, include persons in employment as those aged 15 and over, who, during the reference week, performed some work, even for just one hour per week, for pay, profit or family gain.	Thousand people
Physical Capital Stock	it is calculated using the perpetual inventory method	Million Euro
Transport Infrastructure	Total railway lines	Kilometer
Communication infrastructure	Internet use: participating in social networks (creating user profile, posting messages or other contributions to facebook, twitter, etc.)	Percentage of the individuals
Local Infrastructure	Total gross electricity production	Giga watt-hour

Empirical Results

Table 2 presents the result of cross sectional dependence tests (Moran's I and the Pesaran's statistics) that calculate the correlation degree across spatial units. A positive and significant z-value shows a positive spatial autocorrelation.

Table 2. Spatial Dependence Tests

	Agriculture Output	Industry Output	Service Output
LMerror(Robust)	3.0797 (.0793)*	2.971 (.000)*	3.041 (.000)*
LMerror(Burridge)	2.4104 (.1205)*	3.212 (.001)*	2.081 (.005)*
LMsar(Robust)	5.1923 (0.00)*	4.56 (.000)*	3.64 (.000)*
LMsar(Anselin)	4.9679 (0.00)*	3.25 (.005)*	4.23 (.001)*
LR test spatial lag	8.01 (0.045)*	5.26 (.003)*	8.62 (.000)*
LR test spatial error	10.60 (0.005)*	6.23 (.001)*	9.23 (.001)*
Moran'S I	0.5297 (0.0084)*	0.3913 (.004)*	.4923 (.005)*
Geary GC	0.13 (0.008)*	0.4496 (0.0396)*	.2311 (.001)*
Ord's G	-0.9837 (.021)*	-0.671 (.001)*	-.812 (.032)*

Source: Authors
*Statistical significance at the 5% level

For all the sectors, LM tests on the residuals for both error and spatial lag dependence with their respective robust versions reject the null hypothesis of no spatial lag and no spatial error, so the SDM is then recommended. Moreover, this finding is confirmed by LR tests so that the null hypothesis that the Spatial Durbin Model can be simplified to Spatial Lag Model and Spatial Error Model is rejected. As result, the SDM is a proffered model to SLM and SEM models. LM tests on the residuals for both error and spatial lag dependence with their respective robust versions reject the null hypothesis of no spatial lag and no spatial error, indicating the persistence of spatial dependence in the dependent variable.

Table 3 reports estimation results of the SDM; we can find that the coefficients of the labor, physical capital, transport infrastructure, communication infrastructure and local infrastructure are positive and significant in agriculture, industry, and service sectors. The spatial lag of transport infrastructure (W transport) is significant and positive in agriculture and service sectors, while it is negative in the industry sector. The spatial lag of communication infrastructure (W Communication infrastructure) is positive while, in contrast, no significant effect of local infrastructure (W Local infrastructure) is founded in all the sectors[1]. The parameter of spatial dependence (v) in Table 3 implies that a region’s economic output in each sector is affected by the performance of its neighbors, so, the higher (lower) the output of neighboring leading to higher (lower) output of a particular region. We present results for the estimation of the direct and indirect (spillover) effects according to the decomposition approach, which is discussed in Table 4. The direct effect of three types of public infrastructure in three sectors including industry, service, and agriculture is positive which means that by increasing these factors in each region, economic activity increases in that region. The spatial spillover effect (indirect effect) of communication infrastructure is positively significant, which means communication infrastructure contributes to GDP in agriculture, industry, and service

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[1] since these coefficients (W labor, W physical capital Communication infrastructure, W Local infrastructure, W transport infrastructure) cannot simply be interpreted as a partial derivative of a dependent variable with respect to explanatory variables because of the inclusion of spatial interaction effects (for more detail see LeSage & Pace, 2009), the interpretation of coefficient is on the basis of direct, indirect and total impact. When interpreting the coefficients, therefore, the direct effects consider the estimation coefficient of the non-spatial variables and the spatial indirect effects are those related to the spatially lagged variables.

sector indirectly through spillover effect. For all the sectors, communication infrastructure investment in the particular region will increase the economic output of all neighboring regions. The indirect (spillover) effect of transportation infrastructure is negative in the industry sector, while this effect is positive in agriculture and service sectors. Because the increased connectivity of improved railways is developed beyond the area where the infrastructure is located. However, it may be negative in the industry sector due to the absorption of the employees by the region with a better infrastructure from other regions. These results are consistent with the ones obtained for the states of the US in Boarnet's (1998) and in Kelejian and Robinson's (1997) studies. Spillover effect related to local infrastructure is insignificant in all the sectors implying that local infrastructure investment in one region can't produce benefit for other regions.

