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TOTAL FACTOR PRODUCTIVITY, INTANGIBLE ASSETS AND SPATIAL DEPENDENCE IN THE EUROPEAN REGIONS

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Total factor productivity, intangible assets and spatial dependence in the European regions

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Abstract

In the last decade there has been an upsurge of studies on international comparisons of Total Factor Productivity (TFP). The empirical evidence suggests that countries and regions differ not only in traditional factor endowments (labour and physical capital) but mainly in productivity and technology. Therefore, a crucial issue is the analysis of the determinants of such differences in the efficiency levels across economies.

In this paper we try to assess these issues by pursuing a twofold aim. First, we derive a regression based measure of regional TFP, which has the nice advantage of not imposing a priori restrictions on the inputs elasticities; this is done by estimating a *spatial* Cobb-Douglas production function relationship for 199 European regions over the period 1985-2006. Secondly, we investigate the determinants of the TFP levels by analyzing the role played by intangible factors: human capital, social capital and technological capital. The estimations are carried out by applying the spatial 2SLS method and the SHAC estimator to account for both heteroskedasticity and spatial autocorrelation. It turns out that a large part of TFP differences across the European regions are explained by the disparities in the endowments of these intangible assets. This outcome indicates the importance of policy strategies which aim at increasing the level of knowledge and social capital as stressed by the Lisbon agenda.

Keywords: Total factor productivity; human capital; social capital; technology; Europe.

JEL: C31, C33, O47, O52, R11

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1. Introduction

Recent empirical literature on economic growth, both at country and regional level, has shown that the differences in the income levels are mainly due to disparities in the Total Factor Productivity (TFP) levels and to a lesser extent to the factors of production. Easterly and Levine (2001) report that more than 90% of the differences in growth rates among nations are explained by TFP rather than traditional factor accumulation. Moreover, a strong stylized fact that emerges from the empirical literature is that regional disparities are larger and more persistent when compared to cross countries differences, at least within the industrialized economies (see Magrini, 2004, for a review).

Since the differences in productivity turn out to depend on the efficiency levels, the attention of economists has been increasingly devoted to search for additional factors which may contribute to account for such disparities. Several explanations for the TFP gap have been put forward, but among them a key role appears to be played by the intangible factors: human capital, social capital and technology. They create the base of the "knowledge economy" which, in turn, constitutes the most favourable environment to foster the economic performance of countries and regions, as stated by Lisbon declaration in 2000. As a matter of fact, in the industrialized economies the ability to compete in the open markets is increasingly based on production factors like the quality of labour, the degree of cohesion, the level of trust in the society and the accumulation of technological capital. However, there is a lack of systematic studies on the effects of different kinds of intangible assets on the economic performance at the regional level. In a number of studies human capital is often included as a determinant of the efficiency level, other works emphasize the effects of the knowledge-creation process and, only recently, social capital has been considered as a relevant variable in the context of explaining TFP variation across regions.

The main purpose and the novelty of this paper are to assess the effect of three different types of intangible assets on the economic performance at the regional level in Europe. Ideally, such a purpose would be nicely pursued by augmenting the traditional production function model with proxy variables for the intangible factors. However, for the European regions data on human, technological or social capital are not consistently available for all the regions over the entire sample period considered in this study. To deal with this severe lack of data we adopt a two-step estimation strategy. In the first stage, we derive a measure of the TFP for the European regions by estimating a Cobb-Douglas production function that includes only the traditional inputs: physical capital and labour. This is done in a panel data context controlling for spatial dependence, time series non-stationarity and endogeneity. The estimated fixed effects represent an accurate long-run measure of regional TFP which is directly derived from the production function estimation without imposing any (untested) restriction on the inputs elasticity parameters. In the second step we provide some interesting new evidence on the role played by intangible assets in determining the regional level of efficiency by including them as regressors in a model for the TFP data obtained in the first stage. It is worth stressing that, to the best of our knowledge, this is the first attempt to estimate "simultaneously" the effects of three different types of intangible capitals on the regional level of productivity.

The paper is organised as follows. In section 2 we present the results for the Cobb-Douglas production function estimation and derive the TFP variable. In section 3 we discuss the main features of the intangible factors and analyse the related literature. The econometric evidence on the role played by intangible assets in enhancing regional productivity is discussed in section 4. Section 5 offers some concluding remarks.

2. Measuring total factor productivity

2.1 Data description and spatial patterns

Our two step strategy for the estimation of regional total factor productivity starts with the specification of the traditional Cobb-Douglas production function, which includes the conventional inputs, physical capital and labour, for a panel of 199 European regions observed over the period 1985-2006; the regions belong to 15 member countries of the EU15 plus Switzerland and Norway. We follow the NUTS classification provided by Eurostat and select national and sub-national units, combination of NUTS 0, 1 and 2 levels, characterized by an adequate degree of administrative and economic control (see Table A1 in Appendix A for details). A detailed description of the variables used in this study, along with the indication of the sources, is presented in Table A2.

For each region and year, over the period 1985-2006, the stock of physical capital is calculated, by applying the perpetual inventory method, from the flow of gross investment in the previous period and assuming an annual depreciation rate equal to 10%. The capital stock value for the initial year 1984 has been assumed equal to the cumulative sum of investment flows over the ten-year period 1975-1984.

In Map 1 the geographical pattern of value added (panel a) and capital stock (panel b) is depicted by reporting the quintile distribution of the time average; the series are rescaled with respect to the population size in order to reduce the degree of heterogeneity across regions. Map 1.a shows evidence of significant cross-region dependence in the value added distribution that follows a clear spatial scheme: among the worst performers are all the Greek and Portuguese regions, four Spanish regions and the South of Italy. The top region is Denmark followed by Inner London, Zurich, Bruxelles and Oslo. All Swiss high performing regions create a well defined cluster, as well as the Norwegian ones and a group of German and Austrian regions; also the Southern areas of the United Kingdom form a cluster of high value added regions. The spatial distribution of labour units is very similar and is not reported here to save space. Map 1.b shows the distribution of the physical capital stock: Central and Northern Europe show a large high-performance cluster, which starts from Steiermark in Austria, passes through most of the Southern German regions and ends with Denmark and southern regions of Norway. Detached from this cluster, one finds the capital regions of London (which shows the best performance) and Paris (Île de France). The regions displaying the worst performance are located at the European borders: in the West with Portugal and Spain, and in the South with the Southern regions of Italy and the Greek ones. As regards spatial variability, value added shows a stronger dispersion of values across regions, as indicated by a higher coefficient of variation (0.39) with respect to capital stock (0.31) and labour units (0.17).

The presence of spatial dependence, evident in the maps discussed above, is formally tested by means of the cross-section dependence (CD) test proposed by Pesaran (2004) and the panel version of the Moran's *I* test (Kelejian and Prucha, 2001). All tests turned out to be highly significant leading to the rejection of the null hypothesis of no cross section dependence among the European regions[1].

The CD test provides evidence that significant correlation is present between pairs of regions for all variables, while the Moran's *I* test suggests that such a correlation is most likely due to spatial interdependence among regions[2]. The estimation procedure presented in the next section will deal with this aspect of the data.

2.2 Some econometric issues

The traditional Cobb-Douglas production function which includes the conventional inputs, physical capital and labour is formulated as:

$$Y_{it} = A_i K_{it}^{\beta_1} L_{it}^{\beta_2} e^{u} \qquad (1)$$

where Y is value added at 2000 base prices; K is the stock of capital; L are labour units; A is the efficiency level; u is an error term; i=1,2,...N=199 regions and t=1,2…T=22 (period 1985-2006); All variables are normalised to population in order to control for different size of the regions.

[1] The detailed cross-section analysis is reported in Appendix B.
[2] To check the robustness of the results we calculate the Moran's *I* test allowing for different specifications of the spatial weight matrix. A more detailed discussion on the economic aspects of matrix normalization is postponed to the next section.

We estimate the production function in a log–linear form within a spatial lag framework. The empirical panel model is specified as follows:

$$y_{it} = \alpha_i + \beta_1 k_{it} + \beta_2 l_{it} + \rho \widetilde{W} y_{it} + \theta_t + u_{it} \qquad (2)$$

low capital letters represent the log-transformed variables, a_i is the regional fixed effects, which, as will be discussed later on, represent our measure for total factor productivity, $\widetilde{W}y_{it}$ [3] is the spatially lagged dependent variable, $\widetilde{W}$ is the normalized weight matrix; we have also included time fixed effects to account for common shocks affecting the pooled regions.

