

# Interregional Knowledge Spillovers and Economic Growth: The Role of Relational Proximity

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## 1 Introduction

Standard neoclassical growth models (Solow 1956; Mankiw et al. 1992) implicitly assume that the technological progress is characterized by a worldwide global interdependence between economies without frictions. In contrast, recent mainstream contributions to the economic growth literature (López-Bazo et al. 2004; Ertur and Koch 2007) support the idea that technological interdependence is not homogenous across economies (countries or regions) and depends on their geographical connectivity scheme with other economies, which adds to reflections already envisaged in previous studies (Acs et al. 1994; Anselin et al. 2000). An important feature of technology is its aptitude to spread across borders (Coe and Helpman 1995, and Eaton and Kortum 1996, among others). However, the spatial diffusion of technological knowledge may be geographically bounded, so that the stock of knowledge in one region may spill over into other regions with an intensity which decreases with geographical distance (the so-called “spatial friction” hypothesis).

Based on these assumptions, spatial autoregressive reduced forms of the economic growth model have been derived, in which the growth rate of a region depends not only on its initial conditions and on its own structural characteristics (such as population growth rate and human and physical capital accumulation rates), but also on initial conditions, structural characteristics and growth rates of its neighbors. In particular, by assuming that technical progress depends on the stock of physical capital per worker and of human capital accumulated in other

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countries and not merely in the home country, Ertur and Koch (2007) have obtained a growth equation characterized by parameter heterogeneity linked to the geographical location of the economies. In order to test these predictions, spatial econometric tools (such as spatial lag, spatial error and spatial Durbin models) have been largely used in the empirical literature (López-Bazo et al. 2004; Rey and Janikas 2005; Rey 2004; Rey and Montouri 2004). Some authors have also taken into account the possibility of parameter heterogeneity, using either spatial autoregressive local estimation methods (Ertur and Koch 2007) or spatial autoregressive semiparametric additive models (Basile 2008, 2009).

In this paper we test the hypothesis that geographical proximity is not the only dimension to be considered in order to capture the mechanisms governing knowledge spillovers. As already emphasized in the literature, other forms of proximity must be considered as complementary (or alternative) to physical distance: social proximity (Boschma 2005; Capello 2007, 2009a), organizational proximity (Bellet et al. 1993; Rallet and Torre 1995), institutional proximity (Lundvall and Johnson 1994), technological proximity (Cantner and Meder 2007) and specialization proximity (Ciccone 2002; Henderson 2003).

In this study we analyze the joint effect of relational and spatial proximity. The notion of relational proximity is based on a new concept of space, which accounts for the ways in which economic agents potentially interact and for the ways in which this interaction influences learning processes (Capello 2009a). Relational proximity is measured in terms of the difference between trust in two regions. Our assumptions are that knowledge spillovers depend on the presence of both geographical and relational proximity and that the simultaneous presence of geographical and relational proximity enhances the intensity of knowledge spillover.

We test these assumptions on a sample of 249 NUTS2 regions of the EU27 over the period 1990–2004. Along with a traditional spatial weights matrix, we introduce a matrix of inverse relational distance built on a measure of trust, defined as the capacity of economic agents in a regional context to act in cooperation with other actors, a capability which stems from a strong identity and sense of belonging, from shared trust and shared behavioral codes. Operationally, relational proximity is defined as the inverse distance of trust wealth among pairs of regions, normalized by the sum of the trust endowment in those areas. We find strong evidence of a positive role of relational proximity as a source of knowledge spillovers in the analyzed sample. We also produce evidence on the fact that geographical proximity enhances its positive external effects when regions are also close in terms of trust wealth.

The rest of the paper is organized as follows. In Sect. 2 we elaborate on the need to use the concept of relational distance to explain knowledge spillovers. Section 3 describes our dataset and the variables, while also providing an explanation of our measure of relational distance. Section 4 presents the results of an econometric analysis testing the assumptions of a positive role of relational proximity as a source of knowledge spillovers and of the super-additive effect of relational and spatial proximity. Section 5 concludes.

