Knowledge assets and regional performance

Raffaele Paci and Emanuela Marrocu

University of Cagliari, CRENoS

Abstract

Regional competitiveness, especially in the industrialised countries, is increasingly reliant on the availability of an adequate endowment of knowledge assets at the local level, like technological and human capital. These intangible factors enhance regional efficiency directly as inputs of the production function, but they also play a crucial role in allowing the territory to absorb the potential knowledge spillovers from the neighbouring regions.

The aim of this paper is to analyse the role of the internal and external factors in determining the productivity level for a large set of regions belonging to the EU27 plus Norway and Switzerland. We estimate a Cobb-Douglas production function over the period 2000-2008 where, in addition to the traditional inputs of physical capital and units of labour, we consider innovation activities and human capital endowments as relevant knowledge assets. We also control for other geographical and industrial features of the regions. In order to take into account the commonly found geographic association across regions, our analysis is carried out within the spatial panel econometric framework.

Main results, robust to a wide array of sensitivity checks, show that knowledge assets exhibit positive and significant coefficients and the impact of human capital on GDP is higher than the one found for technological capital in most of the estimated empirical models. Moreover, we find evidence of spatial spillovers directly associated with the two immaterial assets, which turn out to be much more effective in the regions of the 12 new accession countries with respect to all other European regions. The significant presence of such spillovers emphasizes the important role played by highly educated labour forces in increasing the regions' absorptive capacity of new external knowledge and in ensuring its effective use in the production process.

Keywords:
knowledge, innovation, human capital, production function, spatial spillovers, European regions

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1. Introduction

The economic picture of Europe is characterised by remarkable regional disparities: in the year 2008 the GDP per capita in the wealthiest region (Inner London) is 48 times higher than in the poorest one (Yuzhen tsentralen in Bulgaria). The differences become astonishing if we compare the ten richest and the ten poorest European regions which show a ratio equal to 22. A similar evidence of strong inequality emerges also when other measures of economic performance, like labour productivity or total factor productivity, are considered. Moreover, regional disparities tend to persist over time: in the period 2000–2008, the coefficient of variation of the GDP per capita regional distribution is quite stable around the value of 0.54.

To explain these huge differences in the economic performance, the attention of economists and policymakers has shifted from the endowments of tangible inputs, like physical capital and units of labour, to more immaterial and interrelated features of the economy, like knowledge, human capital, technological capital, entrepreneurship, institutions, social cohesion and networks.

In the European Union there has been a shift from redistributive policies towards 'place-based' policies (Barca, 2009), aimed at sustaining endogenous regional capabilities in terms of both human capital and technological assets. The accumulation of these factors is seen as a key element for reducing the innovation and technological gap among the European regions, which has deepened following the enlargement process, as less advanced economies joined the European Union.

Looking at the intangible assets, the crucial role played by human capital in influencing the productivity levels and their dynamics has been emphasized in seminal contributions to the growth literature by Lucas (1988), Mankiw et al. (1992) and Benhabib and Spiegel (1994). The availability of skilled and highly educated people has been indicated as the key driver of economic performance, since it increases the efficiency of the existing productions and it stimulates the creation of new products and processes. Moreover, when spatial knowledge spillovers (Jaffe, 1989) are present at regional level the positive role of human capital is amplified since it represents the crucial element for the process of absorbing external knowledge (Cohen and Levinthal, 1990).

The R&D expenditure, as a measure for firms technological capital, has been directly included as input in the production function at the firms level by Griliches (1979) in the so-called knowledge-capital model[1] and, after that, this approach has been used in several contributions (for a comprehensive survey see Audretsch and Feldman, 2004). The extension of the model at the regional – or national – level implies that technology is partly seen as a public good and thus firms

[1] A more comprehensive approach to evaluate the role of intangible factors on firms productivity considers, besides the traditional R&D expenditure, several intangible activities like employee training, economic competencies, software and patents. See Corrado et al. (2009) for the US and Marrocu et al. (2012) for Europe.

may benefit from the availability of a higher degree of technological capital at the local level since it leads to productivity increases.

Thus, human capital and technological stocks have been perceived as the two main interrelated components of the knowledge assets which concur in determining the economic performance of local economies. Other intangible elements have been also examined by the literature under various complementary approaches. Some authors have highlighted the role of social capital as a growth driving factor since a high level of social capital in a certain area facilitates cooperation among agents, reduces transaction costs and supports knowledge diffusion (Knack and Keefer 1997, Hauser et al. 2007, Beugelsdijk and van Schaik 2005). Other authors (Rodriguez-Pose, 1999; Crescenzi and Rodriguez-Pose, 2009) resort to the concept of “social filter” to assemble in a unique indicator the main socio-economic features of the local environment and thus assess their joint effect on economic outcomes. On the same vein Dettori et al. (2011) analyse the effects exerted by three different intangible assets (human, technological and social capital) simultaneously included in an empirical model to explain total factor productivity for the EU15 regions. Another important intangible element, entrepreneurship, has been investigated in the “knowledge filter” approach by underlining the role played by entrepreneurs in converting new ideas into economic valuable knowledge which is expected to enhance regional economic growth (Acs and Plummer 2005, Braunerhjelm et al. 2010).

The existence of networks among economic agents represents a relevant channel which facilitates the transmission and diffusion of knowledge. These relational networks have been measured by different means like cooperation in research programmes (Maggioni et al., 2007), patents citations (Paci and Usai 2009) and inventors’ network (Miguelez and Moreno 2011). In general, the empirical evidence suggests that the extent of local networks and cooperative connections with other regions has a positive impact on the process of knowledge generation, enhancing the regional economic performance.

In general, the variety of tangible and intangible factors which characterises the socio-economic conditions at the regional level can be gathered within the wider concept of “territorial capital” (OECD 2001, Capello et al. 2011). However, regional competitiveness is becoming more and more reliant on increasing endowments of intangible and immaterial components of territorial capital, like innovation and human capital, especially in the industrialised countries. These knowledge factors enhance regional efficiency directly as inputs of the production function, but they also play a crucial role in allowing the territory to absorb the potential knowledge spillovers from the neighbouring regions.

The main purpose of this paper is to analyse the role of the knowledge assets, considered as internal and external factors, in determining the productivity level of 276 regions belonging to EU27 plus Norway and Switzerland. To this aim we estimate a Cobb-Douglas production function over the period 2000-2008 where, in addition to the traditional inputs like physical capital and units of labour, we also include innovation activities and human capital endowments as knowledge factors. Although this issue, given its upmost relevance, has been largely investigated, in this paper we offer a novel contribution since our analysis focuses on the production enhancing effects of the two most important intangible assets for the widest geographical coverage of the European regions.

This is also very relevant from a policy perspective, since the regional level is increasingly considered as the key level to trigger and support growth processes given the presence of localized knowledge spillovers and networks.

