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Inmaculada C. Álvarez, Alberto Gude, Luis Orea

Departamento de Economía

Universidad de Oviedo

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Effects of inter-industry and spatial spillovers on regional productivity: Evidence from Spanish panel data

Inmaculada C. Álvarez
Universidad Autónoma de Madrid and Oviedo Efficiency Group

Alberto Gude
University of Oviedo and Oviedo Efficiency Group

Luis Orea
University of Oviedo and Oviedo Efficiency Group

Abstract

This paper examines the role of both intra and inter-industry spillovers when estimating regional aggregate production functions. To our knowledge, this is the first paper that examines technological and spatial externalities simultaneously using sector-level data. The proposed model also extends the standard spatial econometric models by modeling interregional (spatial) dependence through the economic criteria of migration flows. We apply our methodology to the Spanish provinces over the 2001-2013 period. Our results reveal the simultaneous presence of both Marshallian and Jacobian externalities. The spillovers of private production factors are negative in most of the sectors, indicating the presence of inter-regional and inter-sectoral competition for skilled labor and private capital. Our results also indicate that the core-periphery theory can be applied to both fully efficient and inefficient sectors, a finding that should be examined more deeply in the future.

Keywords: Production function, spatial econometrics, regional spillovers

JEL codes: C23, C24, E23, R12

1. Introduction

Motivated by the desire to identify and tackle the roots of unequal development, the production frontier approach has been applied to many regional datasets over the last two decades. Early contributions using the non-parametric techniques of Data Envelopment Analysis (e.g. Seiford and Zhu, 1998) or the parametric methods based on stochastic frontier analysis models (Gumbau-Albert, 1998) have one element in common: they all suffer from a lack of consideration for interregional linkages. However, based on the theoretical and methodological developments of the spatial econometric models, more recent contributions such as Glass et al. (2016) and Gude et al. (2017) have overcome this shortcoming. Yet, their approach is at the aggregate sectoral level only, and thus they disregard the presence of sector heterogeneity. The contributions for instance of Vidoli and Canello (2016) and Gitto (2017) provide individual estimates by industry but they ignore any possible intersectoral interaction. The same applies to the contributions by Delgado and Alvarez (2007) and Badunenko and Romero (2014) where, compared to the previous ones, spatial interaction is accounted for.

While intra-sectoral or inter-regional externalities have traditionally played a key role on location choice and productivity dynamics, the importance of inter-sectoral externalities cannot be denied for several reasons.[1] For instance, Jacobs (1969) states that the most important source of knowledge spillovers are external to the industry in which the firm operates and that diversity rather than specialization is the operative mechanism of economic growth (Feldman and Audretsch, 1999). Jacobs argues that competition for the embodiment of new ideas is more conducive to knowledge externalities than is the degree of competition prevalent in a particular region. Porter (1990) defends greater technology diffusion among vertically integrated firms and supports that high competition boosts growth, but he disagrees with Jacobs about the primacy of diversity or specialization. On the other hand, the importance of foreign direct investment, licensing and imports for economic growth and productivity has been extensively studied (see, for example, Blalock and Gertler, 2008). In this context, Lopez (2008) points out that the effects of licensing (and most likely the other ways in which technology can be transferred from one region to another) do not only apply to the same industry. If licenses are issued in a downstream sector, it is plausible to imagine technology transfer to its upstream sector, and vice versa. As a result, the upstream (downstream) sector might benefit by greater productivity, better prices or higher quality. Finally, it should be noted that, from a strict econometric point of view, the intersectoral spillovers could control for unobserved variables that are "common" to other industries, in the same fashion that the intrasectoral (spatial) spillovers are often included in the models to mitigate the bias arising from the omission of spatially dependent regressors (LeSage and Pace, 2008; Pace and LeSage, 2008; Orea et al, 2018).

As a result, this paper tackles the challenge of conceptualizing and estimating the simultaneous presence of interregional and intersectoral linkages in a production function framework. Using a similar framework, both effects have been included and proven significant in the study of interregional spillovers of R&D between firms (see, e.g. Goya et al., 2012; Autant-Bernard and LeSage, 2011). We instead use macro data and apply our somewhat novel methodology to 48 Spanish provinces over the 2001-2013 period. To our knowledge, the present research is the first paper to use a regional aggregate production function with technological and spatial externalities. In addition, to account for both intra- and inter-industry

[1] Inter-sectoral linkages come from the idea of knowledge spillovers, which have received an increasing attention in the knowledge production functions literature initiated by Griliches (1979). The theoretical foundations of both inter-regional and inter-industry spillovers, called Marshallian and Jacobian externalities, were originated by the papers by Marshall (1890) and Jacobs (1969). Both Marshallian and Jacobian externalities are related to the concept of agglomeration economies, which has proved to be of importance on efficiency and productivity growth.

spillovers, this article extends the empirical literature on spatial autoregressive models by modeling interregional dependence through the economic criteria of migration flows. Unlike the traditional proximity-based weight matrix, our matrix based on migration flows takes into account the difference in spatial dynamics between industries, as well as the relationship structures behind them.

Regarding the use of weight matrices, it is should be emphasized that estimating a production function model with both interregional and intersectoral linkages is challenging. Indeed, Elhorst et al. (2012) pointed out that the use of multi-dimensional weight matrices in spatial econometric models might cause problems of identification and interpretation, in particular if endogenous lagged variables are included in the model (e.g. if a Spatial Durbin model is estimated). In such models, the exact boundaries for the autoregressive parameters are difficult to impose in practice. They also state that unsound autoregressive coefficients can be obtained if the weight matrices partially overlap. Furthermore, the interpretation of such spillovers would be problematic as the calculation of the direct versus indirect effects would take place over the product of two different matrices. Elhorst (2010) and Parent and LeSage (2010) show that the direct and indirect effects of a model with spatial and temporal weight matrices can be separated from each other in space and time. However, Elhorst et al. (2012, p. 217) show that this cannot be done in more general settings. On the other hand, Elhorst and Halleck-Vega (2017) noted that the spatial models with local spillovers tend to outperform the spatial models with global spillovers if the weight matrices are not sparse. Our spatial weight matrices based on distances and migration flows and the weight matrices used to capture the inter-sectoral interactions are highly dense. This suggests again the use of simple spatial models with no lags of the endogenous variable. For these reasons, in this paper we adopt a conservative strategy and focus our empirical exercise on the so-called SLX model that only includes local spillovers in both inter-sectoral and intra-sectoral dimensions.[2]

Our analysis focuses on the Spanish regional system. In regional economics, there has been a growing interest in the analysis of spillover effects. Indeed, a vast literature analyzes interregional externalities in the production function and, in particular, the role of the spillover effects of public investment, mainly for transport infrastructures (e.g. see Pereira and Andraz, 2004; and Crescenzi and Rodriguez-Pose, 2008). In the Spanish case, which we use to illustrate our methodology, we find relevant studies which adopt a production function approach, such as for example Cantos et al. (2005), Pereira and Roca-Sagales (2003), Arbues et al. (2015) and Alvarez et al. (2016a,b). We extend these papers in the sense that we use sectoral level data and examine the role of inter-sectoral spillovers between different industries. A few other few studies estimate regional economic performance by introducing spatial dependence and disaggregating by sectors. For example, for Spanish provinces Delgado and Alvarez (2007) estimate the effect of transport infrastructures spillovers using a stochastic frontier approach by sectors, while Badunenko and Romero (2014) incorporate intra-sectorial dynamic in productivity, following a non-parametric approach. They however ignore the existence of inter-sectoral spillovers. Therefore, to our knowledge, there is no prior study that examines simultaneously the presence of inter-regional and inter-industry linkages in a production function framework using data from Spanish provinces.

The remainder of the paper is organized as follows: Section 2 describes the set of models that are estimated in this paper. Section 3 starts by describing the data and continues with the specifications of the spatial weight matrices. We present and comment on the empirical results in Section 4, while the last section underlines the main results and offers some concluding remarks.

[2] We however briefly compare our main results with those obtained using a SDM-type model in Section 4.4.

2. Empirical specifications of the production functions

2.1. General specification

Our starting point is a modified version of a Cobb-Douglas production function with Hicks neutral technology. Assuming that this technology exhibits constant returns to scale for capital and labor, the production function can be written as follows:[3]

$$y_{its} = A_{its} K_{its}^{\alpha_{Ks}} L_{its}^{1-\alpha_{Ks}} \exp(\alpha_{Hs} H_{its})\, G_{it}^{\alpha_G} \tag{1}$$

where Y_{its} represents the output for every sector $(s = 1, \dots, S)$, province $(i = 1, \dots, N)$ and time period $(t = 1, \dots, T)$;, K_{its} and G_{it} are the physical private and public capital respectively, H_{its} represents human capital and L_{its} is the employment level. The term A_{its} captures the level of technological knowledge or the productivity level of all inputs. Notice that the public capital variable does not vary across industries as it is a province-level variable, and that we have used an exponential form for the human capital variable because, unlike other inputs, it is an a dimensional variable defined in percentage terms.