## 2 Knowledge Spillovers: The Role of Physical and Relational Distance

Economic theory is increasingly aware of the strategic role played by – voluntary or unintended – technological interdependence among economic actors. In particular, the interest in knowledge spillovers lies in the fact that they represent pure externalities, producing non-compensated advantages for receivers; a discrepancy between private and social optimum generates the need for specific policy interventions.

The concept of knowledge spillovers has stimulated interest in economic theories with rather different approaches, from mainstream to heterodox views. In neoclassical growth models, the dominant paradigm is that national growth rates depend on the growth rates and income levels of other countries. Stylized facts demonstrate that economic activity is concentrated at different spatial levels – countries, regions, cities (Easterly and Levine 2001), the reason lying in the strong global interdependence of technological progress. Knowledge accumulation affects the technological development (à la Solow 1956), the physical capital accumulation (à la Romer 1986) and the human capital accumulation (à la Lucas 1988) in the home country; what is new is the idea that knowledge accumulated in one country affects technological development and growth *of other countries*. In these models the intensity of the knowledge spillover effect depends on socio-economic or institutional proximity, measured by an exogenous variable, namely the geographical proximity of countries (Ertur and Koch 2007).

Regional economists and economic geographers achieve the same result, developing the concept at a more spatially disaggregated level of analysis. Knowledge spillovers imply that knowledge created by an organisation generates positive effects not only within it, but also for other organisations located in neighbouring regions (Fischer et al. 2006). This literature differentiates with mainstream economics as knowledge spillovers are interpreted as a spatially-bounded phenomenon: they take place mainly among regions or cities, rather than countries. This in turn would facilitate the exchange of information, face-to-face contacts, trade and market relationships, all within a pure gravity type logic. Such explanations date to Marshall's identification of high flows of information and ideas between firms of a region – what is “in the air” – as one of the main reasons for concentration of activities in space (Marshall 1920). In a pure spatial/geographical approach, the knowledge transmission channels are epidemiological contacts among local agents (Capello 2007).

More recently, doubts have been expressed on the idea that the mere geographical proximity is able to interpret all mechanisms behind knowledge spillovers (Boschma 2005; Capello 2007, 2009a, b). Geographical proximity justifies knowledge spillover effects through simple gravity-type processes, that hold at country, region or city levels, which limit the interpretation of the spillover effects under two perspectives (1) on the one hand, its validity at different geographical levels makes the spillover an a-spatial concept; (2) on the other, a pure geographical, gravity-type

approach does not explain the learning processes of agents and contexts: learning on how to translate knowledge into innovation, learning on how to get the highest benefits from the presence of a multinational enterprise, learning to attract resources at the local level and to apply them in a creative and innovative way. Different learning processes explain why two regions at the same distance from a third highly innovative region may have a completely different absorption capacity of knowledge spillovers.

This implies that as other regions face endogenous growth processes, the extent to which a region can benefit from the external stimulus depends also, in our conceptual framework, on the relative differences in trust between the regions. As differences in trust decline, the ease with which knowledge travels and can be understood, decoded and efficiently exploited increases (Capello et al. 2010). Lower differences in trust between regions implies therefore higher absorptive capacity of firms, individuals and institutions, as well as lower transaction costs in the process of knowledge decoding and transfer.

Recent work has taken the need for non-geographical notions of distance seriously. In Maggioni et al. (2007) the effect of relational proximity, along with more traditional geographical proximity on growth spillovers is explored, with the use of data on research networks built up with EU Fifth Framework Programme and EPO co-patent applications. Ponds et al. (2010) proceed a step beyond and use the geographical and relational spatial lag of the performance measure as an independent variable simultaneously.

In order to introduce learning mechanisms in the explanation of knowledge spillovers, a relational approach is required, that explains the ways in which agents and contexts learn: this approach mainly interprets knowledge accumulation as the accumulation of knowledge through cooperative learning processes (Camagni 1991; Keeble and Wilkinson 1999, 2000), nourished by spatial proximity (“atmosphere” effects), network relations (long-distance, selective relationships), interaction, creativity and recombination capability.