The choice of the spatial lag model specification was motivated by two fundamental reasons; the first one is based on the importance to explicitly model (potential) economic spillovers arriving from neighbouring regions[4]. The second motive is related to the issue of tackling the possible endogeneity of the capital and the labour inputs; as pointed out by Fingleton and Le Gallo (2008, page 230) consistent estimators are only the IV ones derived within a spatial lag specification.

The elements of the (before normalization) weight matrix W are given by the inverse of the square distance expressed in kilometres across regions. This choice was driven by preliminary error diagnostics as the linear weights did not prove adequate to capture the spatial structure present in the data; the square values are supposed to be more

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[3] When the panel data are stacked as T subsequent cross-sections $\widetilde{W} = (I_T \otimes \widetilde{W}_N)$, where I_T is a $(T \times T)$ identity matrix and $\widetilde{W}_N$ is the normalized spatial weight matrix.

[4] Anselin (1988) emphasizes that the aim of spatial econometrics should be on measuring spatial spillovers. The alternative spatial error model specification is just a particular case of non-spherical errors which eliminates spillovers by construction.

informative and more powerful in discriminating between neighbouring and distant regions as they increase the relative weights of the closest ones.

The issue of normalization of the *W* matrix has recently received increasing interest given its economic – rather than pure statistical – content. In most applied studies *W* is row-standardized such that each row sum to unity; in this case the impact of all other regions on a particular region *i* is given by the weighted average of all regions' impacts and it is implicitly assumed that only *relative* rather than *absolute* distance matters[5]. Alternatively, the *W* matrix can be normalized with respect to a single normalization factor, its largest row/column sum or its largest characteristic root. In a recent paper Kelejian and Prucha (2009) argue that such a normalization is sufficient, while row-normalization imposes strong restrictions on the spatial process since each row of the *W* matrix is normalized in a different way.

In this study we apply the largest eigenvalue normalization, which, differently from the row-standardization, has also the nice feature that the symmetry of the weights is preserved[6]; this is particularly important when *W* is an inverse distance matrix used to describe a "distance decay" type of economic behaviour, as stated in Anselin (1988) "scaling the rows so that the weights sum to one may result in a loss of that interpretation"[7].

[5] For a thorough discussion on normalization issues see also Elhorst (2009).
[6] Note that, as emphasised by Anselin et al. (2008), the row-standardization has also the side effect that the sum of all the elements in *W* equals *N*, the number of cross-sectional observations, and that the induced asymmetry in the weights "is an unusual complication with significant computational consequences".
[7] See Baltagi et al., 2008, for a discussion on the relevance of absolute distance *vs* relative distance in economic phenomena.

As far as the endogeneity issue is concerned, model (2) above is characterized by an "intrinsic" endogeneity problem arising from the inclusion of the spatial term, which induces a two-way causality in the neighbour relation in space. In this case consistent estimators are the ones derived from the maximum likelihood method or from the two-stage least squares (2SLS) one, based on the inclusion of instrumental variables. In the growing empirical literature on spatial models great care has been devoted so far in tackling the endogeneity due to the spatially lagged term while the potential endogeneity of the explanatory variables has often been overlooked, particularly in the panel data context[8]. In this study we attempt to take also into account the endogeneity between output and the production factors which can arise from system feedbacks or measurement errors[9]. Since the usual Durbin-Wu-Hausman (DWH) test points out that the stock of capital and (marginally) the labour units can be considered endogenous with respect to value added[10], we adopt the 2SLS estimation method in order to estimate the single structural equation we are interested in – the production function - without explicitly modelling the entire system relationships causing simultaneity (as in Fingleton and Le Gallo, 2008). Following Dall'Erba and Le Gallo (2008), in this work the instruments for the productive factors are derived by applying the 3-group method proposed by

[8] For cross-section analyses exceptions are represented by Kelejian and Prucha (2004, 2007), Anselin and Lozano-Gracia (2008), Fingleton and Le Gallo (2008) and Dall'Erba and Le Gallo (2008), see Elhorst et al. (2007) for a panel application.

[9] TFP is estimated using measured inputs, a possible cause of the disparities among regions relies on measurement errors; moreover there may be problems of misspecification of the production function (Caselli, 2005).

[10] Similar results are found when testing for weakly exogeneity of capital and labour within an error correction model framework; only labour can be considered weakly exogenous (the *p*-value for the null hypothesis that the adjustment term is zero in the labour ECM model is equal to 0.293).

Kennedy (2008). For each explanatory variable the instrument takes the value -1, 0, or 1 according to whether the value of the instrumented explanatory variable is in the lower, middle or upper third of its ranking ranging from 1 to 199 in each period. Spatial lags of the 3-group instruments are considered for the spatially lagged dependent variable (Kelejian and Prucha, 1999).

2.3 Econometric results

The estimation results are reported in Table 1. We first present the estimated results of a sort of a "benchmark" model, which is a standard fixed effects model with time dummies of the log-linearized version of the Cobb-Douglas function reported in (1), we then propose different specifications of spatial panel models which explicitly take into account the geographical correlation among the European regions.

The first column (1.1) reports the OLS estimation results for the basic model which, besides the individual intercepts and the dummy variables, includes only the traditional productive factors. The estimated coefficients are 0.27 for the capital stock and 0.30 for the labour input. At the bottom of the column we report the LM test for (remaining) spatial error correlation[11] and the Moran's *I* test; both tests indicate that, as expected, the estimated residuals are affected by spatial dependence[12].

[11] The panel version of the test is reported in Anselin et al. (2008).

[12] Given that our sample refer to a period of 22 years we also carried out a panel cointegration analysis in order to guard against the spurious regression problem. Evidence of a nonstationary kind of behavior was detected for the individual variables by means of the CIPS unit root tests (Pesaran, 2007). The existence of a spurious relation among the variables of interest was ruled out by the results of the well-known cointegration tests developed by Pedroni (1999, 2004), which allowed us to reject the null hypothesis of no cointegration. All detailed results are reported in Appendix C.

We have also estimated models which account for the two sources of endogeneity separately (1.2 and 1.3). The model estimated by IV without the spatial term, as expected, yields spatially autocorrelated residuals; this results points out the importance of modeling explicitly the spatial pattern. On the other hand, the spatial lag model for which the productive inputs are not instrumented (estimated by the ML method) ensures that the residuals do not exhibit spatial autocorrelation, but the coefficients for the capital and labour regressors are quite similar to the OLS ones, signaling that the endogeneity bias is still present.

Regression 1.4 results from the application of the spatial 2SLS estimator, which allows to jointly take into account the two different sources of endogeneity discussed above; the instruments included are the 3-group-method instruments for capital and labour and functions of their spatial lags, their adequacy is assessed by the Sargan's test, which yields a *p*-value of 0.14. The estimated coefficients are 0.291 for capital and 0.278 for labour; no evidence of spatial correlation is detected for the estimated residuals according to LM test and the Moran's *I* one[13].

Note that the coefficients associated with each production input cannot be *directly* interpreted as an elasticity due to the presence of spillover effects, which through the spatial multiplier, lead to a different spatial steady-state equilibrium as a consequence of a unit (or percentage) change in one of the regressors. The spatial multiplier can be derived from the following compact reduced form expression for model (2):

$$y = \left[\left(I_T \otimes (I_N - \rho\widetilde{W}\right)\right]^{-1} X\beta + \left[\left(I_T \otimes (I_N - \rho\widetilde{W}\right)\right]^{-1} u \qquad (3)$$

where the labour and capital input are included in the X matrix.

[13] For 2SLS estimated models the Moran's *I* test is calculated as suggested in Anselin and Kelejian (1997) for the case of IV residuals.

Assuming that the weight matrix is row-standardized, LeSage and Pace (2009) explain that the direct effect of a unit (or percentage) change in the *rth* variable for region *i* is obtained as the own-partial derivative of y_i with respect to x_{ir} calculated from the function $S(\widetilde{W}) = [(I_T \otimes (I_N - \rho\widetilde{W})]^{-1} I_{TN}\beta_r$, while indirect effects are given by the cross-partial derivatives; the total effect is obtained as the sum of direct and indirect effects.

For regression 1.4 we calculate the average summary expressions for the three effects; for the capital input the direct effect is 0.291 and the total one is 0.294; while for the case of labour they are 0.278 and 0.281, respectively. These reported values have to be cautiously interpreted since the summary measures are computed under the assumption that the weight matrix is row-standardized, while, as discussed above, we have preferred the largest eigenvalue normalization[14]. Notwithstanding this point, the estimated model provides valuable indications on the role played by productive inputs and spatial spillovers in determining the regional output level in Europe.