Table 3. SDM Results with Different GDP Sector Compositions

Variable	Agriculture Output	Industry Output	Service Output
Labor	1.176(0.000)*	1.260(0.000) *	1.328(0.000) *
Physical stock	.660(0.000) *	.675(0.000) *	.988(0.000) *
Transport infrastructure	.899(0.000) *	1.207(0.000) *	1.097(0.000) *
Communication infrastructure	.356(0.040) *	.0895(.000) *	1.563(0.005) *
Local infrastructure	.875(0.000) *	.0828(0.000) *	1.167(0.000) *
W Labor	.303(.000)	.235(.010) *	.605(0.002) *
W Physical stock	.318(0.032) *	.340(0.032) *	.614(0.036) *
W Transport infrastructure	.123(.001)*	-.084(.011) *	.302(0.000) *
W Communication infrastructure	.240(.024)*	.317(0.040)*	.558(0.000) *
W Local infrastructure	.162(.071)	.155(.069)	.347(0.000) *
Spatial autoregressive parameter (υ)	.08(.000) *	.062(.000) *	.058(.000) *

Source: Authors

The variables W Labour, W Physical stock, W Transport infrastructure, W Communication infrastructure and W Local infrastructure correspond to lag spatial variables, respectively, of Labour Physical stock Transport infrastructure Communication infrastructure Local infrastructure.

**Statistical significance at the 5% level*

Table 4. Direct and Spillover Effects of SDM Results

Variable	Agriculture Output	Industry Output	Service Output
Direct effects			
Labor	.042 (0.000)*	.031(0.000) *	.022(.003) *
Physical stock	.123(0.000) *	.184(0.000) *	.241(.000) *
Transport infrastructure	.321(0.000) *	.141(0.000) *	.123(.000) *
Communication infrastructure	.156(0.040) *	.221(.001) *	.192(.001) *
Local infrastructure	.075(0.000) *	.0828(0.000) *	.0721(.000)
Indirect(Spillover) effect			
Labor	.021(.000) *	.025(.000) *	. 11(.000) *
Physical stock	.018(0.032) *	.040(0.032) *	.054(.001) *
Transport infrastructure	.123(.000) *	-.084(.001) *	.149(.000) *
Communication infrastructure	.240(.005) *	.317(0.040) *	.262(.030) *
Local infrastructure	.062(.061)	.055(.058) *	.032(.073) *
Total effects			
Labor	.063(.003) *	.056(.032) *	.132(.042) *
Physical stock	.141(.021) *	.224(.000) *	.295(.004) *
Transport infrastructure	.444(.000) *	.057(.000) *	.272(.001) *
Communication infrastructure	.396(.003) *	.538(.034) *	.454(.005) *
Local infrastructure	.137(.0.13)	.1378(.09)	.104(.21)

Source: Authors

**Statistical significance at the 5% level*

Summary and Conclusions

This paper analyzes the differential impact of public infrastructure, in terms of different GDP sector composition, on economic growth. We estimated an aggregate production function for EU-28 regions from 1995 to 2015 incorporating labor input, the stocks of physical capital and public capital. Our results indicate that there is a positive effect of transportation, communication, and local infrastructure capital on aggregate output in the agricultural, industry, and service sectors. This research provides important policy implications in order to invest in communication infrastructure in the entire sector because this type of infrastructure not only is important in the production within the sector but also between the regions. We find that the estimated spatial spillover (indirect) effect with respect to the communication infrastructure is significantly positive in all the sectors, indicating that EU-28 regions can benefit from form spatial spillover of neighboring regions due to the connectivity characteristics. The transport infrastructure improvement in one region negatively affects the output of neighboring regions in industry sector indicating that the development of transportation system in EU-28 regions produce negative externality for their neighboring regions because of migrating factor production from less developed regions to places with the best infrastructure stocks (Boarnet, 1998). Since infrastructure enhances economic activity in the region where they are located (Moreno et. al., 2003), the spillover effect of local infrastructures is insignificant. Moreover, positive spatial autocorrelation coefficient indicates that the characteristics of neighboring economies are important to explain the processor economic growth in a particular economy so that EU-28 regions can experience beneficial public infrastructure spillover from their neighbors in agriculture, service, and industry sector outputs.

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