This approach entails a relational definition of space. Functional/hierarchical, economic and social interactions take place in this space and are in turn embedded into geographical space (Camagni 1991; Camagni and Capello 2009). Relational space plays a role in learning processes. It develops and reinforces interactive processes between actors at the local level. It forms the set of shared behavioural codes, common culture, the capital of trust among agents and the sense of belonging. In turn, it depends on the social glue that is present in the region, which represents a pre-requisite for a creative interaction. These characteristics act on the capacity of firms to engage in market interactions. They develop and enhance collective learning processes by means of specific territorial channels through which knowledge flows by virtue of (a) the huge mobility of professionals and skilled labour – among firms but internally to the local labour market defined by the district or the city, where mobility of this kind is highest, and (b) intense co-operative relations among local actors and, in particular, customer-supplier

relationships in production, design, research and, finally, knowledge creation (Camagni and Capello 2002).<sup>1</sup>

Territorial channels of knowledge flows are typical of production contexts characterised by the presence of small and medium sized firms (SMEs). The average dimensions of firms fostering the exchange of knowledge and the mutual transcoding of tacit information is not sterile: in fact, previous streams of literature, such as the *milieu innovateur* and the industrial district theory, have suggested that tacit knowledge exchange is maximized in SMEs. However, they are also relevant in contexts where large firms develop their own internal knowledge, culture and know-how by enhancing internal interactions and boosting selective external interaction with industrial partners, universities, professionals and research centres. In this view, the channels through which knowledge spreads are *territorialized*, embedded into the socio-cultural structure of a local system and, therefore, anchored by definition to the local area. Thus, the territorial reasons for a spatially-bounded effect of knowledge spillovers are identified and the limits of a-spatial theories in which knowledge spillovers concept is applied indifferently to countries, regions or cities are overcome.

Relational proximity – defined as the similarities of two areas in terms of shared behavioural codes, common culture, mutual trust, sense of belonging and cooperation capabilities – plays an important role in the capacity of a region to absorb knowledge spillovers. Cooperative learning processes are nourished by spatial proximity (“atmosphere” effects), network relations (long-distance, selective relationships), interaction and cooperation. Therefore, while geographical proximity is a good proxy for the “atmosphere effect”, relational proximity measures the potential interaction and cooperation capabilities in knowledge accumulation. Relational proximity is therefore at least as important as geographical proximity in order to understand the micro-foundations of knowledge spillovers and the channels through which knowledge diffuses. Being geographically close to a region with similar relational capacity reinforces knowledge diffusion between the two areas. By the same token, relational proximity reinforces the effects generated by geographical closeness thanks to synergies and increasing returns.

From this conceptual framework we obtain two testable assumptions: *H1*. “knowledge spillovers depend on the presence of both geographical and relational proximity” and *H2*. “the simultaneous presence of geographical and relational proximity enhances the intensity of knowledge spillovers”. Hypotheses *H1* and *H2* will then be empirically tested in Sect. 4 by introducing a relational distance effect within the Ertur and Koch’s (2007) approach.

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<sup>1</sup>A collective learning process of this kind was first hypothesized by the GREMI group (Camagni 1991; Perrin 1995) and subsequently widely adopted as a sound theoretical concept for the interpretation of knowledge-based development and innovation (Keeble and Wilkinson 1999, 2000; Capello 1999; Cappellin 2003).

### 3 Data and Variables

#### 3.1 Basic Variables

We test our two hypotheses by estimating growth regression models on a sample of 249 NUTS2 regions belonging to the enlarged Europe (EU27). The dependent variable is the labour productivity growth rate computed for the period 1990–2004,  $\gamma_y = T^{-1}(\ln y_T - \ln y_0)$ . Basic data come from EUROSTAT Regio and Cambridge Econometrics databases, which include information on real gross value added, employment, investment, secondary education attainment and R&D investments. We measure labour productivity,  $y$ , as the ratio between total real value added and total employment; the saving rate,  $s_k$ , as the average share of gross investments on real gross value added; the human capital accumulation rate,  $s_h$ , as the average percentage of a region's working population in secondary school. Finally,  $n$  is the average growth rate of total employment.