The above production function imposes constant returns to scale on K and L, which implies decreasing returns to scale. Therefore, equation (1) can be rewritten in per worker terms as follows (Calderon *et al.*, 2015):

$$y_{its} = A_{its} k_{its}^{\alpha_{ks}} \exp(\alpha_{Hs} H_{its})\, G_{it}^{\alpha_G} \tag{2}$$

where $y_{its} = Y_{its}/L_{its}$ and $k_{its} = K_{its}/L_{its}$. Taking logs, this equation can be expressed in a more compact fashion as follows:

$$ln y_{its} = lnA_{its} + \alpha lnX_{its} \tag{3}$$

where for notational ease we have assumed the existence of a unique input.[4] In the spirit of Ertur and Koch (2007), Fischer (2011), and Dall'erba and Llamosas-Rosas (2015), the various specifications estimated in the next sections differ in terms of how the total factor productivity term (A_{its}) in equation (3) is specified econometrically.

2.2. FE model

The first model simply treats the total factor productivity term (A) with time-varying individual effects that are estimated with other parameters of the model. As all models are estimated for each sector, these fixed effects also vary across sectors. In particular, the FE model assumes that:

$$A_{its} = \exp(\mu_{its}) \tag{4}$$

Merging (4) in (3) and adding the traditional zero-mean noise term leads to:

$$\ln y_{its} = \mu_{its} + \alpha lnX_{its} + v_{its} \tag{5}$$

where $v_{its} \sim N(0, \sigma_v^2)$. The previous production frontier model may be interpreted within the framework of the stochastic frontier literature. Indeed, following Cornwell *et al.* (1990) (CSS

[3] This assumption reduces the number of parameters to be estimated and overcomes potential problems of multicollinearity.

[4] Notice that if the unique input represents human capital, the log in lnX_{its} should vanish because in this case X_{its} follows an exponential function. On the other hand, if several inputs are involved, X_{its} can be interpreted as an aggregated input:

$$X_{its}(k_{its}, H_{its}, G_{it}) = k_{its}^{\alpha_{ks}/\alpha} \exp\left(\frac{\alpha_{Hs}}{\alpha} H_{its}\right) G_{it}^{\alpha_G/\alpha}$$

model), we hereafter assume that all fixed effects are second-order polynomial functions of time, that is:

$$\mu_{its} = \mu_{0is} + \mu_{1is}t + \mu_{2is}t^2 \tag{6}$$

Similar to the model of Schmidt and Sickles (1984), we estimate the above model in two stages. First, we apply the within estimator to obtain consistent estimates of all the input elasticities in equation (5) and the estimated residuals of the model (i.e. $\hat{\varepsilon}_{its} = \ln y_{its} - \hat{\alpha} lnX_{its}$). These residuals are then regressed on a constant, a time trend, and the square of the time trend for each province-sector. The fitted values from these regressions provide estimates of μ_{its} in (6).

The CSS model uses (again) a two-stage to get time-varying efficiency scores for each production unit. Cornwell *et al.* (1990) define the maximum for each year and calculate efficiency relative to the best unit in that year. That is, the individual efficiency scores of each sector and province are obtained from $\hat{u}_{its} = max_j(\hat{\mu}_{jts}) - \hat{\mu}_{its}$ and $TE_{its} = exp(\hat{u}_{its})$. This approach yields several advantages: (i) no strong distributional assumptions on the inefficiency term are required, (ii) the correlation of technical efficiency with the explanatory variables is admitted, and (iii) the time-varying efficiency allows us to compare the performance of each sector against the economic deprivation.

2.3. SLX Model

The Spatial Lag Model (SLX) extends the specification above by including spatial externalities or intra-sectoral spillovers as follows:

$$A_{its} = \exp(\mu_{its}) \cdot \prod_{j \neq i}^{N} X_{jts}^{\rho_s w_{ij}} \tag{7}$$

where the terms with subscript $j = 1, \dots, N$ allow us to formalize the connectivity between regions by means of the spatial weight terms w_{ij}. The coefficient ρ_s measures the extent to which the TFP term emanating from private, human and public capital, spills over space.[5] Merging the log linearized equation (7) in (3) and adding a traditional noise term leads to:

$$\ln y_{its} = \mu_{its} + \rho_s \sum_{j=1}^{N} w_{ij} lnX_{jts} + \alpha lnX_{its} + v_{its} \tag{8}$$

This model can be rewritten using matrix notation as follows:

$$\ln y_s = \mu_s + \rho_s W lnX_s + \alpha lnX_s + v_s \tag{9}$$

where v_s is a NTx1 vector of random terms, y_s and X_s are respectively NTx1 vectors of outputs and inputs, and W is a NTxNT spatial weight matrix in which the diagonal terms are equal to zero. The terms positioned outside the diagonal are equal to zero in a particular period t if the TFP term of a particular province *j* is assumed to be uncorrelated with the TFP of province *i*, these proving different from zero otherwise.[6] We consider two alternative weighted matrices with the terms positioned outside the diagonal being based upon the inverse of the distances between the spatial units and migration flows, respectively. Therefore, we consider different specifications based on geographic and economic characteristics.

[5] Equation (7) seems to state that the total factor productivity term of a particular province-sector depends on the input levels in other (adjacent) regions, but not on the inputs in our own province and sector. If we extend our specification of A_{its} á la Dall'erba and Llamosas-Rosas (2015) and allow A_{its} to be an increasing function of own physical private and public capital, and human capital, their coefficients would not be identified without adding more structure to the model. The above authors address this issue adding the spatial lag of the A_{its} in equation (7). However, this would yield a SDM-type model that is more difficult to estimate and interpret as mentioned in the introduction section.

[6] Quite often the spatial-weight matrix is row-normalized so that $\sum_{j=1}^{N} w_{ij} = 1$.

2.4. ILX Model

The Inter-Industry Lag (ILX) Model expands the FE specification by including inter-industry externalities as follows:

$$A_{its} = \exp(\mu_{its}) \cdot \left(\sum_{r\neq s}^{S} m_{rs} X_{itr}\right)^{\phi_s} \tag{10}$$

where subscript $r = 1, \dots, S$ indicates industries and m_{rs} formalizes the connectivity between industries, and the parameter ϕ measures the strength of inter-industry externalities. For both inputs k_{its} and H_{its} we use labor-weighted average means in other sectors (i.e. $m_{rs} = L_r/\Sigma_{r\neq s}L_r$). Notice that we have not mentioned public capital here because it is a province-specific variable and thus common to all sectors. Combining (10) and (3) and adding a noise term leads to:

$$\ln y_{its} = \mu_{its} + \phi_s ln\bar{X}_{its} + \alpha lnX_{its} + v_{its} \tag{11}$$

where $\bar{X}_{its} = \sum_{r\neq s}^{S} m_{rs} X_{itr}$.[7] This model can be rewritten using matrix notation as follows:

$$\ln y_s = \mu_s + \phi_s ln\bar{X}_s(M) + \alpha lnX_s + v_s \tag{12}$$

where $\bar{X}_s(M) = MX_s$, and M is a NTxNT spatial weight matrix in which the diagonal terms are equal to zero, and the terms positioned outside the diagonal in a particular period t are equal to $1/(S-1)$ if the X variable is capital or labor, or equal to $L_r/\Sigma_{r\neq s}L_r$ if the X variable is human capital.

2.5. ISLX model

Finally, the Inter-Industry Spatial Lag (ISLX) Model captures both inter-sectoral and spatial dependence. The total factor productivity term in this case is modeled as follows:

$$A_{its} = \exp(\mu_{its}) \cdot \left(\prod_{j\neq i}^{N} X_{jts}^{\rho_s w_{ij}}\right) \cdot \left(\sum_{r\neq s}^{S} m_{rs} X_{itr}\right)^{\phi_s} \cdot \left[\prod_{j\neq i}^{N} \left(\sum_{r\neq s}^{S} m_{rs} X_{jtr}\right)^{\lambda_s w_{ij}}\right] \tag{13}$$

This expression combines the expressions (7) and (10) and extends it by adding the spatial lags of other sectors located in other (adjacent) provinces (see the last term in brackets in equation 13). After combining the log-linearized equations (13) and (3), the ISLX model leads to:

$$\ln y_{its} = \mu_{its} + \rho_s \sum_{j=1}^{N} w_{ij} lnX_{jts} + \phi_s ln\bar{X}_{its} + \lambda_s \sum_{j=1}^{N} w_{ij} ln\bar{X}_{jts} + \alpha lnX_{its} + v_{its} \tag{14}$$

This model can be rewritten using matrix notation as follows:

$$\ln y_s = \mu_s + \rho_s W lnX_s + \phi_s ln\bar{X}_s(M) + \lambda_s W ln\bar{X}_s(M) + \alpha lnX_s + v_s \tag{15}$$

Two comments are in order regarding our most comprehensive model. First, the proposed model can be viewed as a second-order spatial model that includes a cross-product term of spatial lags. For instance, using our notation, one of the models discussed in Elhorst et al. (2012) (see their equation 7) includes the following cross-product term: $WMlnX_s$. Generally, $WM \neq MW$, so they suggest to also reverse the roles of W and M before drawing any final conclusions. In our specification we do not use a product of two weight matrices as M is used before taking logs in the case of capital and labor. Second, if we add the spatial lag of the dependent variable in equation (15), we would get a similar productivity term to that proposed in Ertur and Koch (2007), and Dall'erba and Llamosas-Rosas (2015). These authors do not examine intersectoral spillovers and thus they implicitly assume that $\phi_s = \lambda_s = 0$. In contrast they replace all input-specific spatial terms $(\prod_{j\neq i}^{N} X_{jts}^{\rho_s w_{ij}})$ with a unique or global spatial term $(\prod_{j\neq i}^{N} A_{jts}^{\rho_s w_{ij}})$. As

[7] As noted on footnote #4, , the log in $ln\bar{X}_{its}$ should vanish if X_{its} represents human capital because human capital is an a dimensional variable.

mentioned before, this would yield a spatial Durbin model with spatial lags of the endogenous variable, which is more difficult to estimate and interpret.