Moreover, we carry out an extensive robustness analysis in order to test the sensitivity of our findings with respect to three alternative economic indicators, namely GDP, per capita GDP and labour productivity. We also control for other territorial and industrial features of the regions, which are likely to affect the economic performance, like population density, urban settlement pattern, sectoral specialisation in low tech manufacturing and knowledge intensive services. In order to take into account the presence of geographical association, widely documented at regional level, the empirical analysis is carried out within a spatial panel econometric framework.

The main finding is that both knowledge assets - human and technological capital - exhibit significant and sizeable elasticities, which confirm both of them as key determinants of the production performance at the regional level. This result proves to be robust to alternative model specifications, entailing different economic indicators as response variable and the inclusion of other determinants of regional production, such as territorial typology and industrial specialisation. The importance of the knowledge factors is accentuated by the finding that the specialisation in the knowledge intensive sectors, common to most urban areas in the western countries, exerts a considerable effect on GDP. Finally, we find evidence on the reinforcing effect of neighbouring regions' knowledge endowments; the estimated impacts are significant and sizeable in magnitude, with human capital externalities outperforming the technological ones, especially in the lagging regions of EU12 countries. This finding signals the importance of being located within highly knowledge endowed territories in order to benefit from cross-border knowledge externalities in terms of production enhancements.

The paper is organised as follows. In the second section, after the introduction, we describe the variables included in the production function. The third section discusses the estimation issues related to the econometric analysis and it defines the empirical model. The results for the basic model are presented in the fourth section together with a broad robustness analysis on the dependent variable. The fifth section presents a sensitivity analysis of the main explanatory variables when additional or alternative determinants of the production level are considered; a further investigation related to the spatial features of the data is also proposed. The paper ends with some concluding remarks.

2. The knowledge assets in the production function

The basic empirical model employed in this analysis is represented by a Cobb-Douglas production function, which includes the traditional capital stock and labour inputs but is also augmented with two intangible assets, namely human capital and technological capital. As illustrated in the introduction, the inclusion of such productive inputs is motivated by the extensive theoretical and empirical literature which has established both of them as crucial determinants of productivity and a key source of long-run economic growth. When both technological and human capital are included in the aggregate production function, the latter is expected to capture the impact of non-codified innovation (learning by doing, on the job learning) and to increase the ability of firms to acquire and absorb new knowledge, which in turn makes the use of tangible inputs more effective (Engelbrecht, 1997). The general form of our model is the following:

$$Y_{it} = A_i K_{it}^{\beta_1} L_{it}^{\beta_2} HK_{it}^{\beta_3} TK_{it}^{\beta_4} \tag{1}$$

for our sample i=1, … 276 regions, t=2000, … 2008; Y is Gross Domestic Product (GDP), A is the efficiency level, K is physical capital stock, L are labour units, HK is human capital and TK is technological capital.

We now briefly describe the variables included in the production function, focusing specifically on the knowledge assets. The summary statistics are shown in Table 1 while the detailed sources and definitions of the variables are reported in the Appendix 1. The list of countries considered with their regional breakdown can be found in the Appendix 2.

The dependent variable is regional GDP expressed in constant terms as year 2000 million euros. As we have already remarked in the introduction the distribution of GDP shows large regional disparities exhibiting a clear spatial pattern. More specifically, the European setting is currently characterized by a remarkable West-East gap that differentiates the 15 old member countries of the EU with respect to the 12 new accession countries, which joined the European Union in the period 2004-2007. Considering the year 2000, at the beginning of the period analysed, the GDP per capita of the 15 countries plus Norway and Switzerland (EU15+ from now on) was

19% above the European average, while the EU12 one accounted for just the 24% of the overall European product. In dynamic terms, however, the EU12 regions are outperforming the others, their GDP growth rate (5.6%) over the period 2000-2008 is almost four times as large as the EU15+ regions one (1.5%) signalling that a convergence process is taking place across the enlarged Europe. Therefore, to take into account this profound difference among the European regions, in the empirical specification of our model we include a dummy variable for the 56 regions belonging to the EU12 countries.

The capital stock, K, expressed in constant million euros, is calculated for each region and year, by applying the perpetual inventory method over a long time span starting in the year 1985, from the flow of gross investment in the previous period and assuming an annual depreciation rate equal to 10%. Labour is computed in thousands of full time equivalent labour units.

The human capital variable is expressed as thousands of economically active individuals that have attained at least a tertiary education degree (ISCED 5-6). This proxy has been also used for the European regions by Sterlacchini (2008) and Fischer et al. (2009a). At the regional level a higher availability of well educated labour forces represents an advantage for the localization of innovative firms thus promoting local productivity (Rauch, 1993).[2] In Map 1 the geographical pattern of human capital across the European regions is represented by reporting the quintile distribution of the time average 2000-2008; the series are rescaled with respect to the population size. It clearly turns out that the presence of highly educated people follows a well defined spatial pattern where the national dimension seems to play a relevant role. For instance Italy, Portugal and, in general, the eastern countries stands out for having most of their regions in the lowest classes while the Scandinavian, Baltic and northern European countries show a relatively high endowment of graduate population. Looking at the regional level, the highest share of graduate population is recorded, as expected, in the capital cities like Oslo, London, Madrid, Brussels, Athens, Stockholm, Helsinki and Paris.

The second element of the knowledge assets considered is the technological capital that is expected to enhance the productivity of the firms and of the local economy as a whole through the effect of external spillovers. As an indicator for technological capital we use the number of patent applications presented to the European Patent Office. Given that the protection of innovation at the international level is costly, this choice guarantees that only patents with a high economic value are likely to be granted. Patent data have been regionalised on the basis of the inventors' residence; in the case of patents with multiple inventors, proportional quotas have been attributed to each region.

[2] Florida (2002) suggests to proxy human capital with the individuals working in creative occupations. However, for the case of the European regions, the creativity component of human capital turns out to be outperformed by the education one (Marrocu and Paci, 2012).

The distribution of technological capital, expressed in per capita values, across the European regions over the period 2000-2008 is represented in Map 2. Its main trait is the existence of a high-performance cluster with the most technologically advanced regions appearing contiguous to each other. This spatial polarization is confirmed by the high value (1.88) of the variation coefficient of the regional distribution of technological capital reported in Table 1, which is much larger when compared to the other variables considered. The cluster of high performing regions departs from the Rhône-Alpes region in France, passes through the Northern regions of Italy and embraces most regions in Switzerland, Germany, Netherlands, Denmark and southern Scandinavian areas. On the other hand, all southern and eastern European regions are characterized by very low levels of technological capital.

Patent application is the most used indicator of technological activity given its advantage of providing an extensive temporal, territorial and sectoral coverage (Griliches, 1990; Acs et al. 2002). However, in order to assess the robustness of this indicator, in the empirical estimation we also use R&D expenditures as an alternative proxy for technological capital.