In the last set of estimates we carry out a robustness check, controlling for other variables that modern regional growth theory considers as potentially relevant in explaining regional performance: sectoral composition (Perloff et al. 1960), agglomeration externalities (Ciccone and Hall 1996; Ciccone 2002), externalities associated to sectoral diversity (Jacobs 1969; Glaeser et al. 1992; Beaudry and Schiffaurova 2009) and R&D intensity (Sterlacchini 2008).

Sectoral composition is measured by the share of agricultural employment on total regional employment,  $Share(agr)$ , assuming that a higher share of agriculture may subsequently reduce economic performance. Agglomeration externalities,  $dens$ , are measured by the density of employment (ratio between total employment and regional surface in  $\text{km}^2$ ) Jacobs externalities are measured as the median of Balassa indices,  $Jacobs = median\left(\frac{E_{is}/E_i}{E_s/E}\right)$ , where  $i$  denotes the region and  $s$  indexes the sector,  $E_{is}$  stands for average employment in the  $s$ -th sector (at two-digit level of the classification of economic activity)<sup>2</sup> for the  $i$ -th region,  $E_i$  is the average overall employment in the  $i$ -th region,  $E_s$  indicates the employment in the  $s$ -th sector in Europe, while  $E$  is the overall European employment.<sup>3</sup> Finally, R&D intensity,  $r\&d$ , is measured by the percentage of total intramural R&D expenditure on gross value added.

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<sup>2</sup>Namely, sector DA (food products, beverages and tobacco), DB (textile and textile products), DC (leather and leather products), DD (wood and wood products), DE (pulp, paper and paper products; publishing and printing), DF (coke, refined petroleum products and nuclear fuel), DG (chemicals, chemicals products, and man-made fibres), DH (rubber and plastic products), DI (other non-metallic mineral products), DJ (basic metals and fabricated metal products), DK (machinery and equipment n.e.c.), DL (electrical and optical equipment), DM (transport equipment) and DN (manufacturing n.e.c.).

<sup>3</sup>Since the Balassa index follows an asymmetric distribution (with a fixed lower bound, 0, and a variable upper bound,  $E/E_i$ ), its median turns out to be the most appropriate indicator of the distribution position. When the median is low, an economy shows a comparative advantage in a large share of sectors and its productive structure is therefore diversified, and vice versa. So, we use the median as a direct measure of diversification.

Spatial lags of residuals and variables are computed using different distance-based spatial weights matrices. More precisely, for the diagnostics of residuals from the estimates, we use a binary spatial weights matrix with a distance based cut-off, whose elements  $w_{ij}$  assume value of 1 if the distance between the centroids is lower than 424 km (the minimum distance which allows all regions to have at least one neighbour) and zero otherwise:

$$w_{ij} = \begin{cases} 1 & \text{if } d_{ij} \leq 424 \text{ km} \\ 0 & \text{otherwise} \end{cases}$$

Elements  $w_{ii}$  on the main diagonal are set to zero by convention, whereas elements  $w_{ij}$  indicate whether region  $i$  is spatially connected to region  $j$ . For the computation of spatial lag variables, we compute a more general inverse-distance spatial weights matrix

$$w_{ij} = \begin{cases} d_{ij}^{-1} & \text{if } d_{ij} \leq 424 \text{ km} \\ 0 & \text{otherwise} \end{cases}$$

where, again,  $w_{ii} = 0$ . In order to normalize the outside influence upon each region, the weights matrix is row-standardized, so that the spatial lag of a variable is simply the weighted average of the neighbors' observations.

The chosen time span (1990–2004) encompasses, among others, two major breaks in the European history. First, it starts with the fall of the Communist regimes in Eastern countries. Then, it ends with the years of the biggest wave of enlargements (2004 and 2007, respectively) of the European Union, which coincided with the inclusion of 12 more countries in the EU. Although the enlargements themselves have physically taken place after the period surveyed in the present paper, the theory of rational expectations offers support to the idea that most of the effects of the 2004 enlargement may be already captured in the final years of the sampled period.