The different specifications we offer are summarized in Table 1.

[Insert Table 1 here]

3. Data and weight matrix description

3.1. Data and data sources

The empirical analysis is based on a balanced panel dataset measured across the 48 NUTS 3 level Spanish provinces (the Canary Islands are excluded due to their remoteness). The data are measured every year over the 2000-2013 period across five industries[8]: agriculture, energy, manufacturing, construction and services. The data come from the Spanish National Statistics Institute (*Instituto Nacional de Estadística*, INE), the BBVA Foundation (FBBVA) and the Institute of Economic Research in Valencia (IVIE).

The gross value added (Y) is measured in basic prices, using the industrial national implicit deflators (base year 2010). L is the total employment in thousands of jobs; its measurement comes from the Spanish National Statistics Institute (INE). Private capital (K) and public capital (G) are net capital stocks. K excludes residential dwellings, public sector as well as public infrastructures while G is comprised of roads, ports, railways, and airport facilities. Both variables are provided by Mas *et al.* (2011) and Serrano-Martínez *et al.* (2017). Human capital (HKp) is the percentage of college degree holders over total employment. The data come from the Bancaja Foundation and IVIE (2014). All the monetary figures are converted in constant 2010 thousand Euros. Table 2 shows the descriptive statistics per industry averaged over the entire 2000-2013 period. The magnitudes presented in this table confirm the existence of important differences between sectors. This therefore suggests estimating a separate model for each sector.

[Insert Table 2 here]

In order to capture an idea of the individual trends in each industry, we depict in Figure 1 the average temporal evolution of the different series averaged across provinces. The most striking feature in Figure 1a) is the abrupt shift in the productivity of the construction sector post-2008. It reflects the burst of the housing bubble (Romero *et al.*, 2012). We also note a constant downward trend in the productivity of the construction sector in subsequent years. We observe that the GVA per labor unit increases in 2009 due to a significant fall in production, which coincides with a massive loss of employment. In the remaining sectors, the crisis slowed down productivity growth. Moreover, figure 1a) confirms that the business cycles in agriculture are not correlated with the ones of the non-agricultural sectors. In contrast, Figure 1b) confirms that the capital stock could not be reduced as abruptly as the number of workers in the construction sector, thus the capital endowment per job rises at a much faster rate in all the sectors except energy. Finally, Figures 1c) and 1d) depict the education indicators. The average years of schooling uncover the effects of an ambitious educational reform for which the period of implementation ended in 2000.[9] Felgueroso et al. (2014) highlight the drastic reduction in school dropouts since early implementation to 1999, and Felgueroso et al. (2016) reveal a gender bias in terms of human capital structural changes. There are substantial intensifications

[8] The analysis focuses on private industries, so non-market activities are excluded (see Appendix A). The industrial groupings are identified by the alphabetical code of the revised statistical classification of economic activities in the European Community (NACE Rev. 2).

[9] The educational reform (Ley Orgánica de Ordenación General del Sistema Educativo, LOGSE) was passed in 1990 with a ten-year time-frame for full implementation. It increased compulsory education from eight years to ten years, until reaching working age (16 years old).

in the shares of females with college degrees or working in the service sector. All these observations may explain the reason why the growth of schooling years is so intensive during the initial years. Moreover, gender bias may also clarify the rise in the share of college degree holders in some industries which in turn remains constant in others. Therefore, less qualified labor tends to be present in agriculture and construction.

[Insert Figure 1 here]

Figure 2 shows the logarithm of the average public capital stock across Spanish provinces. It growths at an almost constant rate until the housing bubble busts and then it keeps constant or even diminishes when depreciation overcomes the investment.

[Insert Figure 2 here]

3.2. Geographic and migration weight matrices

In our study, the weighted matrix W represents the spatial interdependences between provinces using the inverse of the distances. So they are assumed strictly exogenous, something which helps to avoid identifications problems (Manski, 1993). Regional economics literature has used the geographic matrix extensively to capture spillovers, even though some weaknesses must be highlighted. Thus, an inverse distance weights matrix for panel data is created, without imposing any cut-off distance or dampening parameter. Geographical information is provided by Eurostat. The row-standardized inverse distance matrix emphasizes spatial units with few or weak connections (Tiefelsdorf et al., 1999), but in a peninsula that means access to the coast.

In addition, we enriched the study introducing a weight matrix based on national migration flows of the year 2000. Geographical distances frequently mislead true Core-periphery relationships and the location of core and dynamic regions.[10] Consequently, this paper proposes to overcome these limitations through a weight matrix[11] based on economic criteria. We assume that the matrix is fixed over the years and is based on the migration structure of the initial year to avoid endogeneity. Pons et al. (2007) introduce a discussion about the migration trends in Spain from rural to urban areas concluding that it is conditioning to the market potential of the host regions. Therefore, migration flows reveal the capacity of provinces to attract labor according to their economic situation. In a more recent paper, Zofio et al. (2014) shows that changes in population distribution across Spanish provinces in conjunction with substantial reductions in transport cost have influenced the spatial equilibrium structure in economy towards a core-periphery structure. Therefore, a weight matrix based on national migration flows characterizes a more accurate representation of the location and dynamics of economic patterns. It was compiled from microdata of working age population collected by the Residential Variation Statistics (RVS) of the INE (i.e. migrants between 16 and 65 years old).

The hierarchy of spatial structures behind any weighting matrix may be disclosed by its average weight in spatially lagged variables, so in this manner Figure 3 shows the regional structure behind the row-standardized migration matrix. In Figure 3, we observe the migration flows structure and how close it is to the distribution of economic activity.

[Insert Figure 3 here]

4. Estimation and results

[10] In Spain, Catalonia and the Basque Country are dynamic regions (Paelinck and Polèse, 1999), but geometry tell us that they are located in the periphery.
[11] Crozet (2004) point out that migration flows are determined by market potential in the new economic geography theoretical framework.

4.1. *Model selection*

The testing procedure for the proposed models is crucial. For example, Halleck-Vega and Elhorst (2015) highlight that the robust Lagrange multiplier test developed by Anselin et al. (1996), may be considered. As such, we report in Table 3 the log-likelihood values of the various models under investigation. According to those values, we observe that the models with spatial and inter-industry spillovers (ISLX) display the largest values.

[Insert Table 3 here]

However, only a likelihood ratio test can help us confirm that the most comprehensive ISLX model outperforms the restricted FE, ILX and SLX models. The results are presented in Table 4. The two columns in this table indicate that the inter-industry spillovers are substantive phenomena in the explanation of regional production. The significance of inter-industry effects is affected by the inclusion of spatial dependence, so they are especially meaningful when geographic proximity is considered instead of migration flows. This result supports the findings of the empirical literature on knowledge spillovers suggesting the existence of Jacobian externalities that condition localization decisions. The two columns comparing the ISLX and ILX models indicate that the inter-regional or intra-industry spillovers are also significant. Therefore, we can corroborate that production factors located in other provinces affect the internal production. Depending on the sign of this effect, the computed spatial effects just indicate that some provinces benefit from factors located in other provinces (e.g. transport infrastructures) or that they are competing for production factors (Alvarez et al., 2016b). According to the previous tests, the FE model that ignores both types of spillovers is rejected as well. [12]

[Insert Table 4 here]

In summary, the fact that the ISLX model is the preferred model suggests that not only the intra-industry (spatial) externalities are important drivers of industry output as is customary in the empirical literature on regional economics, but also the variables capturing externalities from other sectors. Given our data, we do not know the nature of the inter-sectoral linkages captured in our application. As mentioned in the introduction section, they might be capturing (positive) knowledge or technological spillovers from upstream and downstream sectors, the access to better prices, the competition for limited or high quality inputs (if they are negative), or they are simply controlling for unobserved variables that are "common" to other industries. Regardless of the nature of the inter-sectoral spillovers, if ignored, the parameter estimates might be seriously biased,[13] and thus both direct and indirect effects might provide misleading conclusions for policy makers.

As the ISLX model is the preferred model in the family of models with local spillovers according to the selected criteria, in the following subsection we use this specification with spatial and inter-industry spillovers to study the determinants of Spanish provinces' production. As we are more interested in estimating direct and indirect effects, we only provide the parameter estimates of the four models proposed in Section 2 in an appendix (see Appendix B) at the end of the paper.

4.2. *Spatial and Inter-industry spillovers*

[12] Similar results are obtained if we compare the ILX and FE models and the SLX and FE models using the corresponding LR tests.

[13] The parameter estimates provided in Appendix B allow us to catch an idea about the magnitude of these biases in our application if either the spatial or inter-industry spillovers are ignored.