In the empirical model we also augment our basic production function inputs by including other factors which are perceived to characterize the local environment and thus to influence the regional economic performance.[3]

The first factor refers to the territorial characteristics of the region. More specifically, we introduce the population density since a high concentration of people implies a higher local demand and a wider supply of local public services that are expected to have a positive impact on firms and regions productivity (Ciccone and Hall, 1996). Alternatively, we use a more complex indicator of regional hierarchy, the Settlement Structure Typology index, which distinguishes six types of regions according to two dimensions, density and city size: the less densely populated areas without centers take value one while the very densely populated regions with large centers, that is the urban areas, take the maximum value of six.

Another important element which may influence the aggregate regional performance is the sectoral specialization of the production structure in each region. We expect regions specialized in less innovative and dynamic industries to be more likely to show a lower economic performance compared to areas where the knowledge intensive services are more relevant. Therefore in the empirical model we control for the regional production structure by introducing two indices of relative specialization of employment. The first accounts for the specialization in low tech manufacturing sectors (food and beverages, textiles and leather, other manufacturing) and the

[3] It is important to remark that other relevant factors which may affect regional performance like social capital, institutions, entrepreneurship are not included due to the lack of data for the whole set of regions and years considered.

second in knowledge intensive services (transport, communications, financial intermediation, real estate and business activities).

3. Econometric analysis: estimation issues

The empirical model is formalized as the log-transformation of the Cobb-Douglas production function reported in equation (1):

$$y_{it} = \alpha_i + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 hk_{it} + \beta_4 tk_{it} + \varepsilon_{it} \qquad (2)$$

where the lower case letters indicate the log-transformed variables defined in the section above.

Before estimating model (2) two relevant econometric issues have to be addressed. The first one is the well-known potential endogeneity problem arising from reversal causality and/or from the correlation of any of the regressors with the productivity shocks included in the error term. Differently from the case when firms level data is used, in our framework of regional aggregated data we cannot make use of the control function approach (Olley and Pakes, 1996) to deal with endogeneity. Since there is no a clear estimation strategy in the case of aggregate data, we tackle the endogeneity by including all the explanatory variables lagged two years[4] (see equation 5). Moreover, as a robustness check, we also estimate model (2) by means of a cross-section regression, where we consider initial period values for the regressors and final period values for the response variable. Under the assumption that the production shocks exhibit at most a first order autocorrelation pattern and the regressors are only moderately persistent, the long lag structure is expected to rule out endogeneity threats.

As our sample observations refer to spatial units, the second econometric issue is related to the existence of cross-regional association, due to the presence of spatial spillovers or to unobserved spatial features, which makes simple OLS estimates not reliable.

Rather than imposing a specific structure of spatial dependence from the onset, we rely on specification tests to assess the kind of spatial association our data is more consistent with. Hence, we apply the LM tests designed for the null hypothesis of no spatial correlation in the residuals of models such as (2); under the alternative hypotheses that either a spatially lag dependent variable (LM test-spatial lag) is omitted in (2) or the error term is spatially autocorrelated (LM test-spatial

[4] We also consider longer lag structures, since the main results do not change appreciably we keep the second lag in order to keep more observations along the time dimension of the data.

error).[5] In the first case the relationship should be specified as a Spatial Autoregressive (SAR) model:

$$y_{it} = \beta X_{it} + \rho W y_{it} + u_{it} \tag{3}$$

where the explanatory variables are collected in the matrix *X*, the term *Wy* captures the spillovers arriving from neighbouring regions as, with respect to region *i*, it is computed as the weighted average of all other regions production levels. The matrix *W* contains the spatial weights used to describe the interconnectivity among the regions as a function of their geographic proximity; in our case each entry of *W* is the inverse of the distance between any two regions in the sample.[6] Note that if the spatial lag *Wy* is indeed relevant, model (2) is affected by the usual omitted variable bias problem. Under the assumption that the SAR specification is the most adequate one, the error term *u* is expected to be approximately an i.i.d. process.[7]

On the other hand, if the errors are correlated according to a spatial kind of structure, the Spatial Error model (SEM) results; it comprises a linear specification as in (2) but the residuals are modelled as in (4):

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + u_{it} \tag{4}$$

where *W* is the same matrix as in (3).

Note that for the SEM model the interpretation of the coefficients as partial derivatives still holds, whereas it is no longer the case for the SAR model; due to the presence of the spatially lagged dependent variable the impact of a change in one of the *X* regressors accounts for the effect attributable to a given region (direct effect) as well as to spillovers (indirect effect) arising from the interactions with nearby regions.

The basic specification, which also includes time fixed effects to control for shocks affecting the regions in a common way, is defined as:

$$y_{it} = \alpha + \beta_1 k_{it-2} + \beta_2 l_{it-2} + \beta_3 hk_{it-2} + \beta_4 tk_{it-2} + \delta_t + \varepsilon_{it} \tag{5}$$

where the explanatory variables are lagged two periods to deal with endogeneity issue discussed above.

[5] For a comprehensive description of spatial models and related specifications, estimation and testing issues refer to Le Sage and Pace (2009) and Elhorst (2010).

[6] Note that the main diagonal elements are set to zero and that in all the estimation and testing procedure *W* is max-eigenvalue normalized. Such normalization is sufficient and avoids strong undue restrictions, as it is the case when the row-standardization method is applied (Keleijan and Prucha, 2010).

[7] Some authors (Corrado and Fingleton, 2012; Gibbons and Overman, 2012) have recently raised some critical concerns on spatial autoregressive specifications for their ‘too casual’ application in empirical analyses. Most applied works are claimed to lack sound theoretical justification that, along with some specific requirements on the interconnectivity matrix, are necessary to identify ‘true’ causal links attributed to the existence of spillovers. In presenting our results we will deal with this issue in detail.

Note that, since for our sample the cross-section dimension (N=276) is much larger than the time series one (T=7), we do not include regional fixed effects as these could not be adequately estimated. However, in order to account for the wide economic differences between the regions of the EU15+ on one side and those of the new accession countries on the other, we also consider specifications which include the binary control variable *EU12*.

Our estimation strategy entails two main steps. First we select the most adequate spatial specification on the basis of the LM tests mentioned above, along with some robustness checks carried out by considering alternative economic performance indicators. Secondly, we perform a sensitivity analysis on the main explanatory variables to examine whether they are robust to the inclusion of additional or alternative determinants of the production level; in the same section we propose a further investigation related to the spatial pattern featured by the data in order to unveil the presence of possible spillovers, in particular for the case of intangible assets.

4. Results for the basic model

In Table 2 we report the results of the OLS estimation for the basic model (5); we consider a specification including just a common constant and, alternatively, time fixed effects. In both cases the LM tests for spatial dependence provide overwhelming evidence in favour of the Spatial Error Model.

When the EU12 dummy is included (third regression of Table 2), the LM tests offer evidence consistent with the two types of spatial dependence, even if the spatial error one is still the kind of cross-section dependence that yields the highest rejection of the null hypothesis. The estimation of both the SAR and the SEM model[8] highlights that the latter specification is to be preferred, as a matter of fact the error spatial autoregressive coefficient turns out to be sizeable (0.880) and highly significant, while the spatial lag term in regression (4) exhibits a very small value and it is not statistically significant. This finding points out that our data do not seem to support the existence of global spillovers; spatial dependence is a feature of the error process, so that the estimation of the SEM specification allows to get unbiased standard errors and more efficient estimates of explanatory variables' effects.