While these two major events are likely to have influenced our results, in particular in terms of growth rates, we believe that this study may shed further light precisely on the reasons of different economic performance of European regions. The switch to a competitive, market-based economic regime, and the announcement effect of the 2004 enlargement may in fact have boosted New Member States (NMS) economies much more than what actually happened. In fact, initial trust differences among regions may contribute to the explanation of growth differentials in EU regions beyond the cyclic effects present in any sample.

### 3.2 *A Measure of Relational Distance*

The core of our tests entails the definition and computation of relational distance. As stated in Sect. 2, we believe collective learning to be enhanced not only by the physical proximity of relevant actors (individuals, firms and institutions), but also

by relational proximity. Holding physical distance constant, knowledge flows more easily when people face low transaction costs in the process of exchanging information: this requires a high level of trust within organizations (La Porta et al. 1997), which in turn facilitates the effectiveness of weak ties (Granovetter 1973).

Among the several dimensions along which we may measure relational proximity, we select the one we believe to have the highest impact on knowledge flows: trust. As levels of trust rise, individuals and firms are more prone to exchange knowledge. Trust enhances local channels of knowledge transmission, especially cooperation among local actors, local firms, clients and suppliers.

We measure trust in the most direct way, exploiting information collected by the EVS.<sup>4</sup> In particular, citizens have been asked “How much do you trust people?” The scale of possible answers ranges from 1 (“I trust them completely”) to 5 (“I don’t trust them at all”). For each region we calculate the percentage of answers 1 and 2 over the subsample of EVS individuals that answered this question.<sup>5</sup> Thus, for each region we have a measure of the average percentage of people who trust others “completely” or “enough”: the vector’s domain is  $trust \in [0, 1]$ .<sup>6</sup> Trust distance between regions  $i$  and  $j$  is therefore calculated as  $w_{rel}^{ij} = d_{ij}^{-1}$ , with  $d_{ij} = |trust_i - trust_j| / (trust_i + trust_j)$ . The inverse-distance trust weights matrix is finally created as the inverse of the absolute distance between trust levels in each region.<sup>7</sup>

Figure 1 plots the values of our relational distance indicator as a function of its numerator and denominator. The indicator increases monotonically with the numerator and decreases monotonically with the denominator. This allows us to conclude that, if two regions display a minor difference between their level of trust, while both having high values of trust, our indicator signals a lower distance than in the case of two regions with low difference between their level of trust and low values of trust. By the same token, our indicator assigns a higher distance between two regions with a high difference in their trust levels and a low amount of total trust

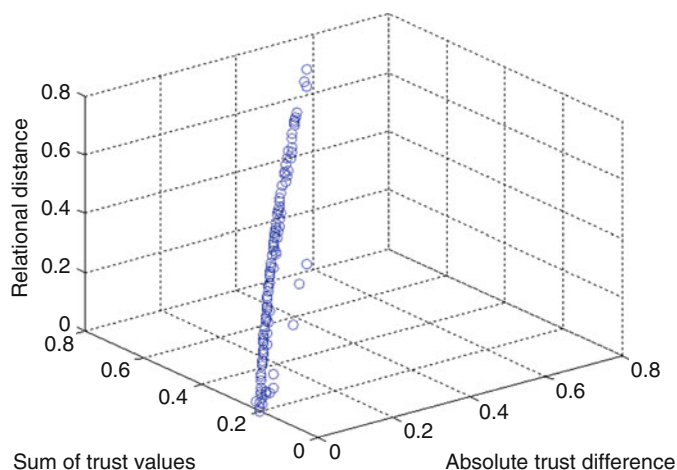
<sup>4</sup>EVS is among the widest surveys comprising statistical information from individual questionnaires on the values of European citizens. This paper uses its 1990 wave, which perfectly matches the initial year of our estimations. More information can be found on [www.europeanvalues.nl](http://www.europeanvalues.nl)

<sup>5</sup>This amounts to 37,107 cases, with just 1,106 individuals missing; hence, the question had a reply rate of about 97% of the individuals interviewed. The EVS sample was drawn from the population of adult citizens over 18 years of age. In some countries, random sampling was applied, in others quota sampling. The samples were weighted to correct for gender and age: the survey, therefore, correctly represents the population of each region.