We study in this section the impact of inter-industry spillovers on aggregate production at sectoral level. As the ISLX model is the preferred one, we carry out this analysis allowing for the possibility of spatial dependence. Tables 5 and 6 show the direct and indirect effects of all private and public inputs following LeSage and Pace (2009). While Table 5 compares the effect of inter-industry spillovers and spatial dependence in regressors using the geographical weighting matrix for the spatial dependence, Table 6 uses the migration flows. This allows us to analyze the impact of the nearest (in terms of distance and migration flows) provinces´ in production.

[Insert Table 5 here]

[Insert Table 6 here]

There are several relevant findings. In the first place, the direct effect of own capital is positive and relevant in all sectors, except for manufacturing. As we use a specification of the production function in per worker terms, the positive coefficient of capital implies a positive direct effect of labor on sector production. Therefore, the direct effect of both private inputs follows conventional growth accounting, where labor elasticity is about 2/3 and capital elasticity is around 1/3. Regarding the other private input, human capital, we find a significant positive effect on sector production in the sectors that employ more skilled workers, i.e. in the case of Energy, Manufacturing and Services. Álvarez and Barbero (2016) also found evidence of the positive impact of human capital investments on gross domestic product for the Spanish provinces, from 1980 to 2011. During the period considered, the direct effect of public capital is not significant (except in the agriculture sector), possibly because it includes social capital.

We obtain some empirical evidence on the existence of negative spatial spillovers of private and human capital in most of the sectors. This can be viewed as spatial competition for production factors. In this sense, several studies find negative spillovers between neighboring regions, which they attribute to the competition for factors of production (Crescenzi and Rodriguez-Pose, 2008). The exceptions are Energy and Construction for private capital and Energy and Services for human capital. In these sectors the internal province production benefits from private factors in the nearest provinces. This finding tends to support the existence of Marshallian externalities in private factors, although not for all sectors of the economy, a result that is consistent with previous literature analyzing the Spanish economy (see, for instance, Ramos et al., 2010 and Boschma et al., 2012). Regarding the production factor provided by public administrations, the spatial spillover of public capital is positive. Overall, these results are in line with those obtained in previous studies using pre-crisis period data of many different countries (Pereira and Andraz, 2013) and by Álvarez and Barbero (2016) and Álvarez et al. (2016a), who considered spatial spillover effects in human and public capital between Spanish provinces. They are also coherent with studies carried out using data of the Spanish manufacturing sector. Overall, our results thus support the estimation of aggregate production functions including some measures capturing the spatial spillovers in public capital, as in Aviles et al (2003), and Cantos et al., (2005).

Regarding inter-industry effects, the effects of private capital and human capital from the rest of sectors are mostly negative. We believe that this result indicates that a strong competition exists for skilled labor and private capital between firms operating in the same province but in different industries. According to Barde (2010) these results corroborate the findings of the empirical literature on knowledge spillovers suggesting that spillovers occur between sectors that require similar skills, implying competition for specific factors of production (Combes and Duranton, 2006). In our case, this competition is highly relevant for qualified labor, but varies with the sectors´ level of technology. The largest (negative) inter-industry effects are found in Agriculture, Construction and Services. These sectors are specially penalized when other sectors increase the demand for capital and labor. The inter-industry effects coming from human capital are not generally significant except in the energy sector. This seems to indicate that the competition for private inputs between sectors is for low qualified workers. In contrast, the energy sector has problems in employing highly qualified employees when other sectors increase the demand for these highly skilled workers.

Tables 5 and 6 examine spatial and inter-industry spillovers using two different weighting matrices for spatial dependence, i.e. in terms of distance and migration flows respectively. Comparing the results of both tables, we find that public capital spillovers maintain their significance when we use a migration weight matrix, whereas the spillovers of private and human capital are less relevant using an economic-based matrix. Therefore, geographical proximity tends to intensify the spatial spillovers of private inputs. This might suggest that the competition for private inputs is mainly between neighboring or close provinces, rather than with the provinces originating the migration flows.

Regarding the direct effects, the estimated effect of own private capital is not significant using a distance-based weight matrix in the manufacturing sector, but it becomes significant if a migration weight matrix is used. Indeed, considering the migration weight matrix, private capital affects the manufacturing sector positively, which is a result more in accordance with the literature analyzing production functions (Pereira and Roca-Sagales, 2003). The signs of the direct effects of human capital are robust to the specification of the weight matrix. However, it is worth mentioning that the magnitude of these effects is larger (in absolute value) when we use a migration-based weight matrix, especially in the manufacturing and services sectors. Some of our results are in line with those presented in the article by Triguero and Fernandez (2018), published in a monograph about innovation and geographic spillovers in Regional Studies journal. These authors analyze knowledge spillovers from firms in the same industry and from different industries in the same region. Their results corroborate some of our conclusions in the sense that they confirm the existence of positive intra-industry spillovers and negative inter-industry spillovers as a kind of competition in terms of innovation.

When the spatial spillover interacts with intersectoral effects (i.e. we use the spatial lag of other sectors), we observe that the indirect effect of human capital affects the sectors' production positively, except in the services sector where the effect is not significant or even negative using migration flows. Therefore, the production in Services does not take advantage of the qualified labor present in the rest of sectors situated in "close" provinces in terms of migration flows. This result might indicate that the services sector cannot absorb labor with different skills currently employed in other sectors. Regarding the private capital used elsewhere in other sectors, although the results are more difficult to interpret from an economic point of view, we again obtain different coefficients in the service sector compared to the others.

Finally, it should be pointed out that, in general, we find that the intra-industry (spatial) effects outweigh the inter-industry (technological) effects using both geographic and migration flow matrices. This seems to suggest that the Marshallian externalities have a stronger effect on the location choice of labor than the Jacobean ones.

4.3. Technical efficiency

We mentioned in our methodological section, that all models can be used to estimate time-varying efficiency scores for each industry, using the method introduced by Cornwell et al. (1990). The ISLX Model is the most comprehensive model (i.e., spatial and sector-specific externalities are integrated), so that efficiency scores are computed using the parameter estimates of this specification. We next present the results for both the geographic and economic-based spatial weight matrices.

Figure 4 depicts the average point estimates of technical efficiency. The most competitive sectors in terms of their efficiency levels are Services, Manufacturing and Agriculture. In general, we find a growing trend in efficiency levels until the beginning of the crisis period. From then onwards, the efficiency scores tend to decline. As our efficiency scores are relative measures of production performance, this decline suggests that the reactions to the economic crisis of the sectors located in different provinces have been very heterogeneous. Notably we observe opposite trends in the agriculture sector, which seem to indicate that the inefficient agricultural sectors have been forced to deal better with the economic crisis than the more efficient agricultural sectors. The results are absolutely robust to the spatial matrix specifications, except for manufacturing, which is the sector with the highest mobility in qualified labor and with the least land competition according to the Dixit-Stiglitz (1977) framework.

[Insert Figure 4 here]

Figure 5 enriches the previous analysis focused on relative performances by providing information about technical change, i.e. the performance of the most efficient sectors in our sample. To better compare the results with those in Figure 4, we use cumulative indices of technical change in Figure 5. Despite the fact that the evolution of technical change is very different across sectors, the computed patterns are very similar regardless whether we use geographic or migration-based spatial matrices.[14] Again the technical change pattern in the agricultural sector is different from the patterns obtained for other sectors. This result again suggests that the firms operating in these sectors do not perceive the economic crisis similarly to the firms operating in other sectors. Thus the managerial strategies to deal with a deterioration in the economy are of a different nature to those used in other industries.

[Insert Figure 5 here]

In Figures 6 and 7 we show the distribution of the efficiency scores across provinces using geographic and migration matrices respectively. We will focus our discussion on the disparities or similarities of the geographical patterns found in each sector. Figure 6 shows that the most efficient agricultural sectors are located in provinces with more agricultural population around Madrid. The best efficiency scores in Energy are located in Madrid and in provinces close to Madrid with relatively scarce energy resources, such as Avila, Burgos, etc. These two spatial patterns are different to the patterns found in the other three sectors. Indeed, the patterns for Manufacturing, Construction and Services are similar where Madrid appears as one of the most efficient provinces, even though we have already controlled for spatial spillovers that often yields a core-periphery model where Madrid has a better performance due to its centrality or it benefits from spatial spillovers (Álvarez et al., 2016b).

[Insert Figure 6 here]

Regarding the above discussion, it is worth mentioning that it is possible to perceive a clearer core-periphery geographical configuration in Figure 7 for the Manufacturing, Construction and Services sectors if we use a migration-based matrix (see, in particular, the map depicted for the service sector). Indeed, again not only Madrid has a better performance, but also other provinces located far from the center of Spain or in the periphery have a better performance. Notice that the migration-based spatial components of the production frontier function already incorporates the insights of the core-periphery model that is supported by the so-called New Economic Geography (NEG). Therefore, our results using migration flows indicate that the core-periphery theory can not only be applied to model the performance of fully efficient production units (sectors), but also to explain the relative performance of inefficient sectors located in particular provinces. Thus, our results using a frontier framework seem to support even more the core-periphery theory of the NEG. Moreover, our paper seems

[14] It should be noted here that the province with the highest efficiency level, which is used as a reference to compute other efficiency scores, can vary within the same sector depending on the weighted matrix.

to suggest that we should use key variables of the core-periphery theory to model the inefficiency term in a heteroscedastic specification of our regional production frontier function. As this approach relies on distributional assumptions of the inefficiency term, we leave this extension of the model for future research.