Focusing on the explanatory variables of our preferred model (5), the results confirm their positive contribution to gross product creation. As expected, the *EU12* dummy exhibits a negative coefficient as it accounts for the lower production level of most Eastern regions. More specifically,

[8] Both models are estimated by applying the Maximum Likelihood method; we acknowledge the use of the Matlab codes kindly made available by J.P. Elhorst for spatial static panel data models (http://www.regroningen.nl/elhorst/).

as far as the traditional inputs are concerned, labour turns out to be quite effective when compared to the capital stock as GDP is more responsive to changes in labour units (elasticity of 0.52) than to changes in capital (0.12). Both intangible assets exhibit significant and substantial elasticities, which make them key determinants of the production performance at regional level. In particular, according to our results a 1% change in the human capital endowment is capable of activating a 0.17% increase in GDP, whereas technological capital turns out to be as effective as physical capital in enhancing production growth.

In order to provide some indications of what such estimated elasticities would entail in terms of GDP increases we carry out a suggestive what-if kind of exercise. Considering that in 2008 the European regional average human capital is represented by 231 thousand people with a university degree, if such an endowment increases by 1%, the estimated elasticity would imply a raise in GDP of almost 68 million euros in real terms. Note that in this case the computation is carried out by referring to the overall average values; if it is redone distinguishing between EU15+ regions and the EU12 ones, the increases in GDP would be quite far a part: 80 millions in the wealthier regions and nearly 19 in the new accession countries ones. Analogously, a 1% increase in the stock of technological capital, whose overall average value in 2008 was 192 patents, would result in an increase in GDP of 59 million euros in the Western European regions and of just 14 in the Eastern ones (average increase 49.5 million euros).

The estimate of human capital elasticity confirms recent findings provided at the local level for the EU15+ regions in the context of a TFP model (Dettori et al., 2011). Evidence on the positive influence of human capital for the European regions case has been also found by Sterlacchini (2008) and Fischer et al. (2009a) in a productivity growth model. Technological capital, on the other hand, turns out to be much more effective in the present analysis for the whole sample of the European regions with respect to the evidence reported in Dettori et al., 2011. Within a spatial framework, a positive influence on TFP due to technology, measured by patent stocks, is also reported in LeSage and Fischer (2012) and Fischer et al. (2009b) for the European regions and in Madsen (2008) for the OECD countries. The analyses proposed by Sterlacchini (2008) and Rodriguez-Pose and Crescenzi (2008) are more general and, controlling for other regional determinants like human capital and infrastructures, they offer robust support to the positive role exerted by R&D expenditure on the GDP growth rate.

In Table 3 we report the results of the analysis carried out to assess the robustness of the basic model with respect to the endogeneity issue and to the use of alternative indicators for economic performance. The first regression (1) is estimated on a cross-section sample of data, the

GDP variable is considered for the year 2007[9], whereas the explanatory variables are included with a seven year lag, at their 2000 values, to clear out any correlation with the error term. The main results reported for the spatial error model of Table 2 are generally confirmed, the capital stock elasticity is lower and the technological capital slightly outperforms the human capital one.

As alternative indicators of economic performance we consider labour productivity and GDP per capita. In the first case the estimated elasticities are quite similar to the ones discussed for the basic model. For the production function expressed in per capita terms we find evidence of reduced elasticity estimates for both physical capital and labour inputs (0.06 and 0.15, respectively); the intangible assets turn out to be quite effective, exhibiting very similar elasticities, 0.13 for human capital and almost 0.14 for technological capital. Such evidence, although subject to the usual caveats of any empirical analysis, is suggestive of the great economic potential of the knowledge assets and highlights the importance of policies aimed at supporting their accumulation in order to foster the overall level of production and to speed the narrowing of the gap for a non negligible portion of laggard European territories.

5. Extensions of the basic model and robustness analysis

In this section we discuss the results of the robustness analysis carried out on the main explanatory variables by augmenting the basic model with additional regressors which, as highlighted in section 2, are expected to affect the production process at the regional level.

We first consider two alternative indicators of the local territorial structure, population density and the urban settlement pattern; the latter combines density with the presence of large inhabited centres. Both variables are expected to capture the additional productive gains arising from agglomeration economies. The results reported in the first two columns of Table 4 point out the concentration of economic activities in a limited area is quite production enhancing, in particular when density is included (0.05 vs. 0.02 for the urban settlement pattern); moreover, this positive finding rules out adverse effects due to congestion phenomena.

In regression (3) we further augment the model by including production specialization indices while still keeping the density variable. The new indicators are expected to capture to what extent the specialization pattern affects the production performance. According to our findings, a region relatively more specialized in knowledge intensive sectors can expect higher returns in terms of GDP (elasticity estimated in 0.14) with respect to a region, with the same amount of inputs

[9] We do not consider the final available year 2008, since it could be affected by the international financial crises and we cannot account for by including a year dummy as it was the case for the models reported in Table 2.

endowment, but specialized in low tech manufacturing productions; such kind of specialization has actually a detrimental effect (-0.05) on economic outcomes. This result is particularly relevant for the EU12 regions, which are currently specialized in low tech industrial sectors as the result of the delocalization process triggered by the European integration. This has induced EU15+ countries firms to move eastwards their mature standardized manufactures in order to exploit lower input costs and to take advantages of the most innovative and profitable productions at home (Marrocu et al., 2010). Note however that the employment share related to KIS sectors is steadily increasing all over Europe.

It is worth emphasizing that across models (1)-(3) of Table 4, both the tangible and the intangible assets turn out to be quite robust to the inclusion of the four additional regressors considered so far.

On the basis of the discussion reported in the second section on how to measure technological assets, in regression (4) we include R&D expenditure in place of the EPO patents; note that the two alternative indicators are highly correlated, the sample correlation coefficient being equal to 0.86. The R&D effect on GDP, estimated in 0.22, is very sizeable and leads to halving the effect previously found for human capital, which now exhibits an elasticity of around 0.08. This result may be due to a sort of crowding out effect with respect to human capital since on average 50% percent of R&D expenditure is paid for researchers' wages, so that the two variables overlap to some extent (their sample correlation coefficient is equal to 0.77).[10] Moreover, there can be an additional demand side effect on GDP, which cannot be accounted for by human capital, that is due to the fact that some expenditures classified as R&D are not directly related to knowledge activities as is the case of research laboratory buildings. For these reasons we argue that the number of patents is a more adequate proxy for technological capital; patents represent more accurately the economic value of codified knowledge, since international intellectual protection is costly, only innovations with high profitable potential are applied for.[11]

Finally in regression (5), on the basis of the documented disparities in the economic performance between EU12 regions and the EU15+ ones, we investigate whether there are significant differences in the effects associated with the two intangible assets in the two main macro-areas. We, thus, include two additional terms, which are obtained as the interaction of the EU12 dummy with each intangible input. The results point out that in this respect the two territories are not distinguishable as the two new regressors are not significant at conventional levels; however, when they are included one at a time the human capital interactive term is positive

[10] The sample correlation coefficient between human capital and patents is 0.59.
[11] A positive association has been found between strong patent protection and higher levels of total factor productivity, higher returns to domestic as well as external R&D capital (Coe et al., 2009).

and significant. This results prompts for a deeper investigation of the spatial pattern of the soft inputs effects.