<sup>6</sup>The actual range of the variable goes from 0.03 (recorded for Sardinia) to 0.64 (corresponding to Sydsverige).

<sup>7</sup>Glaeser et al. (2000) reviews the use of the EVS trust question. They find the question may also capture the level of trustworthiness of individuals, while also detecting high correlations among the EVS trust level measured *within the survey* and the outcome of two experiments aiming at identifying trust *behaviors*.





**Fig. 1** Relational distance indicator as a function of its components

than between two regions with a high difference in their trust levels and a high amount of total trust (and vice versa).<sup>8,9</sup>

As for the correlation between physical and relational distance, Pearson's correlation index is equal to  $-0.18$ , significant at the 99% confidence level. Although in absolute terms not particularly high, the correlation coefficient implies that pure geographical proximity does not necessarily imply relational proximity. Spatially neighbouring regions may actually enjoy significantly different levels of trust, which therefore contributes to our understanding of why, *ceteris paribus*, regions with similar endowments of physical factors and with analogous locations display significantly different growth rates.

The issue of missing values is quite relevant for two reasons. First, as the data coverage starts from 1990 and includes former-communist regions, several statistics are missing for the first years after the fall of communist regimes. Second, we exclude Slovenia, Cyprus, Latvia and Malta in order to avoid problems with weights matrices (either spatial proximity is difficult to define or else EVS data are missing, as is the case for Cyprus). We also exclude Bulgarian regions in order to fully exploit the EUROSTAT Regio database and, in particular, its ATECO

<sup>8</sup>Notice that, as easily detectable from the Figure, and clear from the social distance formula, the indicator takes on value zero (whatever the sum of trust levels in the regions) when the numerator is zero. This may, however, happen for all the regions sharing the same level of trust. For such regions, it does not matter whether they share a high, medium or low level of trust: our indicator scores zero anyway. This is shown in Figure 1 with the dots on the  $xy$  plane.

<sup>9</sup>The same conclusions could be obtained mathematically. In fact, both the numerator as well as the denominator of the social distance measure are of first order, thus converge asymptotically with the same speed; besides, they both map on the positive half of the real numbers. This line of reasoning is behind the shape of the plot depicted in Fig. 1.

2-digits level occupation series, which is not available for this country. We end up with 249 NUTS 2 regions covering 22 European Countries.

## 4 Relational Proximity in Knowledge Spillovers

### 4.1 Linear Growth Model and Spatial Interaction Effects

We begin the empirical analysis of the growth behaviour of the EU-27 NUTS-2 regions by estimating the linear specification of neoclassical growth model proposed by Mankiw et al. (1992).

$$\gamma_y = \beta_0 + \beta_1 \ln y_0 + \beta_2 \ln s_k + \beta_3 \ln s_h + \beta_4 \ln(n + 0.05) + \varepsilon \quad (1)$$

The estimation results (not reported, but available upon request), obtained using heteroskedasticity-corrected variance-covariance matrices as suggested by Cribari-Neto (2004), confirm the theoretical predictions: regional productivity growth rates are positively affected by physical and human capital accumulation rates and negatively influenced by employment growth rates and initial productivity levels. Thus, the conditional convergence hypothesis cannot be rejected, but the speed of convergence (equal to 0.427%) is rather slow and the corresponding half-life is 162 years (almost three times the one estimated for Western Europe regional samples by Le Gallo et al. 2003, among others).