[Insert Figure 7 here]

4.4. Robustness check

As we pointed out in the introduction, the use of multi-dimensional weight matrices might cause identification and interpretation problems if endogenous lagged variables are included in the model. With due caution, we will briefly compare here our main results with those obtained using a SDM-type model only for robustness grounds. This model (hereafter ISDM) introduces intersectoral effects, allowing the possibility to study global and local spatial dependence with inter-industry effects.

To simplify the comparison, we have presented Table 7 to show only the signs of the direct and indirect effects using both ISLX and ISDM specifications. Several comments are in order. Once we include global spatial dependence (i.e. the spatial lag of the dependent variable), the direct effects associated with private and human capital keep their signs and significance. In contrast, some of the coefficients (indirect effects) measuring local spillovers from private and public production factors lose their significance, a result that is common in the literature of production functions (see. e.g. Fingleton and Lopez-Bazo, 2006; and Alvarez et al., 2016a,b) because part of the spatial dependence in the data is now being captured by the spatial lag of the dependent variable of the ISDM specification. Although the same happens in an application that also includes inter-industry effects, most of the direct effects of private and human capital of other sectors do not lose their significance, except human capital in the service sector, when we move to an ISDM model. Thus, our conclusions regarding the existence of Jacobian or inter-industry externalities using a ISLX are robust for the inclusion of spatial lags of the dependent variable.

5. Conclusions

This paper examines the role of both intra-industry Marshallian externalities and inter-industry Jacobian spillovers when estimating regional aggregate production functions. To our knowledge, this is the first paper that examines technological and spatial externalities simultaneously using sector-level data. Another main contribution of this paper is the use of a weight matrix of migration flows representing spatial interactions. The geographic matrix has been widely used to capture spillovers, even though core and dynamic regions are not determined by the geometric center. Moreover, spatial dynamics differ among industries, as well as the relationship structures behind them. Consequently, we propose this weight matrix based on economic criteria to overcome these limitations.

Given the availability of a data set for Spain at regional level, we use a panel data at the provincial level (NUTS-3) over the period 2001-2013 across five industries. We base our analysis on the effect exerted by public capital, mainly infrastructures, and education on economic activity. The selected period is of special interest because of the crisis on 2008 originated by the housing bubble.

Regressions extend the standard SLX model introducing inter-industry effects, which are highly significant in our application. Thus our results reveal the simultaneous presence of both Marshallian and Jacobian externalities. The spillovers of private production factors are negative in most of the sectors, indicating the presence of inter-regional and inter-sectoral competition for skilled labor and private capital. We also obtain different efficiency patterns across provinces. Overall, these results indicate that public policies aiming to improve both sectoral and provincial efficiency should be tailored individually for each sector and province.

Our results also indicate that the core-periphery theory can be applied to both fully efficient and inefficient sectors, a finding that should be examined more deeply in the future. Another natural extension of this paper is using a multi-dimensional spatial econometric model with endogenous lagged variables once the estimation and interpretation problems mentioned in the introduction are addressed in the literature. Finally, we have studied average inter-industry effects. Thus, another promising area for future research could be to use a model that allows distinguishing the inter-industry effects associated to single industries.

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Table 1. Spatial and inter-industry effects

Models	FE	SLX	ILX	ISLX
Inter-industry externalities	No	No	Yes	Yes
Spatial spillovers	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes

Table 2. Descriptive statistics for the 2000-2013 period (in 2010 constant euros)

Variable	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Gross Value Added (per labor unit)				
Agriculture	30,514	7,772	14,644	55,816
Energy	131,235	62,786	18,083	370,707
Manufacturing	46,096	14,108	18,721	103,833
Construction	40,331	12,382	18,336	81,181
Services	44,838	8,759	25,020	68,039
Private Capital Stock (per labor unit)				
Agriculture	72,071	39,961	14,809	277,460
Energy	534,131	410,795	63,829	4,158,020
Manufacturing	91,128	31,098	43,151	278,993
Construction	91,438	46,414	24,954	297,583
Services	55,635	9,770	37,114	108,937
Human Capital				
Agriculture	4.99%	3.55%	0.00%	20.05%
Energy	24.12%	18.08%	0.00%	100.00%
Manufacturing	11.55%	4.88%	2.18%	36.45%
Construction	6.81%	4.10%	0.00%;	47.00%
Services	20.26%	5.08%	10.43	38.83%
Public Capital	4,550	4,697	1,080	30,100

Source: Own elaboration using data from INE, IVIE and Bancaja

Table 3. Log-Likelihood values

			Geographic weighting matrix		Migration weighting matrix	
	FE	**ILX**	**SLX**	**ISLX**	**SLX**	**ISLX**
Agriculture	358.5	359.5	363.2	387.2	376.9	386.7
Energy	-50.5	7.9	171.17	185.9	137.4	159.7
Manufacturing	445.5	469.0	747.9	769.2	702.7	741.9
Construction	187.5	248.6	652.0	696.0	483.4	595.5
Services	623.3	692.7	1202.9	1237.6	1140.1	1170.3
Parameters	51	53	54	58	54	58
Observations	624	624	624	624	624	624

Source: own elaboration

Table 4. Likelihood-ratio test. ISLX model relevance

	Geographic weighting matrix					
	FE		***ILX***		***SLX***	
	X2(df=7)	p-value	X2(df=5)	p-value	X2(df=4)	p-value
Agriculture	57.46	0.000	55.37	0.000	47.97	0.000
Energy	472.84	0.000	355.94	0.000	29.48	0.000
Manufacturing	647.38	0.000	600.25	0.000	42.47	0.000
Construction	1017.05	0.000	894.68	0.000	88.03	0.000
Services	1228.66	0.000	1089.80	0.000	69.36	0.000
	Migration weighting matrix					
	FE		***ILX***		***SLX***	
	X2(df=7)	p-value	X2(df=5)	p-value	X2(df=4)	p-value
Agriculture	56.50	0.000	54.42	0.000	19.62	0.000
Energy	420.54	0.000	303.63	0.000	44.64	0.000
Manufacturing	592.78	0.000	545.65	0.000	78.38	0.000
Construction	816.04	0.000	693.68	0.000	224.13	0.000
Services	1094.10	0.000	955.25	0.000	60.48	0.000

Source: own elaboration

Table 5. Model ISLX. Direct and Indirect Effects Estimates (Geographic weighting matrix)

	Agriculture	Energy	Manufacturing	Construction	Services
DIRECT EFFECT					
lnk	0.238 ***	0.416 ***	0.067	0.086 ***	0.114 ***
	[0.051]	[0.037]	[0.045]	[0.030]	[0.022]
lnk(M)	-0.305 ***	0.264 *	0.056	-0.200 ***	-0.057 ***
	[0.097]	[0.150]	[0.046]	[0.063]	[0.021]
H	-0.179	0.191 ***	0.243 **	-0.081	0.174 **
	[0.197]	[0.054]	[0.121]	[0.119]	[0.077]
H(M)	-0.268	-1.343 **	-0.272	0.103	-0.062
	[0.385]	[0.584]	[0.200]	[0.235]	[0.096]
lnG	0.238 ***	0.106	0.015	-0.078	0.015
	[0.082]	[0.113]	[0.044]	[0.049]	[0.021]
INDIRECT EFFECT					
lnk	-0.510 **	0.613 **	-0.408* *	0.284 ***	-1.024 ***
	[0.208]	[0.308]	[0.242]	[0.084]	[0.096]
lnk(M)	-0.329 *	-2.669 ***	-0.112	-2.374 ***	0.367 ***
	[0.193]	[0.616]	[0.202]	[0.296]	[0.046]
H	-4.671 ***	1.326 ***	-2.364 ***	-1.584 **	2.283 ***
	[1.177]	[0.335]	[0.764]	[0.724]	[0.429]
H(M)	7.074 ***	5.298 ***	5.194 ***	1.827 **	0.367
	[1.271]	[1.817]	[0.836]	[0.800]	[0.592]
lnG	0.229	4.276 ***	1.773 ***	2.917 ***	0.938 ***
	[0.325]	[0.489]	[0.156]	[0.155]	[0.075]

Notes: Standard errors in brackets. *** p<0.01, **p<0.05, *p<0.1
Source: Own elaboration

Table 6. Model ISLX. Direct and Indirect Effects Estimates (Migration weighting matrix)

	Agriculture	Energy	Manufacturing	Construction	Services
DIRECT EFFECT					
lnk	0.238 ***	0.424 ***	0.095 **	0.083 **	0.096 ***
	[0.052]	[0.041]	[0.046]	[0.034]	[0.024]
lnk(M)	-0.314 ***	0.200	0.056	-0.163 **	-0.027
	[0.097]	[0.156]	[0.048]	[0.074]	[0.023]
H	-0.185	0.204 ***	0.389 ***	-0.054	0.266 ***
	[0.198]	[0.057]	[0.126]	[0.139]	[0.084]
H(M)	0.005	-1.171 *	-0.193	0.358	0.088
	[0.372]	[0.601]	[0.207]	[0.269]	[0.105]
lnG	0.249 ***	0.079	0.031	-0.002	-0.005
	[0.083]	[0.120]	[0.047]	[0.059]	[0.024]
INDIRECT EFFECT					
lnk	-0.216 **	-0.015	0.124	0.348 ***	-0.773 ***
	[0.107]	[0.149]	[0.188]	[0.064]	[0.069]
lnk(M)	0.078	-1.200 ***	-0.702 ***	-2.679 ***	0.257 ***
	[0.161]	[0.355]	[0.150]	[0.205]	[0.037]
H	-2.223 ***	-0.132	0.683	0.619	2.985 ***
	[0.422]	[0.230]	[0.428]	[0.496]	[0.273]
H(M)	1.926 **	8.012 ***	4.677 ***	4.574 ***	-0.806 ***
	[0.857]	[1.257]	[0.583]	[0.639]	[0.274]
lnG	0.132	2.340 ***	1.043 ***	1.772 ***	0.863 ***
	[0.149]	[0.206]	[0.103]	[0.105]	[0.041]