Regression 1.4 represent the base model for the calculation of the regional TFP variable, while the last two regressions reported in Table 1 allow to evaluate some particular aspects of the production function relationship. Specifically, regression 1.5 allows us to check for the robustness of a different measure of the labour input. We include the variable "hours worked per year" in place of "units of labour" to control for differences in the weekly worked hours provided for by different

[14] For the same reason we do not report the measures of dispersion for the impact estimates. Note also that for the normalized matrix adopted each entry has a very small value.

national legislation. The estimated coefficients (0.26 for labour and 0.33 for capital) are in line with those obtained from the previous specification.

Finally, as the estimation of the regional production function is relevant in its own right - beside serving as the base for measuring total factor productivity – we also investigate whether Objective 1 regions exhibit a significantly different performance with respect to the average of the regions; the results point out that, for the same level of capital and labour endowments, the Objective 1 regions show a considerable lower level of production; it is worth noting that in regression 1.6 no fixed effects are included and this results in higher estimated coefficients for both productive inputs while the spatially lagged term is associated with a very low coefficient; this results in a misspecified model with spatially autocorrelated errors as diagnosed by the LM test and the Moran's *I* test.

For the estimated models reported in Table 1 we guard against possible heteroskedasticity and remaining spatial correlation by extending to our panel data framework the spatial heteroskedasticy and correlation consistent (SHAC) estimator for the variance-covariance matrix, proposed by Kelejian and Prucha (2007). The estimator is based on a set of assumption that is satisfied for a large class of Cliff-Ord type models and is robust to measurement error in the spatial distance metric. Kelejian and Prucha (2007), by referring to a cross-section sample of n observations, assume that the error term, u, of a particular Cliff-Ord model with endogenous regressors, can be represented as $u=R\varepsilon$ where ε is a vector of innovations and R is an nxn matrix of unknown elements; this formulation for the disturbance process allow for general unspecified form of correlation and heteroskedasticity. The asymptotic distribution of the IV estimator implies the following variance-covariance matrix $\Psi = n^{-1}H'\Sigma H$, where H is the instruments matrix and $\Sigma(\sigma_{ij})$ is the variance-covariance matrix of *u*. Kelejian and Prucha (2007) show that the SHAC estimator for the *(r,s)th* element of $\hat{\Psi}$ is:

$$\hat{\psi}_{r,s} = n^{-1}\sum_{i=1}^{n}\sum_{j=1}^{n} h_{ir}h_{js}\hat{u}_i\hat{u}_j K(d_{ij}/d_n)$$

where d_{ij} is the distance between unit i and unit j, while d_n is the bandwidth of a given kernel function (K) with the usual properties, $K(0)=1$, $K(x)=K(-x)$ and $K(x)=0$ for $|x|>1$. Finally, they show that small sample inference regarding the parameters vector, say δ, can be based on the approximation: $\hat{\delta} \sim N(\delta_0, n^{-1}\hat{\Phi})$, where $\hat{\Phi} = n^2(\hat{Z}'\hat{Z})^{-1}Z'H(H'H)^{-1}\hat{\Psi}(H'H)^{-1}H'Z(\hat{Z}'\hat{Z})^{-1}$, Z is the regressors matrix (including both exogenous and endogenous variables) and $\hat{Z} = H(H'H)^{-1}H'Z$.

In the case of the models reported in Table 1 we chose the Parzen kernel as defined in Andrews (1991)[15]. The bandwidth assumes the following values: 100, 300, 600 and 1200 kilometers; the first is a very short distance, the others distances correspond approximately to the lower decile, the lower quintile and the median of all the regional distances considered.

In Table 2 we report the results for the *t*-ratios based on the SHAC estimates; in order to save space we present those for the main

[15] The Parzen kernel, with x=d_{ij}/d_n, is defined as $K(x) = \begin{cases} 1-6x^2+6|x|^3 & \text{for } 0 \le |x| \le 1/2 \\ 2(1-|x|)^3 & \text{for } 1/2 \le |x| \le 1 \\ 0 & \text{otherwise} \end{cases}$

explanatory variables of model 1.4 of Table 1[16]. Overall the results obtained confirm the significance of all the regressors included in the model specifications considered; as expected *t*-ratios (standard-errors) tend to decrease (increase) as a function of the bandwidth selected[17].

2.4 Total Factor Productivity

Total factor productivity at regional level, which, as known, measures the efficiency in transforming physical capital and labour into output, is derived from the fixed effects obtained from the estimation of regression 1.4. This approach was advanced, among others, by Islam (1999 and references therein) and it allows to measure TFP as long run equilibrium (average) values[18].

The average values of TFP, computed as index relative to the European average, for the period 1986-2006 are reported in Map 2.a. Denmark is the leading region, with values nearly triple the European average, way ahead of the other regions in the ranking. Zurich, the capital regions of, Luxembourg, Belgium (Bruxelles) and Norway (Oslo) follow at some distance. Note that the efficiency index displays greater variability in the high end of the ranking, compared to the tail.

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[16] All the other results are available from the authors upon request.

[17] We also checked the robustness of our results with respect to the kernel function, similar results are obtained when using Bartlett weights ($K(x)= 1-|x|$ for $|x|\leq 1$ and zero otherwise) instead of the Parzen ones.

[18] Note that possible changes in the relationship 1.4 are accounted for by the temporal dummies. We did not carry out a subsample analysis in order to check the robustness of our result as splitting the sample would result in a loss of valuable information needed to estimate the fixed effects accurately (it is well known that the fixed effect estimator make use of the within dimension of the sample information which in our case is constituted by 22 time observation).

As for the geographical distribution of the index, we observe in the centre of Europe the concentration of high values around Switzerland and Western Germany regions. Moreover the TFP map shows the highest levels for all Norwegian regions, North Eastern and Eastern Scotland, a cluster of regions in the south area of UK, three Dutch regions (Groningen, Utrecht and Noord-Holland), Lombardia (Italy) and the capital regions of France (Île de France), Sweden (Stockholm) and Austria (Wien). Good results are also displayed by the Swedish regions, the French regions of Rhône-Alpes, Provence-Alpes-Côte d'Azur and Alsace, the western regions of Aquitaine and Midi-Pyrenees, and the Centre-north of Italy (Trentino, Lazio, Val d'Aosta and Emilia Romagna). Most of the regions of Portugal, Spain (except for the capital Madrid), Southern Italy and Greece (except for Sterea Ellada) stay in the lower part of the ranking. A very low value is unexpectedly found for the region of Outer-London, this might be due to the presence of a high flow of labour commuting to Inner London.

Map 2.a clearly depicts a spatial correlation pattern for the regional values of total factor productivity values across Europe; this is confirmed by the significant value (17.02) we found for the Moran's *I* test. In the following sections we investigate the determinants of TFP levels within a spatial lag model framework.

3. Intangible assets

An original aspect of this paper is that we analyse the concurrent effects of three types of intangible capitals: social capital, human capital and technological capital. In general, these intangible inputs are supposed to enhance the level of regional efficiency by creating a more favourable economic environment for the localised firms; for this reason in the Lisbon agenda they are considered strategic in economic growth policies. A complementary perspective, based on micro data, considers the intangible assets as part of business investment, like software, R&D expenditure, patents, economic competencies, employee training (OECD Secretariat, 1998). It is worth noting that Marrocu et al. (2009) for a large panel of European companies estimate that the share of the intangible assets over the tangible one is rapidly increasing and in 2006 it has reached, on average, the value of 42%, thus confirming the importance of including intangibles assets as determinants of productivity.

As mentioned in the introduction, one novelty of our contribution is to consider how regional productivity levels in Europe are influenced by social capital, which is an aspect often neglected in economic analyses as pointed out, among others, by Coleman (1990) and Temple and Johnson (1998). In his well known contribution on regional development in Italy, Putnam (1993) stated that social capital is a complex feature of social organization – represented by networks, norms and trust – which improves the efficiency of the local society by facilitating the coordination among actors. Since then a growing number of papers have tried to assess its role remarking how a high level of social capital in a certain area is associated with a reduction of transaction costs for both firms and consumers (Diani, 2004), a wider diffusion of knowledge and innovation among firms (Hauser et al., 2007) and widespread trust which, in turn, facilitates cooperation among the members of a community; all these effects are proved to enhance the economic performance (Knack and Keefer, 1997).