Even though OLS estimates tend to corroborate the hypotheses suggested by Mankiw et al. (1992), the diagnostics of the residuals reveal that the linear augmented Solow model is mis-specified due to (a) the assumption of homogenous behaviour (the RESET test raises doubts on the capacity of the linear functional form to properly capture the data generating process) and (b) the omission of variables that capture technological interdependence (Moran's I tests yields to reject the assumption of spatial independence of the residuals).<sup>10</sup> Given these results, we relax the hypothesis of linearity and spatial independence and estimate a semiparametric spatial Durbin model (SDM) as well as a semiparametric spatial lag model (SAR).

The semiparametric spatial Durbin growth regression model can be specified as (Basile 2008, 2009).

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<sup>10</sup>Moran's I tests have been performed using distance-based binary spatial weights matrices. Many distance cut-offs, ranging from 420 km (the minimum distance which allows all regions to have at least one neighbour) to 1,020 km with a step of 50 km, have been adopted. All corresponding spatial weights matrices yield significant values of Moran's I. The highest standardized Moran's I value occurred in correspondence to the minimum distance.

$$\begin{aligned}
\gamma_y = & \beta_0 + f_1(\ln y_0) + f_2(W_{dist} \ln y_0) + f_3(\ln s_k) + f_4(W_{dist} \ln s_k) \\
& + f_5(\ln s_h) + f_6(W_{dist} \ln s_h) + f_7(\ln(n + 0.05)) + f_8(W_{dist} \ln(n + 0.05)) \\
& + \rho_{dist} W_{dist} \gamma_y + \varepsilon
\end{aligned} \tag{2}$$

where  $f_j(\cdot)$  are unknown smooth functions of the covariates,  $W_{dist}$  is a spatial weights matrix, the smooth terms  $f_2(\cdot)$ ,  $f_4(\cdot)$ ,  $f_6(\cdot)$  and  $f_8(\cdot)$  capture the effect of the spatial lags of the exogenous variables,  $\rho_{dist}$  is a parameter measuring the amount of global spatial externalities (or spatial technological interdependence) and  $\varepsilon$  is a vector of independently distributed errors. This specification is consistent with the economic growth model developed by Ertur and Koch (2007) based on the assumption that technological knowledge spread across regions/countries with an intensity which decreases with geographical distance. The matrix  $W_{dist}$  used to estimate this model has been described in the previous section.

LeSage and Pace (2009) suggest that the SDM specification can also be derived from a data generating process characterized by unobserved heterogeneity and that the SDM nests both SAR and SEM (spatial error model). However, the SDM specification implies an inflation of smooth terms (especially when two different weight matrices are used in the same model and the number of exogenous variables is not negligible). An alternative method to control for unobserved spatial heterogeneity, rather diffused in spatial statistics (Venables and Ripley 2002), consists of including in the model a spatial trend surface, that is a bi-dimensional smooth function of northing ( $no$ ) and easting ( $e$ ),  $f(no, e)$ , instead of spatially lagged exogenous variables:

$$\begin{aligned}
\gamma_y = & \beta_0 + f_1(\ln y_0) + f_2(\ln s_k) + f_3(\ln s_h) \\
& + f_4(\ln(n + g + \delta)) + f_5(no, e) + \rho_{dist} W_{dist} \gamma_y + \varepsilon
\end{aligned} \tag{3}$$

Both models (2) and (3) include the endogenous term  $W_{dist} \gamma_y$ .<sup>11</sup> In order to deal with endogeneity problems in a nonparametric framework, Blundell and Powell (2003) have proposed to use the “control function” approach which consists of two steps. In the first one, an auxiliary nonparametric regression  $W_{dist} \gamma_y = \beta_0 + f_1(\cdot) + \dots + h(Z) + v$  is considered, with  $Z$  a set of conformable instruments and  $v$  a sequence of random variables satisfying  $E(v|Z) = 0$ . The second step consists of estimating an additive model of the form  $\gamma_y = \beta_0 + f_1(\cdot) + \dots + \rho W_{dist} \gamma_y + f_J(\hat{v}) + \varepsilon$ .