In selecting the spatial specification in section 4.1 we found that our sample data was not consistent with the Spatial Autoregressive model, which entails a 'general' productive kind of spillover. However, it is worth investigating whether 'specific' spillovers, directly linked to a particular input, are present; more specifically, we test whether it is the case for the two intangible assets. The general model (3) of Table 4 is thus further extended by including the spatial lag of human capital and technological capital; each of the two new terms is therefore obtained as a weighted average of all other regions endowment in human capital and technological capital; the weights are proportional to the inverse of the distance between any two of the 276 regions.[12]

The two spatial lags exhibit a high degree of linear association (the correlation coefficient is equal to 0.72), it is reasonable to presume that this is due to the fact that they actually operate as a proxy for almost the same kind of information, that is knowledge created in nearby areas. In order to avoid multicollinearity problems, the intangible assets spatial lags are included one at time in the regression model (1) and (2) of Table 5. The estimation results point out that both spillovers are significant and sizeable in magnitude, with human capital externalities turning out to be more effective than the ones based on patents information. This finding signals the importance of being located within highly knowledge endowed territories in order to benefit from cross-border knowledge externalities in terms of production enhancements (see the recent surveys by Döring and Schnellenbach, 2006 and Malmberg and Maskell, 2006).

In regressions (3) and (4) we test whether the knowledge spillovers have different effects in the two macro-areas of EU15+ and EU12 countries. Both human capital and technological capital spatial terms are positive and significant; note also that the effects of all other explanatory variables turn out to be quite robust with respect to the inclusion of the new regressors, only the non-spatial terms for both human capital and technological assets decrease when their spatial counterparts are included, this was also the case for the first two models.

Note that the spatial terms in regression (3) and (4) now exhibit a much higher and significant impact for regions belonging to the EU12 area. This result is certainly due to the fact that such territories are lagging behind the rest of Europe so that there is more scope for larger improvements in their economic outcomes. Moreover, it is worth remarking that as far as human capital is concerned the EU12 regions are better equipped than it is the case for other indicators, their average for graduate people being 76% of the corresponding average for the overall Europe.

[12] Note that in this case the spatially lagged terms are included for (some of) the explanatory variables, so that our model is not affected by the critics mentioned in footnote 7.

We claim that this is reflected in the higher spillover impact found for EU12 regions, as the presence of highly skilled workers is an important prerequisite to take advantage of external sources of innovative ideas, a region's absorptive capacity and the ability to effectively use such new knowledge are decisively related to high human capital availability.[13] This evidence, if further supported by policies aimed at sustaining the accumulation of human capital and at strengthening the existence of regional networks, is consistent with the expectation that the gap between rich and poor territories could be narrowed in a relative short time span.

6. Concluding remarks

One of the most evident stylised fact in Europe is the existence of huge economic disparities across regions which appear particularly remarkable when we compare the economic level of the western and eastern regions. In this paper we try to explain these wide differences looking at the role played by the knowledge factors, like technological and human capital, in determining the regional GDP levels. These intangible assets are particularly relevant since they play a double role. First, they enhance regional efficiency directly as inputs of the production function, in addition to the traditional inputs, like physical capital and labour units. Second, the intangible factors are the means through which the territories are able to absorb the knowledge flowing from the neighbouring regions through different kinds of channels.

We estimate a Cobb-Douglas production function over the period 2000-2008 for 257 regions belonging to 29 European countries within a spatial panel econometric framework to take into account the presence of spatial association. We also perform a robustness analysis to test the sensitivity of our results with respect to alternative economic indicators and by controlling for other territorial and industrial features of the regions that are likely to affect the economic performance.

Our results confirm, for the enlarged Europe, that both knowledge assets, human and technological capital, are crucial and complementary drivers of the economic performance at the regional level. More specifically, human capital shows a higher impact on regional production with respect to technological capital which, in turn, results as effective as physical capital in enhancing the local performance. It means that increasing by 1% the number of European people with a university degree would induce an increase in GDP of almost 68 million euros and, in the same vein, an increase of 1% in the number of patent would raise GDP by nearly 50 million euros.

[13] In a recent paper Coe et al. (2009) find evidence that countries (OECD ones) with a high quality of tertiary education systems tend to benefit more from their own knowledge R&D efforts and from international spillovers.

This result proves to be robust to different model specifications and to the inclusion of other determinants of regional production such as population density and the specialisation of the production structure. Moreover, we find that regions specialised in the knowledge intensive services, mainly the urban areas in the western countries, show a higher economic performance and this result strengthens the fundamental influence of the knowledge factors.

Finally, we investigate whether specific spatial spillovers, directly linked to the knowledge inputs of the nearby regions, are affecting the local economic performance. Interestingly, we find out that the impact of the spatially lagged values of the knowledge assets is significant and sizeable in magnitude with human capital externalities outperforming the technological ones. This finding signals the importance of being located within highly knowledge endowed territories in order to benefit from cross-border knowledge externalities in terms of production enhancements.

It is important to remark that when we allow the impact to be different between the subsample of EU15 regions on one hand and the group of EU12 ones on the other, the knowledge assets spillovers turn out to be much more effective in boosting regional production in the new accession countries. Such territories are lagging behind the rest of Europe so that there is more scope for larger improvements in their economic outcomes due to the absorption of knowledge spillover coming from all other European regions. More specifically, the EU12 countries show an elasticity for the human capital spatial lag which is five times higher than the one for the EU15. Indeed, the new accession regions are characterized by a relatively good endowment of highly skilled workers which allows them to take advantage of external sources of innovative ideas and new knowledge.

The evidence provided in this paper remarks the great economic potential of the knowledge assets as internal production inputs and, even more important, as essential factors in the absorption of the external knowledge especially for the lagging regions. This indicates the importance of policies aimed at supporting the accumulation of human and technological capital in order to foster the overall level of production and to speed the narrowing of the gap for a non negligible portion of laggard European territories.

References

Acs Z. and L.A. Plummer (2005) Penetrating the “Knowledge Filter” in Regional Economies, *Annals of Regional Science*, 39, 439–456.

Acs Z., L. Anselin and A. Varga (2002) Patents and innovation counts as measures of regional production of new knowledge, *Research Policy*, 31, 1069–1085.

Audretsch D. and M. Feldman (2004) Knowledge spillovers and the geography of innovation, in Henderson V. and J.F. Thisse (eds.) *Handbook of Regional and Urban Economics: Cities and Geography*. Amsterdam: Elsevier.