It is not an easy task to measure a complex, and often informal, phenomenon as social capital (Glaeser et al., 2002) and in the empirical works several indicators have been used. We list some relevant contributions to give an idea of the huge variability that characterizes the selection of *sound* and *satisfactory* indicators for social capital: newspaper reading and referenda turnout (Helliwell and Putnam, 1995), blood donation (Guiso et al., 2004), social infrastructure (Hall and Jones, 1999), level of trust (La Porta et al., 1997), density of voluntary organisation (Paldam and Svendsen, 2000), associational activity (Beugelsdijk and van Schaik, 2005). In this paper, as a proxy for regional social capital, we use the notion of "active social participation" measured by the share of population that have taken part at least once in the last 12 months in social activities such as voluntary service, unions and cultural associations meetings over total population. This proxy, as emphasized in Putnam (1993) seminal paper, considers the structural features of social capital which are assumed to facilitate the creation of "bridging networks", social ties and coordination among local agents. A dense network of association and participation encourages cooperation skills and collective efforts, therefore enhancing the efficiency of the local economy. The data on social participation come from the European Social Survey and have the advantage of giving a homogeneous measure of social capital at the regional level for the European countries considered.

The distribution of social capital across the European regions for the year 2002 is presented in Map 2.b[19]. With reference to the geographical distribution of social capital in Europe note that high values are located next to areas characterised by much lower values. The regions boasting the highest value of our indicator are located in the Scandinavian peninsula, in the four regions of Germany's Baden-Württemberg, in France's Mediterranean and Pyrenees areas and in the UK's South-West.

The literature has also emphasized the positive role of human capital on productivity level and growth (Mankiw et al., 1992; Benhabib and Spiegel, 1994). 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). As a proxy of "high" human capital we use the share of population that has attained at least a university degree (ISCED 5-6). This proxy has been used for the European regions also by Bottazzi and Peri (2003) and Sterlacchini (2008).

The distribution of human capital across the European regions for the year 2002 is represented in Map 2.c. Italy stands out for having all regions in the lowest class, while all other countries, although displaying values below the European average, show greater variability and have at least one region higher up in the rankings. This is the case with Portugal (with the Lisboa region) and Greece (with Attiki e Kentriki Makedonia). Note the excellent performance of Norway, Scotland, Finland's

[19] For some regions in France, Germany and United Kingdom data are available at NUTS1 level so that we have assumed that value for the included NUTS2 regions.

southernmost regions (Etela-Suomi and Lansi-Suomi) and eastern Spain (Cataluña, Aragona, Navarra, Pais Basco and Cantabria).

The inclusion in the production function of a direct measure of technological stock has been originally suggested by Griliches (1979) and afterwards the knowledge-capital model has been used in several contributions at firms level and also extended to macroeconomic models both at regional and country level. The idea is that technology is partly a public good, firms benefit from a higher degree of knowledge capital available in their areas since it leads to an increase in productivity. There is a huge number of contributions, based on different theoretical approaches, that have studied the effect of technology on the economic performance and also how this effect spills over the regional boundaries to influence contiguous areas (for a comprehensive survey see Audretsch and Feldman, 2004). Some recent studies, in the same vein of our contribution, have examined the effects of knowledge capital on the economic performance of the European regions. Fischer et al. (2009b) find a positive influence of patent stock on TFP together with a significant interregional knowledge spillovers effect. The analyses proposed by Sterlacchini (2008) and Rodriguez-Pose and Crescenzi (2008) are more general and offer support to the positive role exerted by R&D expenditure on GDP growth rate controlling also for other regional determinants like human capital and infrastructures.

There is a long standing debate on how to measure technological activity and all the proposed measures have pros and cons. Among them patent counts have the clear advantage of providing long time span along with large regional and sectoral coverage; moreover it has been proved that they are closely correlated with other measures of innovation, like R&D expenditures and new products (Griliches, 1990; Acs et al. 2002). Therefore, in this paper, as an indicator for technological capital we use the number of patent applications adhering to the Patent Cooperation Treaty; this choice ensures that only patent with a good economic value are likely to be considered since this international protection of innovation is costly. In order to control for the high variability of the regional annual series, the indicator is computed as patent stock in the previous five years, over total population[20]. The 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.

The distribution of technological capital across the European regions in the year 2002 is represented in the last panel of Map 2; its per capita values show a large high-performance cluster, which starts from Rhône-Alpes (in France), passes through all Swiss regions and ends at the South-central part of Germany (Oberbayern, Freiburg, Stuttgart, Rheinhessen-Pfalz, Mittelfranken, Karlsruhe, Oberpfalz, Darmstadt, Tubingen, Unterfranken, Oberfranken). Close to this agglomeration are those of Düsseldorf and Köhln. These top-performance regions are surrounded by other high-performance countries. Detached from this cluster, one finds the capital region of Paris (Île de France). Sweden, Finland and Denmark show top-high innovation performance, suggesting the presence of a Scandinavian cluster. All southern European regions are characterised by very low levels of technological capital.

[20] In the base specification, we have also used R&D expenditure, available for different years for each country, and the results are almost identical. The correlation coefficient between patents and R&D is equal to 0.82.

4. Econometric estimation and results

The purpose of this section is to provide empirical evidence on the role of intangible assets in determining the level of TFP for the European regions. As stated in the introduction, due to the lack of available long time series for variables such as social capital, our analysis is now carried out in a cross-section framework. The estimations are based on the model specification reported below:

$$a_i = c + \beta_1 sk_i + \beta_2 hk_i + \beta_3 tk_i + \rho \widetilde{W}_N a_i + \varepsilon_i \qquad (4)$$

where small letters indicate values in logs; *i* are the 199 regions, *a* is total factor productivity, *sk* is social capital, *hk* is human capital and *tk* is technological capital; $\widetilde{W}_N a_i$ is the spatially lagged dependent variable computed with the same normalized weight matrix adopted in section 3. All variables are normalised to population in order to control for different size of the regions. TFP is derived from regression 1.4 in Table 1. For the explanatory variables the values refer to the 2002 year.

Due to potential system feedbacks, omitted variables and measurement errors, endogeneity problems can also be present in model (4); following Anselin and Lozano-Gracia (2008), we, therefore, apply the spatial 2SLS method, which allows guarding against endogeneity bias coming from different sources. The instruments for the explanatory variables are constructed by following the 3-group method, as discussed in the previous section, while the spatial lag term is instrumented by the spatial lags of the other instrumental variables[21].

[21] In the special case in which the omitted relevant variables follow a spatial autoregressive process and are also correlated with the included spatially correlated ones, LeSage and Pace (2009) show that this leads to a spatial Durbin model specification. The

The results for the TFP spatial lag model estimated by 2SLS are reported in Table 3. The first column presents the base model where all the intangible assets exhibit positive and significant coefficients: 0.14 for social capital, 0.17 for human capital and 0.06 for technological capital. With the caveats already reported in the previous session, we have calculated the direct, indirect and total impacts for the three intangible assets. For social capital the direct impact is 0.142 and the total one is 0.151; for human capital they 0.177 and 0.188, respectively, while for technological capital they amount to 0.063 and 0.068. Although these effects are to be cautiously interpreted, the estimation results provide convincing evidence on the crucial role played by intangible productive factors as determinants of regional TFP.

As we have already pointed out this is the first time that the simultaneous effect of these intangible assets on productivity is examined, we can not therefore compare the magnitude of our results with previous literature. Within a knowledge production function model, the positive effects of various form of "soft" inputs (human capital, R&D, social capital) for a small sample of European regions has been shown by Tappeiner et al. (2008). For the case of Italian regions the positive role of some intangible inputs was documented by Marrocu and Paci (2010) and by Di Giacinto and Nuzzo (2006). Evidence on the influence of human capital for the European regions case has been found by Bottazzi and Peri (2003) within a knowledge production

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2SLS method is more general as it allows to tackle different sources of endogeneity bias. Note also that in applying the latter method instruments are represented by the explanatory variables spatial lags, so that it is not possible to include them as regressors, as would be required by the spatial Durbin model estimation. Moreover, as reported in the discussion of the empirical results, evidence of omitted relevant spatially correlated variables was not detected by the spatial diagnostics carried out on the residuals.

function model and by Sterlacchini (2008) and Fischer et al. (2009a) in a productivity growth model; the latter authors also find an unexpected spatial indirect negative effect coming from neighbouring regions. As far as the social capital variable is concerned, a positive effect of the active participation in associational activity on GDP growth rate of 54 NUTS-1 regions belonging to 7 European countries is found by Beugelsdijk and van Schaik (2005), who also show that trust is never significant. A positive influence of technology, measured by patent stock, on TFP is shown, within a spatial model, by LeSage and Fischer (2009) and Fischer et al. (2009b) for the European regions and by Madsen (2006) for the OECD countries.