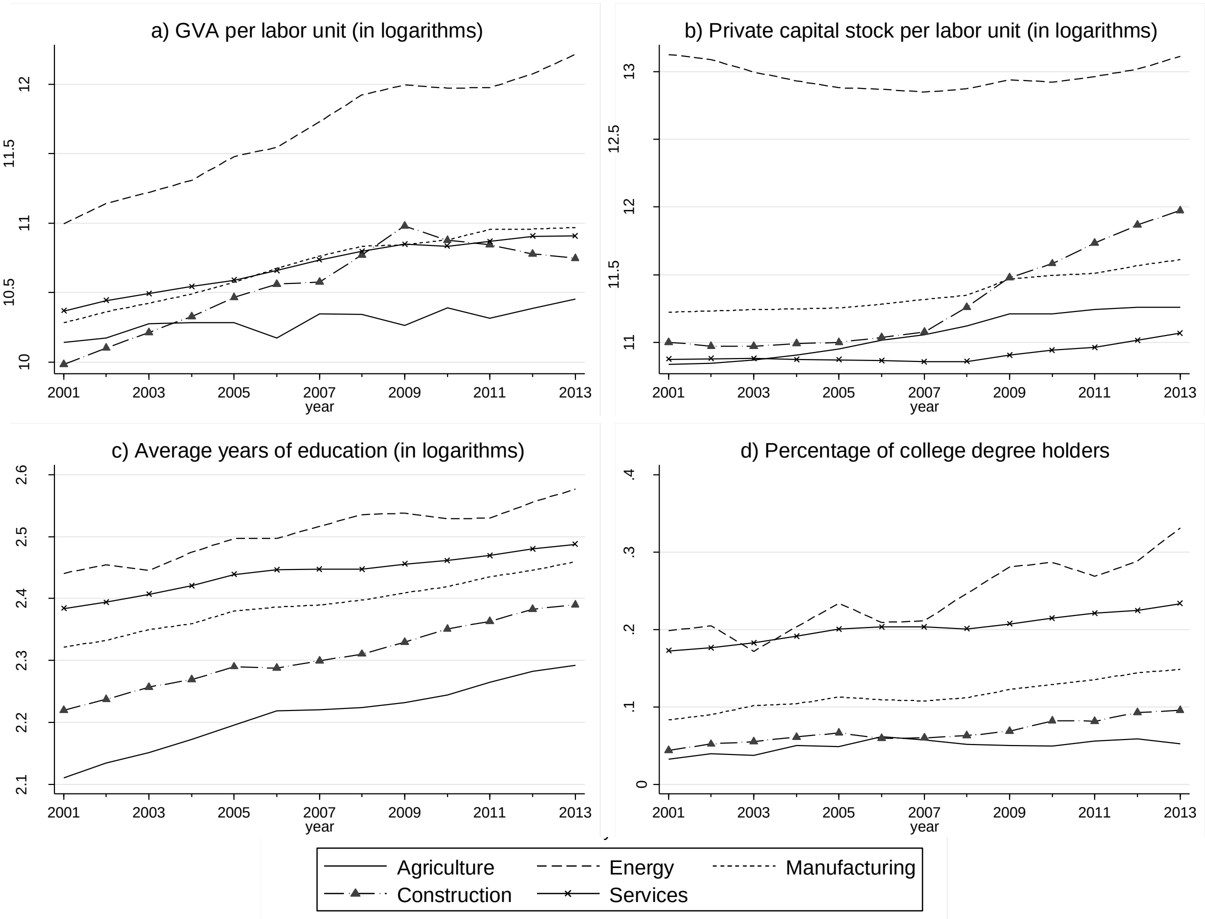
Notes: Standard errors in brackets. *** P-value<0.01, **p-value<0.05, *p-value<0.1
Source: Own elaboration

Table 7. ISDM vs. ISLX sign estimates

	Agriculture		Energy		Manufacturing		Construction		Services	
	G	F	G	F	G	F	G	F	G	F
DIRECT EFFECT										
lnk	+	+	+	+	+	+	+	+	+	+
	+	+	+	+	n.s.	+	+	+	+	+
lnk(M)	n.s.	n.s.	+	+	+	+	n.s.	n.s.	+	+
	n.s.	n.s.	+	+	+	+	n.s.	n.s.	+	+
H	+	+	n.s.	n.s.	+	+	n.s.	+	+	+
	+	+	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
H(M)	–	–	+	n.s.	n.s.	n.s.	–	–	–	–
	–	–	+	n.s.	n.s.	n.s.	–	–	–	n.s.
lnG	n.s.	n.s.	–	–	–	–	n.s.	n.s.	n.s.	–
	n.s.	n.s.	–	–	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
INDIRECT EFFECT										
lnk	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	–	–
	–	–	+	n.s.	–	n.s.	+	+	–	–
lnk(M)	–	–	+	n.s.	n.s.	+	n.s.	n.s.	n.s.	+
	–	–	+	n.s.	–	n.s.	–	n.s.	+	+
H	n.s.	n.s.	+	+	+	+	+	+	+	+
	n.s.	n.s.	+	+	+	+	+	+	+	+
H(M)	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	–	+	+
	–	n.s.	–	–	n.s.	–	–	–	+	+
lnG	+	+	n.s.	+	+	n.s.	n.s.	+	n.s.	–
	+	+	+	+	+	+	+	+	n.s.	–

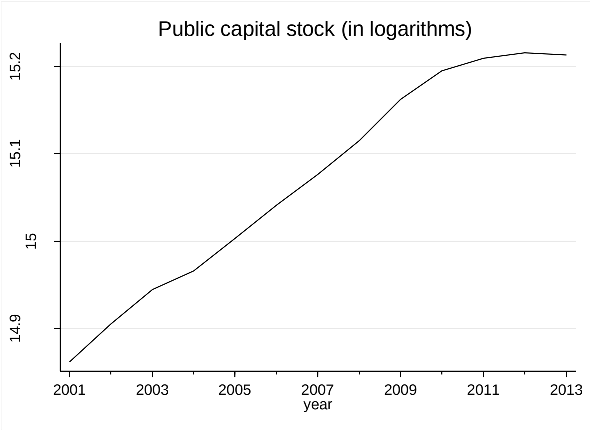
Notes: The ISDM sign estimates (in white colored rows) are above the ISLX sign estimates (in grey colored rows). G= Geographic weighting matrix. F= Migration flows weighting matrix. n.s.= not significant

Figure 1. Gross Value Added, private capital stock and human capital (Mean of Spanish provinces)



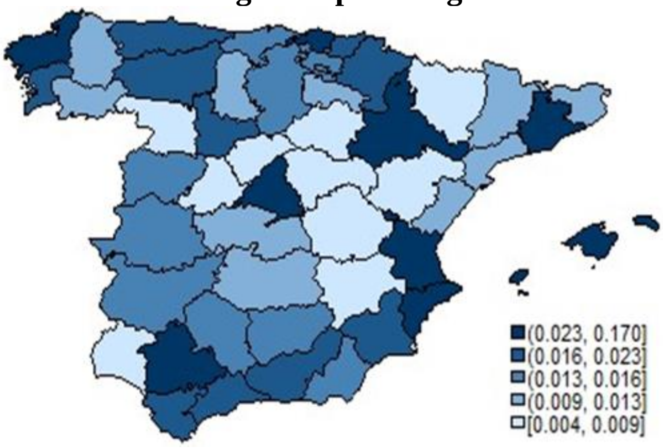
Source: Own Elaboration

Figure 2. Public capital stock (Mean of Spanish provinces)



Source: Own Elaboration

Figure 3. Row-standardized migration flows weighting matrix in year 2000: average weight in spatial lags



Source: Own elaboration

Figure 4. Point estimates of technical efficiency by Industry (Model ISLX)