Barca F. (2009) An Agenda for a Reformed Cohesion Policy, *Independent Report*.

Benhabib J. and M. Spiegel (1994) The role of Human Capital in Economic Development: evidence from aggregate cross-country data, *Journal of Monetary Economics*, 34, 143-174.

Beugelsdijk S. and T. van Schaik (2005) Social capital and growth in European regions: an empirical test, *European Journal of Political Economy*, 39, 301–324.

Braunerhjelm P., Z. Acs, D. Audretsch and B. Carlsson (2010) The missing link: knowledge diffusion and entrepreneurship in endogenous growth, *Small Business Economics*, 34, 105–125.

Capello R., A. Caragliu and P. Nijkamp (2011) Territorial capital and regional growth: increasing returns in knowledge use, *Tijdschrift voor Economische en Sociale Geografie*, 102, 385–405.

Ciccone A. and R. Hall (1996) Productivity and the density of economic activity, *American Economic Review*, 86, 54-70.

Coe D.T., E. Helpman and A.W. Hoffmaister (2009) International R&D spillovers and institutions, *European Economic Review*, 53, 723-741.

Cohen W.M. and D.A. Levinthal (1990) Absorptive capacity: a new perspective on learning an innovation, *Administrative Science Quarterly*, 35, 128-152.

Corrado L. and B. Fingleton (2012) Where is the economics in spatial econometrics?, *Journal of Regional Science*, 52, 210-239.

Corrado C.A., D.E. Sichel and C.R. Hulten (2009) Intangible capital and U.S. Economic growth, *Review of Income and Wealth*, 85, 661–685.

Crescenzi R. and A. Rodríguez-Pose (2009) Systems of innovation and regional growth in the EU: endogenous vs. external innovative efforts and socio-economic conditions, in U. Fratesi and L. Senn (eds.), *Growth and innovation of competitive regions: the role of internal and external connections*. Berlin: Springer-Verlag.

Dettori B., E. Marrocu and R. Paci (2011) Total factor productivity, intangible assets and spatial dependence in the European regions, *Regional Studies*, published on line, DOI: 10.1080/00343404.2010.529288.

Döring T. and J. Schnellenbach (2006) What do we know about geographical knowledge spillovers and regional growth?: a survey of the literature, *Regional Studies*, 40, 375-395.

Elhorst J.P. (2010) Applied Spatial Econometrics: raising the bar, *Spatial Economic Analysis*, 5, 10-28.

Engelbrecht H.J. (1997) International R&D spillovers, human capital, and productivity in OECD countries: an empirical investigation, *European Economic Review*, 41, 1479–1488.

Fischer M.M., M. Bartkowska, A. Riedl, S. Sardadvar and A. Kunnert (2009a) The impact of human capital on regional labor productivity in Europe, *Journal Letters in Spatial and Resource Sciences*, 2, 97-108.

Fischer M.M., T. Scherngell and M. Reismann (2009b) Knowledge spillovers and total factor productivity. Evidence using a spatial panel data model, *Geographical Analysis*, 41, 204-220.

Florida R. (2002) *The rise of the creative class and how it's transforming work, leisure, community, and everyday life*. New York: Basic Books.

Gibbons S. and H.G. Overman, Mostly pointless spatial econometrics, *Journal of Regional Science*, 52, 172-191.

Griliches Z. (1979) Issues in Assessing the Contribution of Research and Development to Productivity Growth, *The Bell Journal of Economics*, 10, 92-116.

Griliches Z. (1990) Patent statistics as economic indicators: a survey, *Journal of Economic Literature*, 28, 1661–1707.

Hauser C., G. Tappeiner and J. Walde (2007) The Learning Region: The Impact of Social Capital and Weak Ties on Innovation, *Regional Studies*, 41, 75-88.

Jaffe A.B. (1989) Real Effects of Academic Research, *American Economic Review*, 79, 957-70.

Kelejian H.H. and I.R. Prucha (2010) Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances, *Journal of Econometrics*, 157, 53-67.

Knack S. and P. Keefer (1997) Does social capital have an economic payoff ? A cross-country investigation, *Quarterly Journal of Economics*, 112, 1251-1288.

LeSage J.P. and M.M. Fischer (2012) Estimates of the Impact of Static and Dynamic Knowledge Spillovers on Regional Factor Productivity, *International Regional Science Review*, 35, 103-27.

LeSage J.P. and R.K. Pace (2009) *Introduction to Spatial Econometrics*. Boca Raton: CRC.

Lucas R.E. (1988) On the mechanics of economic development, *Journal of Monetary Economics*, 22, 3–42.

Madsen J. (2008) Economic growth, TFP convergence, and the world export of ideas: a century of evidence, *Scandinavian Journal of Economics*, 110, 145-167.

Maggioni M.A., M. Nosvelli and T.E. Uberti (2007) Space versus networks in the geography of innovation: A European analysis, *Papers in Regional Science*, 86, 471–493.

Malmberg A. and P. Maskell (2006) Localized Learning Revisited, *Growth and Change*, 37, 1-18.

Mankiw N.G., D. Romer and D. Weil (1992) A contribution to the empirics of economic growth, *Quarterly Journal of Economics*, 107, 407-437.

Marrocu E. and R. Paci (2012) Education or Creativity: what matters most for economic performance?, *Economic Geography*, forthcoming.

Marrocu E., R. Paci and M. Pontis (2012) Intangible capital and firms' productivity, *Industrial and Corporate Change*, 21, 377-402.

Marrocu E., R. Paci and S. Usai (2010) Productivity growth in the Old and New Europe: the role of agglomeration externalities, CRENoS WP 2010/24.

Miguélez E. and R. Moreno (2011) Research Networks and Inventors' Mobility as Drivers of Innovation: Evidence from Europe, *Regional Studies*, published on line, DOI: 10.1080/00343404.2011.618803

OECD (2001) *Territorial Outlook*, Paris: OECD Publishing.

Olley G.S. and A. Pakes (1996) The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica*, 64, 1263–1297.

Paci R. and S. Usai (2009) Knowledge flows across the European regions, *Annals of Regional Science*, 43, 669-690.

Rauch J. (1993) Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities, *Journal of Urban Economics*, 34, 380-400.

Rodriguez-Pose A. (1999) Innovation Prone and Innovation Averse Societies: Economic Performance in Europe, *Growth and Change*, 30, 75-105.

Rodriguez-Pose A. and R. Crescenzi (2008) Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe, *Regional Studies*, 42, 51-67.

Sterlacchini A. (2008) R&D, higher education and regional growth: Uneven linkages among European regions, *Research Policy*, 37, 1096–1107.