In order to check for the correct specification of the spatial pattern we calculate the IV-Moran's *I* test (Anselin and Kelejian, 1997). According to the test result no evidence of remaining residual spatial autocorrelation was found. Note that the coefficient of the spatially lagged term is strongly significant and high in value (0.89) confirming the occurrence of external spillovers from other regions even after controlling for the effects of the intangible factors.

We conduct a robustness check for the base specification by including a different proxy for human capital (regression 3.2) and for technological capital (regression 3.3). For the first case we include an indicator of permanent education (share of population involved in lifelong learning programmes)[22]. The coefficient turns out to be positive

[22] We have also used an indicator for a "low" level of human capital (i.e. the share of population that has attained at most a primary level, ISCED 0-2) and, as expected, it shows a negative and significant influence on TFP, moreover its inclusion reduces the significance of the social capital variable.

and significant although its magnitude (0.053) is much lower than the previous proxy.

The new proxy for technology - called knowledge capital - is calculated as the total funding by European Commission under the Fifth Framework Program (the program covers the 5-year period 1998-2002). Data on individual projects were regionalized by means of the address and postcodes of participants (Maggioni et al., 2007). In case of more than one participant, a proportional share of the funding was assigned to each of them. This new variable is expected to capture the effects of the creation of (new) knowledge on regional TFP; such effects are supposed to be more widespread and less specific, at least with respect to economic efficiency levels, than the ones induced by the patent activity. The coefficient of the knowledge capital variable is of the same order of magnitude as the one associated with technological capital, however its inclusion in the specification makes the coefficient of social capital higher. This result may be due to possible complementarities between the two assets. A thorough investigation of such complementarities in enhancing efficiency levels is left for future research.

Although the focus of this paper is on investigating the role of intangible assets in determining TFP, we are aware that such a complex economic phenomenon may depend on other factors. The empirical literature as identified in a good network of public infrastructure one of these factors[23]. As a proxy for infrastructures in this paper we use a composite index of accessibility based on the potential accessibility by

[23] Starting from the seminal contributions by Aschauer (1989), the literature has investigated the role of infrastructure, and more generally of public capital, on regional performances. See, among others, Eberts (1990) for the Unites States, Marrocu and Paci (2010) for the Italian regions; a useful survey is in Gramlich (1994).

road, train and air and on the time necessary to reach the market (with a negative sign); it takes the value 1 when the accessibility is very low and reaches the value 5 for a very high accessibility level. In order to investigate the potential of physical infrastructure in determining TFP, we augment the base model with the "tangible" accessibility covariate. The results, reported in column 3.4 of Table 3, confirm the estimated coefficients for the intangible assets and offer empirical support to the hypothesis that a high degree of accessibility is TFP enhancing.

The literature has emphasised the localised nature of spatial knowledge spillovers which are facilitated by common institutions and culture and by face-to-face interactions. It is well-known that knowledge flows often spill beyond regional and national borders although they tend to decline with distance (see the recent survey by Döring and Schnellenbach, 2006). Therefore it is an interesting issue to assess which is the "crucial" distance to allow the benefits of one region to spill over the neighbouring ones. We calculate different non-overlapping weight matrices according to the distance selected; we start from a distance of 0-300 km which guarantees that every single region has at least a connection to another region; we then consider three more distance ranges: 300-600, 600-900 and 900-1200. Note that the cut-offs distances - 300, 600 and 1200 km - roughly correspond to the lower decile, the lower quintile and the median of the regional distances among the European regions considered. Although we are aware that the wideness of the interval is arbitrary, on the basis of preliminary investigations we believe that we can derive some interesting insights on the spatial pattern of the regional spillovers.

The results for regression 3.5, where we include the four spatially lagged terms disaggregated according to the range distances, reveal that only the first two are significant thus signalling that the relevant links are those within a 600 km distance. Note that with the exception of the accessibility variable, all the explanatory variables remain significant and the Moran's *I* test does not signal residual spatial autocorrelation. To check our results we then re-estimate regression 3.1 by including only one spatially lagged term in turn (3.6-3.9). The evidence corroborates the previous finding, as only the 0-300 and the 300-600 lagged terms turned out to be significant, however it is worth noting that when considering distances higher than 300 km the residuals are always spatially correlated indicating that the 300 km distance range is capturing most of the spatial dependency present in the data.

These results are in line with previous findings which have remarked the localised nature of geographical spillovers among the European regions, although direct comparisons are problematic given the heterogeneity of the methodological approaches and geographical units considered. More specifically, within a knowledge production function approach, Bottazzi and Peri (2003) find that technological spillovers are positive and significant only up to a radius of 300 km and Moreno et al. (2005) up to 250 km or 2nd order contiguity. In a regional growth model Paci and Pigliaru (2002) show that spatial spillovers influence productivity up to the 3rd order contiguity and Rodriguez-Pose and Crescenzi (2008) up to 3 hours drive (equivalent to approximately 200-300 km). It is worth noticing that in our data set the regions included in 1st order contiguity have an average distance of 158 km, in the 2nd order 287 km and in the 3rd order 418 km. In conclusion, the empirical evidence indicates that spatial spillovers are important in determining the economic performance of the European regions and that their influence tends to rapidly decay once a distance of, roughly, 300 km is reached.

We also calculate the SHAC estimates for the variance-covariance matrix; in Table 4 the t-ratios are reported for the main specification 3.1. All the TFP determinants maintain their significance, thus confirming previous inference and the contribution of intangible assets in determining productivity[24].

5. Concluding remarks

The aim of this paper has been twofold. First, we have derived a regression based measure of regional TFP for Europe, which has the nice advantage of not imposing a priori restrictions on the inputs elasticities; this is done by estimating a Cobb-Douglas production function relationship which includes the traditional inputs as well as a measure of spatial interdependence across regions.

Secondly, we have investigated the determinants of the TFP levels by analyzing the role played by intangible factors: social capital, human capital and technological capital. This was motivated by a wide recent literature providing evidence which suggests that the economic performance across regions differ not only in traditional factor endowments (labour and physical capital) but mainly in technological, human and social capital.

[24] The same kind of results are obtained for all the specifications reported in Table 3. All detailed results are available from the authors upon request.

In the first part of the paper we have estimated a production function model over the period 1985-2006, which serves as the base to derive the regional TFP variable; this is obtained from an adequately specified model which properly accounts for the spatial pattern present in the data, without overlooking relevant econometric issues such as endogeneity and non-stationarity. The estimated TFP levels point out a concentration of high values around Switzerland, Holland, Western Germany and Norway. Most of the Swedish regions, the French Southern and Western regions and the Centre-north of Italy display values above average. Finally, most of the regions in Portugal, Spain and Greece are at the bottom of the ranking.

In the second part of the paper we have investigated the determinants of TFP level among the European regions. At the best of our knowledge, this paper represents the first attempt aimed at assessing the effects of three kinds of intangible assets on the regional efficiency levels in Europe. The estimated models have provided robust evidence on the role played by technological, human and social capital in enhancing economic growth and social cohesion. This result indicates that a region with a higher level of social participation and cooperation enjoys a higher degree of trust among the members of the community and this enhances the economic efficiency. At the same time the local economy benefits from the presence of a well educated labour force which facilitates the localization of innovative firms and thus boosts the productivity of the entire economy. Finally, the presence in the region of high levels of technological capital turns out to be beneficial for the regional total factor productivity since local firms can benefit from the public good characteristic of technology. We have also performed some robustness exercises including different proxy for the human capital (lifelong learning participation) and for technological capital (participation to the Community 5FP) and the results remain unchanged. Moreover we control for the characteristics of the regions in terms of accessibility and this "tangible" asset turns out to positively influence the regional TFP level.

The issue of spatial dependence has been extensively examined through means of spatial lag models. The coefficients of the spatially lagged variable appear always positive and strongly significant confirming the existence of external spillovers from other regions, which through the spatial multiplier reinforce the effects of each region's own intangible factors. More specifically, the spatial spillovers seem to generate their strongest impacts in the range 0-300 km which roughly represents the lower decile of the distances among the European regions considered. This result confirm previous evidence on the fact that spatial spillovers are somehow bounded in space and that knowledge diffusion is more effective among closer regions.

In general our results have some interesting policy implications since they stress the importance of policy strategies aimed at accelerating the accumulation of the intangible assets which constitute highly effective production endowments. Such policies will allow the European economy to become, as put forward in the Lisbon agenda, the most advanced and productive society in the world.