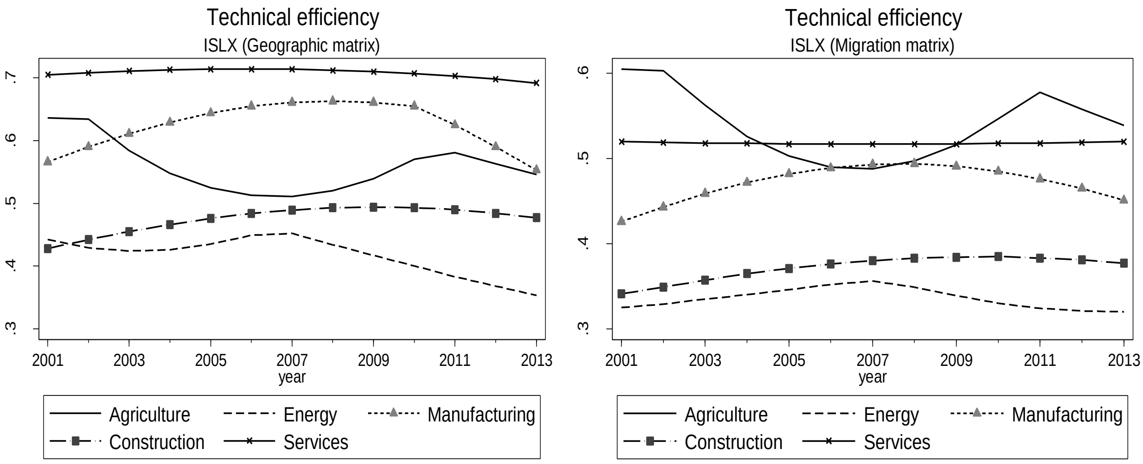


Figure 5. Point estimates of technical change by Industry (Model ISLX)

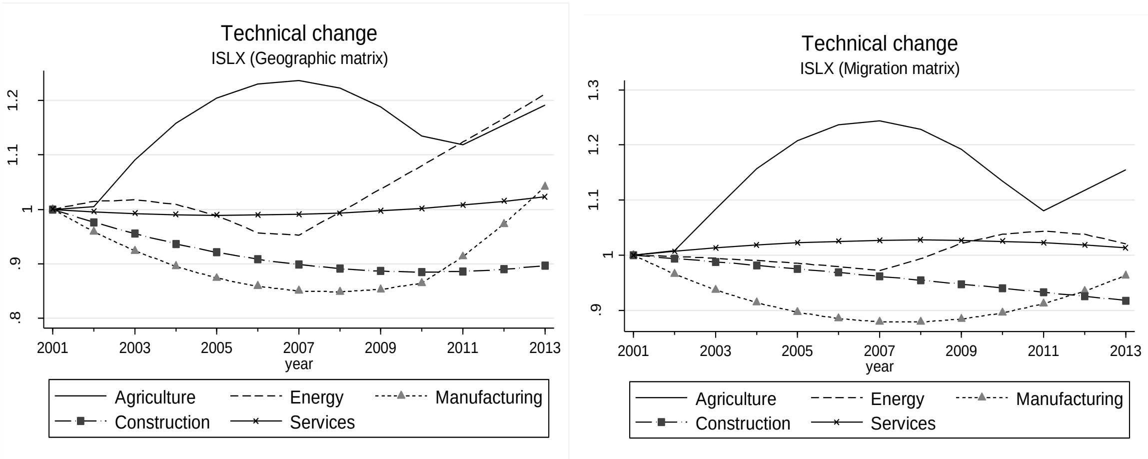


Figure 6: Technical efficiency by provinces (Geographic Matrix)

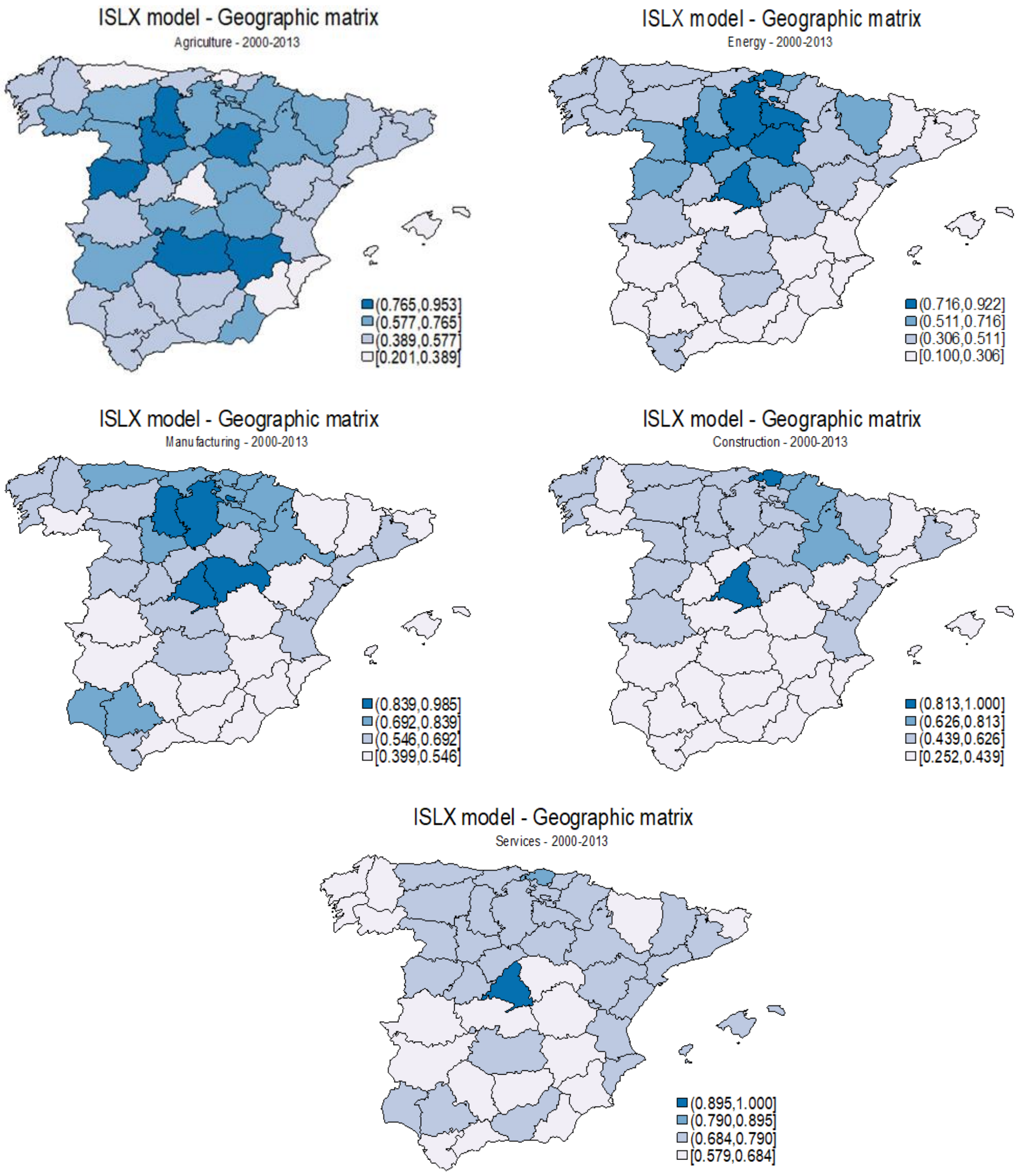
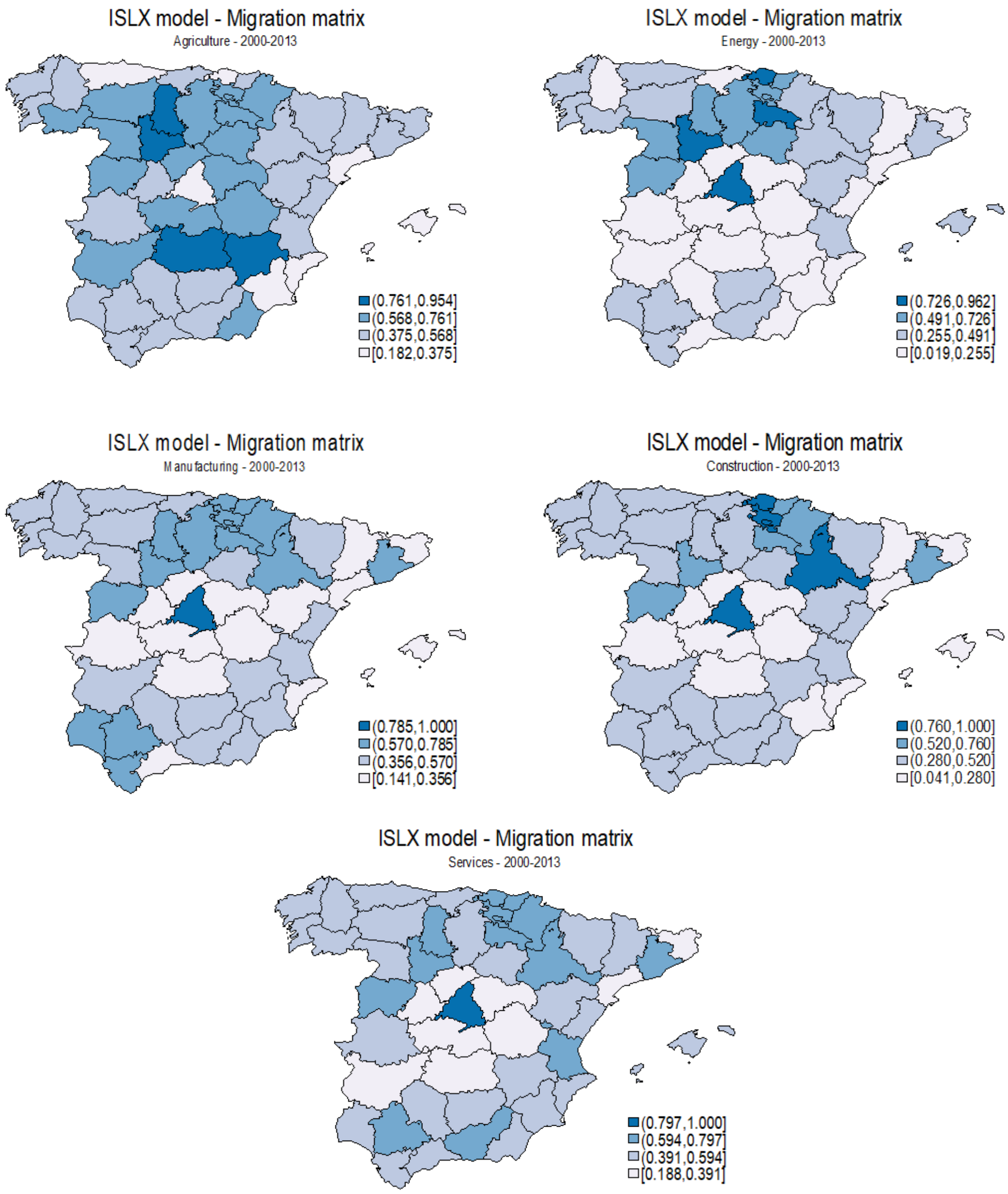