Appendix 1. Data sources and definition

Variable		Primary Source	Years	Definition
Gross Domestic Product	Y	Eurostat	2000-2008	Millions euros, 2000.
Capital stock	K	Own calculation	2000-2008	Millions euros, 2000.
Units of labour	L	Eurostat	2000-2008	Thousands.
Human Capital	HK	Eurostat	2000-2008	Population aged 15 and over by highest level of education attained. Tertiary education - levels 5-6 (ISCED 1997); thousands.
Technological capital	TK	OECD, REGPAT	2000-2008	Patent applications at EPO per priority year and residence region of inventors.
Research and Development	RD	Eurostat	2000-2008	Total intramural R&D expenditure (all sectors); millions of euros, 2000.
Population density	DEN	Eurostat	2000-2008	Resident population per km^2.
Settlement Structure Typology	SST	ESPON project 3.1 BBR	1999	1=less densely populated without centres, 2=less densely populated with centres, 3=densely populated without large centers, 4=less densely populated with large centres, 5= densely populated with large centres, 6=very densely populated with large centres.
Specialisation in Low Tech Manufacturing	ISPLTM	Cambridge Econometrics	2000-2008	Index of relative specialization of employment in 3 sectors: food beverages tobacco, textiles and leather, other manufacturing.
Specialisation in Knowledge Intensive Services	ISPKIS	Cambridge Econometrics	2000-2008	Index of relative specialization of employment in 3 sectors: transport, storage and communications, financial intermediation, real estate renting and business activities.

Appendix 2. Regions and NUTS level

Code	Country	NUTS	Regions	Dummy EU12
AT	Austria	2	9	
BE	Belgium	2	11	
BG	Bulgaria	2	6	x
CH	Switzerland	2	7	
CY	Cyprus	0	1	x
CZ	Czech Republic	2	8	x
DE	Germany	2	39	
DK	Denmark	2	5	
EE	Estonia	0	1	x
ES	Spain (a)	2	16	
FI	Finland	2	5	
FR	France (a)	2	22	
GR	Greece	2	13	
HU	Hungary	2	7	x
IE	Ireland	2	2	
IT	Italy	2	21	
LT	Lithuania	0	1	x
LU	Luxembourg	0	1	
LV	Latvia	0	1	x
MT	Malta	0	1	x
NL	Netherlands	2	12	
NO	Norway	2	7	
PL	Poland	2	16	x
PT	Portugal (a)	2	5	
RO	Romania	2	8	x
SE	Sweden	2	8	
SI	Slovenia	2	2	x
SK	Slovakia	2	4	x
UK	United Kingdom	2	37	

(a) Territories outside Europe are not considered

Table 1. Descriptive statistics (2000-2008)

Variable	Measure	Min	Max	Mean	St. dev.	Var. coeff.
Gross Domestic Product	millions euros 2000	823	460591	37580	43859	1.17
Capital stock	millions euros 2000	278	796016	58786	69776	1.19
Units of labour	thousands	16	5608	806	673	0.84
Human Capital	thousands graduates	3	2338	198	205	1.04
Technological capital	number patents	0	3300	202	380	1.88
Research and Development	millions euros 2000	1	14140	700	1226	1.75
Population density	number	3	9476	335	825	2.47
Low Tech Manufacturing specialisation	index	0.10	3.57	1.07	0.54	0.50
Knowledge Intensive Services specialisation	index	0.48	2.91	1.01	0.26	0.26

Table 2. Basic model and spatial pattern

Dependent Variable: GDP

	1	2	3	4	5
Model	**Pooled**	**Pooled**	**Pooled**	**SAR**	**SEM**
Estimation method	OLS	OLS	OLS	ML	ML
Capital	0.244 ***	0.245 ***	0.114 ***	0.114 ***	0.122 ***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Labour units	0.212 ***	0.201 ***	0.521 ***	0.521 ***	0.516 ***
	(0.26)	(0.026)	(0.023)	(0.024)	(0.024)
Human Capital	0.215 ***	0.226 ***	0.159 ***	0.160 ***	0.167 ***
	(0.023)	(0.024)	(0.019)	(0.020)	(0.021)
Technological capital	0.203 ***	0.202 ***	0.132 ***	0.132 ***	0.122 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
EU12			-0.806 ***	-0.807 ***	-0.802 ***
			(0.025)	(0.026)	(0.027)
Spatial autoregressive coefficient - ρ				0.0003	
				(0.037)	
Spatial autoregressive coefficient - λ					0.880 ***
					(0.032)
Common constant	yes				
Time fixed effects		yes	yes	yes	yes
Square correlation (actual, fitted values)	0.882	0.882	0.923	0.923	0.923
Diagnostics					
Robust LM test - No spatial lag	0.998	0.975	7.665		
p-value	0.318	0.323	0.006		
Robust LM test - No Spatial error	5076.311	5117.773	2717.297		
p-value	0.000	0.000	0.000		

N=276 regions, T=7, 2000-2008 (two lags), NT=1932.
All variables are log-transformed; GDP refers to 2002-08, all explanatory variables refer to 2000-06.
Variables in value are in 2000 million euros.
EU12 is a dummy variable for the 56 regions of the 12 accession countries.
For spatial models and tests the weight matrix is the max-eigenvalue normalized matrix of inverse distance in kilometers.
Robust standard errors in parenthesis; significance: ***1%; **5%; *10%.

Table 3. Basic model with alternative specification of the dependent variable

SEM models	1	2	3
Dependent variable	GDP cross-section	Labour productivity	GDP per capita
Capital	0.075 ***		
	(0.022)		
Labour units	0.614 ***		
	(0.058)		
Human Capital	0.109 **		
	(0.047)		
Technological capital	0.126 ***		
	(0.013)		
Capital per unit of labour		0.120 ***	
		(0.010)	
Human capital per unit of labour		0.169 ***	
		(0.021)	
Technological capital per unit of labour		0.113 ***	
		(0.005)	
Capital per capita			0.059 ***
			(0.009)
Labour units per capita			0.147 ***
			(0.031)
Human capital per capita			0.129 ***
			(0.019)
Technological capital per capita			0.136 ***
			(0.005)
EU12	-0.762 ***	-0.850 ***	-0.910 ***
	(0.074)	(0.027)	(0.025)
Spatial autocorrelation coefficient - λ	0.866 ***	0.880 ***	0.880 ***
	(0.093)	(0.032)	(0.032)
Common constant	yes		
Time fixed effects		yes	yes
Square correlation (actual, fitted values)	0.924	0.827	0.872

For model 1: N=276, GDP refers to 2007, all explanatory variables refer to 2000.
For models 2-3: N=276, T=7, 2000-2008 (two lags), NT=1932; GDP: 2002-08, other variables: 2000-06.
All variables are log-transformed.
Variables in value are in 2000 million euros.
EU12 is a dummy variable for the 56 regions of the 12 accession countries.
The weight matrix is the max-eigenvalue normalized matrix of inverse distance in kilometers.
Robust standard errors in parenthesis; significance: ***1%; **5%; *10%.