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TABLES AND MAPS

Table 1. Production function estimation

Dependent variable: value added	1.1	1.2	1.3	1.4	1.5	1.6
Estimation method	*OLS*	*2SLS*	*ML*	*2SLS*	*2SLS*	*2SLS*
Instruments	--	*3-group instruments*	--	*3-group instruments and their spatial lags*	*3-group instruments and their spatial lags*	*3-group instruments and their spatial lags*
Capital stock	0.270	0.294	0.270	0.291	0.329	0.336
	(21.3)	*(8.0)*	*(21.4)*	*(8.0)*	*(8.8)*	*(23.3)*
Units of labour	0.299	0.280	0.300	0.278		0.868
	(21.4)	*(11.3)*	*(21.6)*	*(11.3)*		*(36.8)*
Dependent variable spatial lag			0.256	0.305	0.328	0.014
			(2.7)	*(3.6)*	*(4.3)*	*(1.9)*
Hours worked per year					0.259	
					(4.6)	
Dummy Objective 1 regions						-0.285
						(-33.2)
Regional fixed effect	yes	yes	yes	yes	yes	no
R^2 (pseudo)	0.98	0.98	0.98	0.98	0.98	0.78
LM test for residual spatial correlation	45.251	44.850	0.790	0.174	0.245	4.290
p-value	*0.000*	*0.000*	*0.374*	*0.677*	*0.621*	*0.038*
Moran's *I* test on residuals*	6.279	6.660	1.530	0.362	0.465	2.070
p-value	*0.000*	*0.000*	*0.126*	*0.718*	*0.642*	*0.038*

Sample period: 1985-2006; NxT=4378; all variables are normalised to population and log-transformed
Spatial weight matrix: square of the inverse of distance in km. Time fixed effects are included in all regressions
Aysmptotic t-statistic in parenthesis. All coefficients are significant at 1% probability
R^2 (pseudo) is calculated as the ratio of the variance of the fitted values to the variance of the actual values
* For models estimated by 2SLS the Moran's *I* test is calculated as the variant proposed in Anselin-Kelejian (1997) for IV residuals

Table 2. Production function model SHAC estimates

Variable	Coefficients	*t* -ratios				
		Classical	SHAC			
			d_n=100	d_n=300	d_n=600	d_n=1200
Regression 1.2 Table 1						
Capital stock	0.291	8.019	6.372	5.661	5.036	4.655
Units of labour	0.278	11.296	9.279	8.122	7.339	7.105

d_n is the Parzen kernel bandwidth in kilometers

Table 3. TFP and intangible assets

Dep. variable: total factor productivity	3.1	3.2	3.3	3.4	3.5
Social capital	0.136 *	0.164 **	0.317 ***	0.161 **	0.188 ***
	(1.722)	*(2.238)*	*(5.168)*	*(2.154)*	*(2.867)*
Human capital	0.170 ***		0.152 **	0.169 ***	0.161 **
	(2.819)		*(2.476)*	*(2.966)*	*(3.045)*
Technological capital	0.061 ***	0.060 ***		0.050 ***	0.038 **
	(4.375)	*(4.347)*		*(3.171)*	*(2.184)*
Long-life learning		0.053 ***			
		(3.388)			
Knowledge capital			0.050 ***		
			(3.426)		
Accessibility				0.070 **	0.040
				(1.925)	*(1.187)*
Dependent variable spatial lag	0.895 ***	0.879 ***	0.924 ***	0.926 ***	
	(4.531)	*(4.559)*	*(4.784)*	*(4.920)*	
Distances for spatial lag (in km)	all	all	all	all	
Spatial lag - distance 0-300 km					0.853 ***
					(2.322)
Spatial lag - distance 300-600 km					0.476 **
					(1.836)
Spatial lag - distance 600-900 km					0.138
					(0.391)
Spatial lag - distance 900-1200 km					-0.253
					(-0.653)
Square correl .	0.42	0.66	0.43	0.68	0.71
IV-Moran	-1.749	-1.909	-1.660	-1.872	-1.773
p-value IV-Moran	*0.080*	*0.056*	*0.097*	*0.061*	*0.076*

All regressions are estimated by applying the 2SLS method with 3-group method instruments

N=199; all variables are normalised to population and log-transformed. all models include a constant term

Spatial weight matrix: square of the inverse of distance in km

For human capital, social capital and technological capital the values refer 2002; for accessibility the values refer to 2001.

Aysmptotic *t*-statistic in parenthesis. Level of significance: *** 1%, ** 5%, * 10%

Square correl . is the squared correlation between the predicted and actual values

IV-Moran is the Moran's *I* test proposed by Anselin and Kelejian (1997) for 2SLS residuals

Table 3. TFP and intangible assets *(continued)*

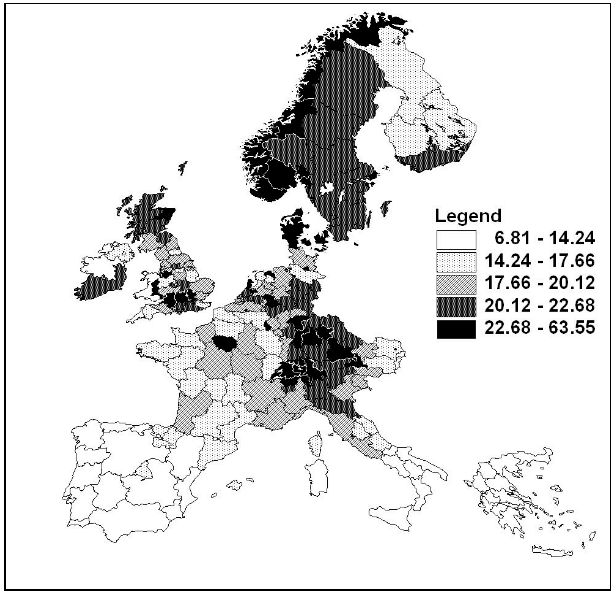
Dep. variable: total factor productivity	3.6	3.7	3.8	3.9
Social capital	0.153 **	0.172 ***	0.196 ***	0.202 ***
	(2.266)	*(2.650)*	*(2.888)*	*(2.698)*
Human capital	0.175 ***	0.137 **	0.104 *	0.140 **
	(3.075)	*(2.300)*	*(1.680)*	*(2.350)*
Technological capital	0.050 ***	0.037 **	0.048 ***	0.046 ***
	(2.954)	*(2.036)*	*(2.669)*	*(2.528)*
Long-life learning				
Knowledge capital				
Accessibility	0.071 **	0.021	0.037	0.062 *
	(2.117)	*(0.543)*	*(0.351)*	*(1.644)*
Dependent variable spatial lag	0.925 **	0.708 ***	0.427	-0.195
	(2.403)	*(2.736)*	*(1.169)*	*(-0.413)*
Distances for spatial lag (in km)	0-300	300-600	600-900	900-1200
Spatial lag - distance 0-300 km				
Spatial lag - distance 300-600 km				
Spatial lag - distance 600-900 km				
Spatial lag - distance 900-1200 km				
Square correl .	0.68	0.67	0.64	0.64
IV-Moran	-1.840	9.702	9.452	8.193
p-value IV-Moran	*0.066*	*0.000*	*0.000*	*0.000*

Table 4. TFP model SHAC estimates

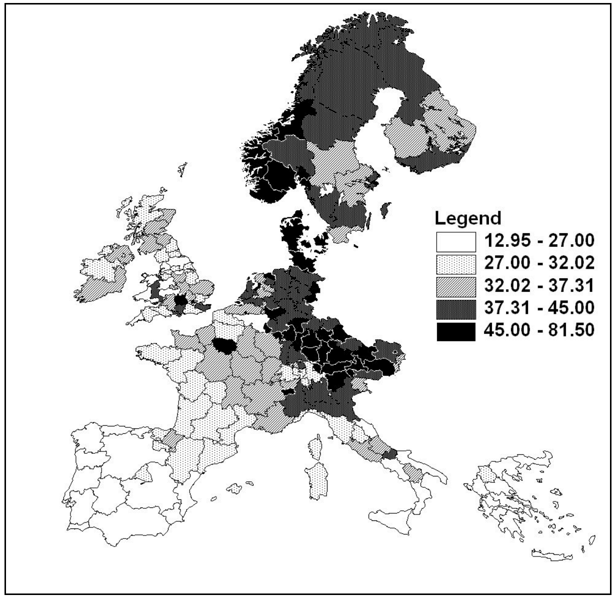
Variable	Coefficients	*t*-statistics				
		Classical	SHAC			
Regression 3.1 Table 3			d_n=100	d_n=300	d_n=600	d_n=1200
Social capital	0.170	2.819	2.933	2.511	2.146	2.058
Human capital	0.136	1.722	2.100	2.048	1.883	1.860
Technological capital	0.061	4.375	4.119	3.359	2.676	2.320

d_n is the Parzen kernel bandwidth

Map 1. Value added and capital stock (average 1986-2006)