Figure 7: Technical efficiency by provinces (Migration Matrix)



Appendix A: Sectorial disaggregation

Code	Statistical classification (NACE Rev. 2, Eurostat, 2006)
A	A. Agriculture, forestry and fishing
BDE	B. Mining and quarrying D. Electricity, gas, steam and air conditioning supply E. Water supply; sewerage, waste management and remediation activities
C	C. Manufacturing
F	F. Construction
G_N	G. Wholesale and retail trade; repair of motor vehicles and motorcycles H. Transportation and storage I. Accommodation and food service activities J. Information and communication K. Financial and insurance activities L. Real estate activities M. Professional, scientific and technical activities N. Administrative and support service activities
O_U	O. Public administration and defense; compulsory social security P. Education Q. Human health and social work activities R. Arts, entertainment and recreation S. Other service activities T. Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use U. Activities of extraterritorial organizations and bodies

Note: the branches from O to U are considered non-market activities.

Appendix B: Parameter estimates

	Agriculture					
	FE	ILX	SLX		ISLX	
			G	F	G	F
lnk	0.267 ***	0.268 ***	0.265 ***	0.245 ***	0.238 ***	0.238 ***
	0.042	0.044	0.052	0.052	0.051	0.052
H	-0.059	-0.092	-0.109	-0.104	-0.179	-0.185
	0.201	0.202	0.202	0.198	0.197	0.198
lnG	0.205 ***	0.212 ***	0.126	0.179 **	0.238 ***	0.249 ***
	0.058	0.067	0.082	0.082	0.082	0.083
lnk(M)		-0.086			-0.305 ***	-0.314 ***
		0.069			0.097	0.097
H(M)		0.376			-0.268	0.005
		0.348			0.385	0.372
Wlnk			-0.501 **	-0.130	-0.510 **	-0.216 **
			0.206	0.103	0.208	0.107
WH			-1.669 *	-2.274 ***	-4.671 ***	-2.223 ***
			0.901	0.402	1.177	0.422
WlnG			0.875 ***	0.281 **	0.229	0.132
			0.311	0.137	0.325	0.149
Wlnk(M)					-0.329 *	0.078
					0.193	0.161
WH(M)					7.074 ***	1.926 **
					1.271	0.857

Notes: Standard errors in brackets. *** p<0.01, **p<0.05, *p<0.1.
G= Geographic weighting matrix. F= Migration flows weighting matrix.
Source: Own elaboration

	Energy					
	FE	ILX	SLX		ISLX	
			G	F	G	F
lnk	0.281 ***	0.156 ***	0.357 ***	0.371 ***	0.416 ***	0.424 ***
	0.048	0.045	0.036	0.036	0.037	0.041
H	0.303 ***	0.180 **	0.185 ***	0.210 ***	0.191 ***	0.204 ***
	0.078	0.072	0.055	0.058	0.054	0.057
lnG	2.316 ***	1.282 ***	0.081	0.068	0.106	0.079
	0.081	0.122	0.111	0.120	0.113	0.120
lnk(M)		0.735 ***			0.264 *	0.200
		0.134			0.150	0.156
H(M)		3.883 ***			-1.343 **	-1.171 *
		0.630			0.584	0.601
Wlnk			-0.494 ***	0.001 ***	0.613 **	-0.015
			0.104	0.089	0.308	0.149
WH			1.115 ***	0.045	1.326 ***	-0.132
			0.327	0.224	0.335	0.230
WlnG			2.680 ***	2.729	4.276 ***	2.340 ***
			0.184	0.150	0.489	0.206
Wlnk(M)					-2.669 ***	-1.200 ***
					0.616	0.355
WH(M)					5.298 ***	8.012 ***
					1.817	1.257

Notes: Standard errors in brackets. *** p<0.01, **p<0.05, *p<0.1
G= Geographic weighting matrix. F= Migration flows weighting matrix.
Source: Own elaboration

Manufacturing						
	FE	ILX	SLX		ISLX	
			G	F	G	F
lnk	0.499 ***	0.417 ***	0.052	0.071	0.067	0.095 **
	0.053	0.060	0.045	0.047	0.045	0.046
H	1.220 ***	0.898 ***	0.329 ***	0.448 ***	0.243 **	0.389 ***
	0.190	0.191	0.122	0.130	0.121	0.126
lnG	0.880 ***	0.754 ***	0.007	0.043	0.015	0.031
	0.054	0.057	0.044	0.049	0.044	0.047
lnk(M)		-0.046			0.056	0.056
		0.060			0.046	0.048
H(M)		1.298 ***			-0.272	-0.193
		0.290			0.200	0.207
Wlnk			-0.423 ***	-0.342 ***	-0.408 *	0.124
			0.086	0.093	0.242	0.188
WH			0.890 *	2.593 ***	-2.364 ***	0.683
			0.517	0.347	0.764	0.428
WlnG			2.139 ***	1.395 ***	1.773 ***	1.043 ***
			0.090	0.078	0.156	0.103
Wlnk(M)					-0.112	-0.702 ***
					0.202	0.150
WH(M)					5.194 ***	4.677 ***
					0.836	0.583

Notes: Standard errors in brackets. *** p<0.01, **p<0.05, *p<0.1
G= Geographic weighting matrix. F= Migration flows weighting matrix.
Source: Own elaboration

Construction						
	FE	ILX	SLX		ISLX	
			G	F	G	F
lnk	0.176 ***	0.248 ***	0.064 **	0.027	0.086 ***	0.083 **
	0.032	0.039	0.030	0.039	0.030	0.034
H	0.264	-0.072	-0.130	-0.124	-0.081	-0.054
	0.262	0.241	0.125	0.164	0.119	0.139
lnG	1.377 ***	1.144 ***	-0.129 **	-0.046	-0.078	-0.002
	0.082	0.079	0.052	0.070	0.049	0.059
lnk(M)		-0.808 ***			-0.200 ***	-0.163 **
		0.120			0.063	0.074
H(M)		3.905 ***			0.103	0.358
		0.410			0.235	0.269
Wlnk			-0.347 ***	-0.230 ***	0.284 ***	0.348 ***
			0.040	0.052	0.084	0.064
WH			-3.486 ***	0.582	-1.584 **	0.619
			0.620	0.508	0.724	0.496
WlnG			3.746 ***	2.642 ***	2.917 ***	1.772 ***
			0.088	0.094	0.155	0.105
Wlnk(M)					-2.374 ***	-2.679 ***
					0.296	0.205
WH(M)					1.827 **	4.574 ***
					0.800	0.639

Notes: Standard errors in brackets. *** p<0.01, **p<0.05, *p<0.1
G= Geographic weighting matrix. F= Migration flows weighting matrix.
Source: Own elaboration

Services						
	FE	ILX	SLX		ISLX	
			G	F	G	F
lnk	0.112 **	-0.182 ***	0.099 ***	0.113 ***	0.114 ***	0.096 ***
	0.049	0.049	0.022	0.024	0.022	0.024
H	1.618 ***	0.986 ***	0.163 **	0.232 ***	0.174 **	0.266 ***
	0.182	0.174	0.078	0.085	0.077	0.084
lnG	0.895 ***	0.601 ***	-0.009	-0.003	0.015	-0.005
	0.033	0.040	0.021	0.024	0.021	0.024
lnk(M)		0.269 ***			-0.057 ***	-0.027
		0.032			0.021	0.023
H(M)		1.158 ***			-0.062	0.088
		0.216			0.096	0.105
Wlnk			-0.396 ***	-0.408 ***	-1.024 ***	-0.773 ***
			0.042	0.047	0.096	0.069
WH			1.522 ***	2.772 ***	2.283 ***	2.985 ***
			0.282	0.225	0.429	0.273
WlnG			1.385 ***	1.021 ***	0.938 ***	0.863 ***
			0.044	0.036	0.075	0.041
Wlnk(M)					0.367 ***	0.257 ***
					0.046	0.037
WH(M)					0.367	-0.806 ***
					0.592	0.274

Notes: Standard errors in brackets. *** p<0.01, **p<0.05, *p<0.1
G= Geographic weighting matrix. F= Migration flows weighting matrix.
Source: Own elaboration