Table 4. Extended model and robustness analysis

Dependent Variable: GDP

SEM models	1	2	3	4	5
Capital	0.106 ***	0.121 ***	0.108 ***	0.122 ***	0.107 ***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)
Labour units	0.496 ***	0.502 ***	0.535 ***	0.473 ***	0.542 ***
	(0.024)	(0.025)	(0.025)	(0.023)	(0.025)
Human Capital	0.174 ***	0.165 ***	0.156 ***	0.080 ***	0.149 ***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)
Technological capital	0.118 ***	0.119 ***	0.119 ***		0.118 ***
	(0.005)	(0.005)	(0.005)		(0.006)
Density	0.052 ***		0.032 ***	0.032 ***	0.033 ***
	(0.007)		(0.007)	(0.007)	(0.007)
Urban settlement pattern		0.017 ***			
		(0.005)			
Specialisation - LTM			-0.051 ***	0.017	-0.046 **
			(0.018)	(0.017)	(0.018)
Specialisation - KIS			0.141 ***	0.159 ***	0.138 ***
			(0.030)	(0.028)	(0.030)
R&D expenditure				0.218 ***	
				(0.008)	
EU12*human capital					0.036
					(0.026)
EU12*technological capital					0.009
					(0.011)
EU12	-0.834 ***	-0.809 ***	-0.771 ***	-0.632 ***	-0.961 ***
	(0.027)	(0.027)	(0.028)	(0.029)	(0.120)
Spatial autocorrelation coefficient - λ	0.898 ***	0.890 ***	0.878 ***	0.875 ***	0.880 ***
	(0.027)	(0.029)	(0.032)	(0.033)	(0.032)
Square correlation (actual, fitted values)	0.925	0.923	0.927	0.935	0.927

N=276 regions, T=7, 2000-2008 (two lags), NT=1932.

All variables are log-transformed.

GDP refers to 2000-08, all explanatory variables refer to 2000-06, except for the Urban Settlement Pattern, which refers to 1999.

Variables in value are in 2000 million euros.

EU12 is a dummy variable for the 56 regions of the 12 accession countries.

All regressions include time fixed effects and are estimated by the ML method.

The weight matrix is the max-eigenvalue normalized matrix of inverse distance in kilometers.

Robust standard errors in parenthesis; significance: ***1%; **5%; *10%.

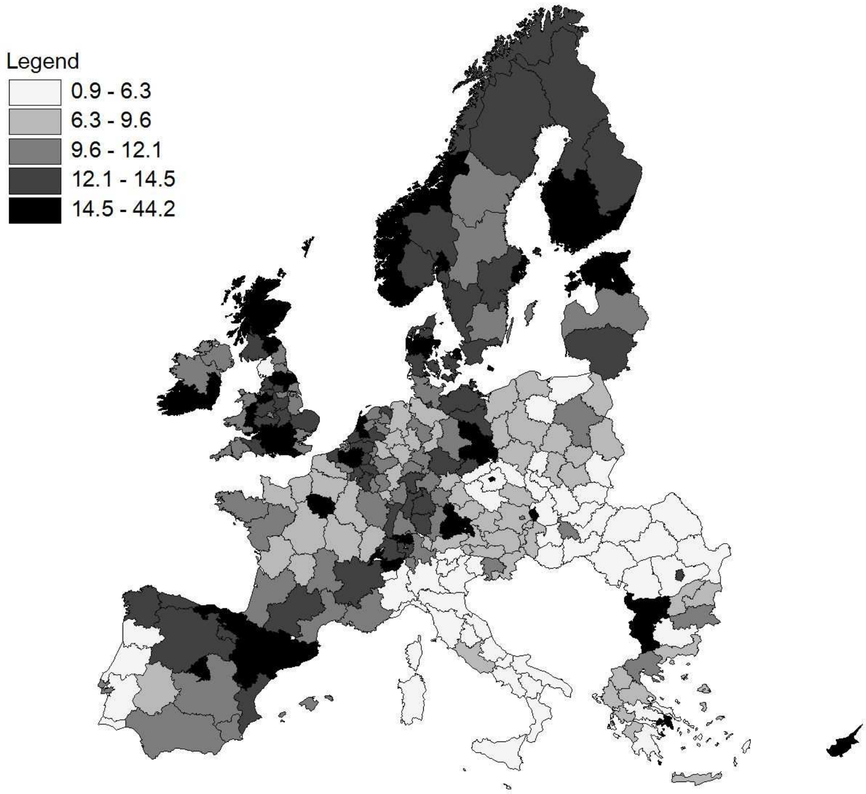
Table 5. Spatial spillovers for intangible assets

Dependent Variable: GDP

SEM models	1	2	3	4
Capital	0.104 ***	0.105 ***	0.099 ***	0.089 ***
	(0.009)	(0.009)	(0.009)	(0.009)
Labour units	0.571 ***	0.590 ***	0.569 ***	0.592 ***
	(0.026)	(0.024)	(0.025)	(0.023)
Human Capital	0.130 ***	0.169 ***	0.134 ***	0.183 ***
	(0.021)	(0.019)	(0.021)	(0.019)
Technological capital	0.116 ***	0.073 ***	0.119 ***	0.079 ***
	(0.005)	(0.006)	(0.005)	(0.006)
Density	0.027 ***	0.012 *	0.031 ***	0.027 ***
	(0.007)	(0.007)	(0.007)	(0.007)
Specialisation - LTM	-0.059 ***	-0.056 ***	-0.049 ***	-0.0003
	(0.018)	(0.017)	(0.017)	(0.017)
Specialisation - KIS	0.161 ***	0.203 ***	0.169 ***	0.201 ***
	(0.030)	(0.029)	(0.029)	(0.027)
Human capital spatial lag	0.340 ***			
	(0.072)			
Human capital spatial lag in EU12 countries			1.381 ***	
			(0.159)	
Human capital spatial lag in EU15+ countries			0.262 ***	
			(0.071)	
Technological capital spatial lag		0.265 ***		
		(0.018)		
Technological capital spatial lag in EU12 countries				0.575 ***
				(0.030)
Technological capital spatial lag in EU15+ countries				0.167 ***
				(0.575)
EU12	-0.755 ***	-0.687 ***	-6.115 ***	-2.078 ***
	(0.029)	(0.028)	(0.737)	(0.115)
Spatial autocorrelation coefficient - λ	0.885 ***	0.899 ***	0.878 ***	0.880 ***
	(0.030)	(0.027)	(0.032)	(0.032)
Square correlation (actual, fitted values)	0.930	0.933	0.930	0.939

N=276 regions, T=7, 2000-2008 (two lags), NT=1932.
All variables are log-transformed; GDP refers to 2002-08, all explanatory variables refer to 2000-06.
Variables in value are in 2000 million euros.
EU12 is a dummy variable for the 56 regions of the 12 accession countries.
The spatial lags for human capital and technological capital are constructed as weighted averages of all other regions values; the weights are proportional to the inverse distance in kilometers.
All regressions include time fixed effects and are estimated by the ML method.
The weight matrix is the max-eigenvalue normalized matrix of inverse distance in kilometers.
Robust standard errors in parenthesis; significance: ***1%; **5%; *10%.

Map 1. Human capital (population with tertiary education over total population, %).



Map 2. Technological capital (patent applications at EPO over million population)