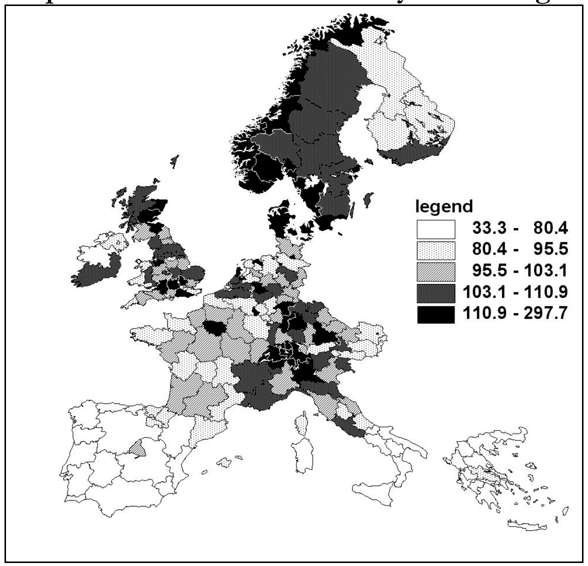


(a) Value added (per capita, thousands euro 2000)

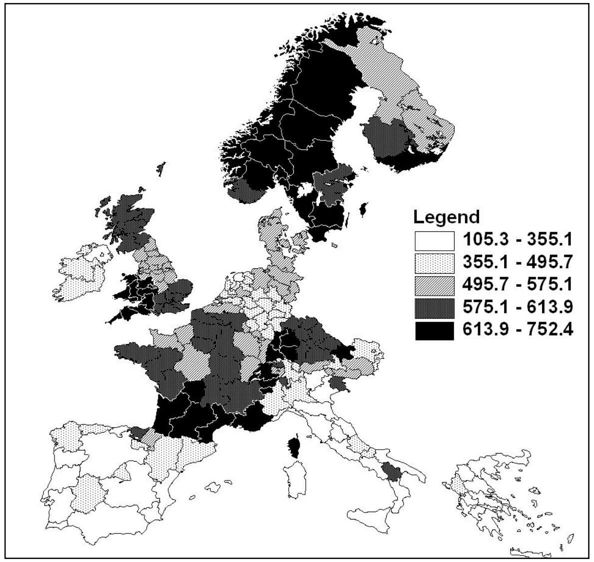


(b) Capital stock (per capita, thousands euro 2000)

Map 2. Total Factor Productivity and intangible assets

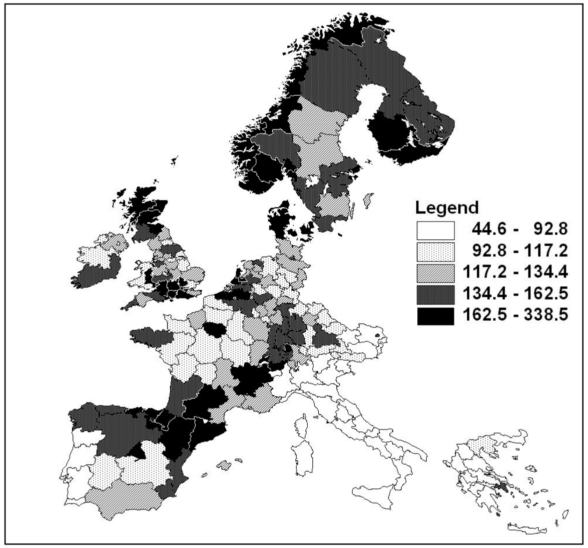


(a) Total Factor Productivity, 2004
index Europe = 100

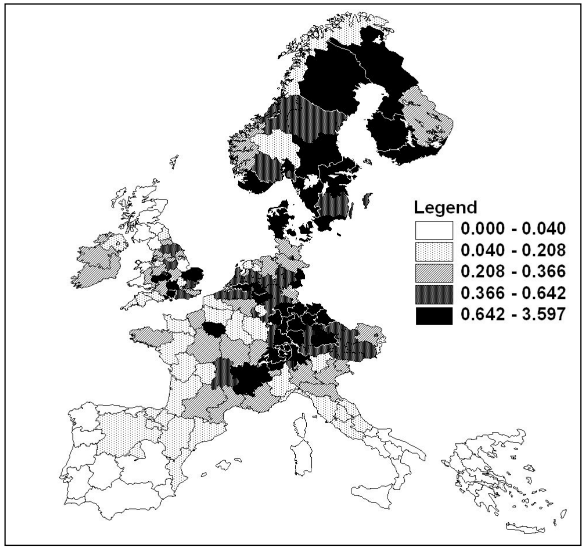


(b) Social capital, *2002*
participation to social activities per thousands population

Map 2. Total Factor Productivity and intangible assets *(continued)*



(c) Human capital, 2002
inhabitants with a degree per thousands population



(d) Technological capital, 2002
patents PCT, 5-years stock, per thousands population

APPENDIX A – Data and sources

Table A1. Regions and NUTS level

Country	NUTS	Regions
Austria	2	9
Belgium	1	3
Denmark	1	1
Finland	2	5
France (a)	2	22
Germany (b)	2	30
Greece	2	13
Ireland	2	2
Italy	2	20
Luxembourg	1	1
Netherlands	2	12
Norway	2	7
Portugal (a)	2	5
Spain (a)	2	17
Sweden	2	8
Switzerland	2	7
United Kingdom	2	37

(a) Territories outside Europe are not considered
(b) Berlin and East Germany regions are not considered
(c) Autonomous provinces of Trento and Bolzano are aggregated

Table A2. Data sources and variables description

Variable	Source	Years	Measurement unit	Description
Value added	Cambridge Econometrics	1985-2006	millions euros, 2000	
Capital stock	Own calculation	1985-2006	millions euros, 2000	
Units of labour	Cambridge Econometrics	1985-2006	thousands	
Hours worked	Cambridge Econometrics, own calculation	1985-2006	levels	total hours worked by employees per year
Population	Cambridge Econometrics	1985-2006	thousands	
Human Capital	Eurostat	2002	% of people over population 15 and over	people with a degree, ISCED 5-6 (over population 15 and over)
Social capital	European Social Survey Round 1 2002, Round 2 2004	2002	% of people over total population	people that have taken part at least once in the last 12 months in social activities such as voluntary service, unions and cultural associations meetings
Technological capital	OECD, REGPAT database	2002	levels	patent applications at PCT (Patent Cooperation Treaty), stock for the previuos 5 years
Long life learning	Eurostat	2002	% of people over population 25 and over	participation of adults aged 25-64 in education and training
Knowledge capital	own calculation from European Commission	1998-2002	euros, current	total funding by European Commission under the Fifth Framework Program (regionalized according to the research projects participants' address)
Accessibility	Espon, Project 2.4.2	2001		regions are classified into five groups (from 1= very low, to 5= very high) according to ther potential accessibility by road, train, air and time to the market.
Dummy Objective 1 regions	Eurostat	2002		regions of the Objectives 1 program for the 2000-06 structural funds, including the transition regions

APPENDIX B – Testing for cross-section dependence

The presence of spatial dependence, evident in Map 1.a and 1.b, is also tested by means of the cross-section dependence (CD) test proposed by Pesaran (2004) and the panel version of the Moran's *I* test (Kelejian and Prucha, 2001). The CD test is a general test which, as shown by Pesaran (2004), is applicable to a large variety of panel data models, including stationary and non-stationary dynamic heterogeneous panel with short *T* and large *N*, as is the case for the panel of data used in this study. The test is also robust to the presence of multi-breaks in slope coefficients and in the error variance. Correct size and satisfactory power are exhibited by the CD test even in small samples. The test, which is based on the average of the pair-wise correlation coefficients, is calculated as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$$

where $\hat{\rho}_{i,j}$ are the sample estimates of the pair-wise correlation of the OLS residuals from individual regressions in the panel; T=22, N=199. Following Pesaran (2004), in our case the residuals are obtained from models where the (log) of the variable being tested is regressed on a constant, a linear trend and two of its own lags[1]. Under the null hypothesis of no cross-section dependence the test follows a standard normal distribution.

[1] Specifications with different dynamics and a model where the first difference of the variable is regressed on region-specific intercept (as done in Baltagi and Moscone, 2009) are also estimated yielding the same qualitative results.

Although the CD test has power against spatial alternatives, we also compute the Moran's *I* test which is explicitly designed for such a case. The test, which under the null hypothesis is normally distributed, is calculated as:

$$I = \frac{\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\hat{u}_{it}\hat{u}_{jt}}{\left(T\sum_{i=2}^{N}\sum_{j=1}^{i-1}\left(w_{ij}+w_{ji}\right)^{2}\hat{\sigma}_i^2\hat{\sigma}_j^2\right)^{1/2}}$$

where $\hat{u}_{it}$ and $\hat{u}_{jt}$ are the residuals obtained from the same models estimated for the CD test, $\hat{\sigma}_i^2$ and $\hat{\sigma}_j^2$ are sample variances and w_{ij} are the elements of the weight matrix, capturing the spatial interconnections among regions, which in our case are measured by the inverse of the distance expressed in kilometres across regions.

The weight matrix W is normalized by dividing each of its elements by the largest eigenvalue. For the discussion on the normalization issues see section 2.2 in the text.

The result for the CD and the Moran's *I* test are reported in Table B1. All the tests are highly significant leading to the rejection of the null hypothesis of no cross section (spatial) dependence among the European regions. To check the robustness of the results we calculate the Moran's *I* test allowing for different specifications of the *W* matrix, we considered both the largest eigenvalue normalization and the row-standardization for linear and square weights[2].

[2] Strong rejections (not reported in Table B1) were also found when the first and up to the second order contiguity matrix is considered.

Table B1. Cross-section dependence tests

Test	Weight matrix	value added	capital stock	labour units
CD		119.88	83.38	115.27
		0.00	*0.00*	*0.00*
Moran's *I*	W	79.73	50.70	42.38
		0.00	*0.00*	*0.00*
	W-square weights	9.58	6.89	2.97
		0.00	*0.00*	*0.00*
	W-rstd	77.61	41.90	40.55
		0.00	*0.00*	*0.00*
	W-rstd -square weights	37.39	23.00	20.97
		0.00	*0.00*	*0.00*

All variables are in log-transformed per capita values

p -values are reported in italics;

W is the weight matrix normalized by dividing each element by the largest eigenvalue,

W-rstd is the same weight matrix row-standardized

APPENDIX C – Testing for non-stationarity and cointegration

C.1. Testing for non-stationarity

The possible non-stationarity property of the data is investigated by applying the cross-sectionally augmented IPS (CIPS) test, recently proposed by Pesaran (2007). The test belongs to the so-called "second generation" of panel unit root tests and has the important advantage to overcome the main limitation of previous tests (see, among others, the widely applied tests suggested by Levin et al., 2002, Im et al., 1995, 2003 and Maddala and Wu, 1999), i.e. the assumption that the individual time series in the panel are cross-sectionally independently distributed; which is a questionable assumption, particularly in the context of cross-country (or region) regressions. The CIPS test, assuming a factor structure in the errors, deals with the cross-section dependence by augmenting the individual ADF regressions with the cross-section averages of the regressors and of the dependent variable. Consider the series y_t in region i, the ADF regression is specified as follows:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{i,t-1} + \sum_{j=0}^{p} d_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + e_{it}$$

where the terms $\bar{y}_{t-1}$, $\Delta \bar{y}_{t-j}$ are the cross section averages for the lagged level and the lagged differences of y_t, respectively. The panel test is then calculated as the average of the individual t-test on the b_i coefficients. The test has satisfactory power and size even for relatively small panels; moreover, by means of an extensive Monte Carlo simulation study, Baltagi et. al. (2007) have shown that the CIPS test performs quite well when the cross-section dependence is originated by spatial correlation.

In this study we apply the truncated version of the test which limits the undue influence of extreme values that could occur when the time dimension is small; the test was calculated for both "intercept" and "intercept and trend" specifications and allowing for the lag order to be at maximum equal to 3 (p=0,1,2,3). The results are reported in Table C1; all the variables exhibit a non-stationary kind of behaviour with the exception of the labour variable[3], but only when p is selected to be equal to 0 or 1. On the contrary, the differenced series are stationary leading us to conclude that a panel unit root is present in the level series[4].

C.2. Testing for cointegration

We carried out the cointegration tests to check whether a long-run non-spurious relation exists among the variable included in model (2) in the text. We perform the well-known cointegration tests developed by Pedroni (1999, 2004) on the residuals obtained from the benchmark model; the tests are calculated for both the panel and group ADF and Phillips-Perron (PP) versions of the statistics and allowing for the two different specifications of the deterministic components, individual intercepts and individual intercepts and trends. The results, reported in Table C2, allow rejecting the null hypothesis of no cointegration in all cases considered. As the tests are derived under the assumption of cross-section independence, we also report the results for the series demeaned

[3] Similar results are also found when the labour input is measured as "hours worked per year".

[4] Although not designed for the case of cross section dependence, we have also computed "first generation" tests (Levin-Lin-Chu test, Breitung t-stat, Im, Pesaran and Shin W-stat, ADF – Fisher, PP – Fisher, Hadri Z-stat) finding the same kind of results: the unit root hypothesis is marginally rejected only for the labour variable depending on the dynamic specification chosen.

by subtracting the cross-section averages and for a model including the spatially lagged dependent variable (*WY*)[5], which explicitly accounts for the cross-section dependence. The evidence supports the existence of a long-run relationship among the variables included in the Cobb-Douglas production function model. Note that in this study, in the spirit of Pedroni (1999), we are interested "in the simple null hypothesis of no cointegration versus cointegration" in order to rule out any spurious correlation among the variables, so we do not address the issue of cointegration vectors normalization; we are assuming that the particular normalization of the variables is the one represented by the production function relationship.

[5] In this case we are considering the spatially lagged variable as a variable which helps to explain the variation in the dependent one, rather than a simple left-hand side variable (Elhorst, 2009).

Table C1. CIPS panel unit root tests

	Intercept only			Intercept and trend		
lags	value added	capital stock	labour units	value added	capital stock	labour units
		levels			*levels*	
p=0	-1.829	-1.256	-1.746	-2.174	-1.857	-2.641 **
p=1	-1.661	-1.687	-1.802	-1.943	-2.330	-2.833 **
p=2	-1.406	-1.621	-1.490	-1.480	-1.849	-2.391
p=3	-1.321	-1.735	-1.413	-1.328	-1.755	-2.453
		first differences				
p=0	-4.007 **	-2.508 **	-4.166 **			
p=1	-3.052 **	-2.380 **	-3.509 **			
p=2	-2.026 *	-1.918	-2.556 **			
p=3	-1.592	-1.705	-2.276 **			

Critical values are tabulated by Pesaran (2007) , Table II(a-c), we report the ones for T=20 and N=200 for the truncated version of the test:

Intercept case: -2.04 (5%); -1.99 (10%)

Intercept and trend case: -2.55 (5%); -2.49 (10%)

"**" and "*" indicates significance of the test at 5% and 10% level respectively

Table C2. Cointegration tests

Variables	Deterministic components	Pedroni tests	Statistic	P-value
Y, K, L	indiviudal intercepts	Panel PP-Statistic	-2.484	0.018
		Panel ADF-Statistic	-4.480	0.000
		Group PP-Statistic	-3.440	0.001
		Group ADF-Statistic	-9.638	0.000
Y, K, L	individual intercepts and trends	Panel PP-Statistic	-6.593	0.000
		Panel ADF-Statistic	-9.709	0.000
		Group PP-Statistic	-8.771	0.000
		Group ADF-Statistic	-14.638	0.000
Y*, K*, L*	indiviudal intercepts	Panel PP-Statistic	-6.615	0.000
		Panel ADF-Statistic	-8.896	0.000
		Group PP-Statistic	-5.498	0.000
		Group ADF-Statistic	-11.036	0.000
Y, K, L, WY	indiviudal intercepts	Panel PP-Statistic	-8.434	0.000
		Panel ADF-Statistic	-10.754	0.000
		Group PP-Statistic	-16.450	0.000
		Group ADF-Statistic	-16.333	0.000

Y, K and L stand for value added, capital stock and labour respectively; Y*, K*, L* are the same variables demeaned by subtracting the cross-section average

Null hypothesis: no cointegration

Alternative hypothesis: common autoregressive coefficient for panel specification or individual autoregressive coefficients for the group specification

Lag selection: Automatic SIC with a max lag of 4

Newey-West bandwidth selection with Bartlett kernel

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