We employ the methodology proposed by Wood (2006) to estimate models (2) and (3) with spline-based penalized regression smoothers which allows for automatic and integrated smoothing parameters selection via GCV. For the two spatial dimensions  $no$  and  $e$ , an isotropic thin plate regression spline basis function is used, as suggested by Augustin et al. (2009). The econometric results reveal that the two

<sup>11</sup>In linear spatial regression analysis, Kelejian and Prucha (1998) have proposed a 2SLS procedure to estimate the spatial autocorrelation regression model and have suggested using spatial lags of the strictly exogenous variables as instruments.

models perform quite similarly in terms of adjusted  $R^2$ , percentage of explained deviance, GCV score and AIC. Both specifications allow to predict the spatial variability in growth behaviour better than non-spatial linear and nonlinear models and to solve the issue of spatial autocorrelation in the residuals (Moran's  $I$  statistics are no more significant). Given the similarity between the two models, and due to the lower number of smooth terms included in the augmented spatial lag model (3), we will keep this specification as the preferred one to continue our from-particular-to-general estimation strategy.

Two-step estimation results of model (3) are reported in Table 1. The  $F$ -tests for the overall significance of the smoothed terms have  $p$ -values lower than 0.05 in all cases, while the number of effective degrees of freedom ( $edf$ ) suggests that the relationship between regional growth and its determinants is far from being linear. Figure 2a–d show the fitted univariate smooth functions (solid lines), alongside Bayesian confidence intervals (shaded grey areas) at the 95% level of significance, computed as suggested by Wood (2006). In each plot, the vertical axis displays the scale of the expected values of regional growth, while the horizontal ones report the scale of each determinant.

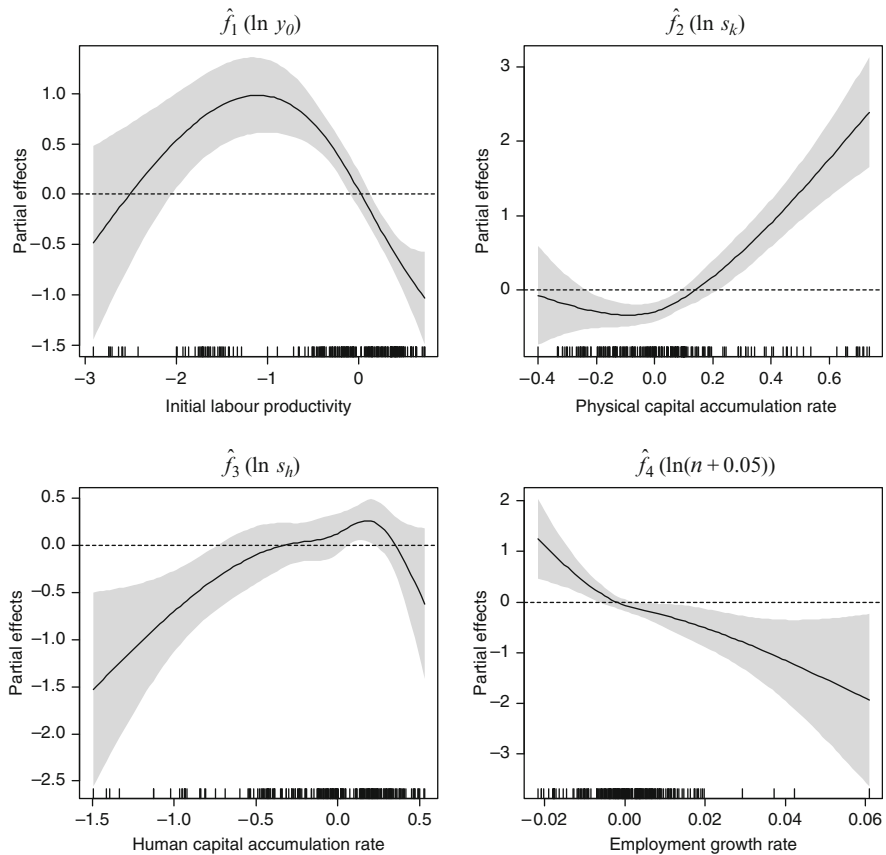
An inverted U-shaped relationship between growth and initial conditions emerges (Fig. 2a), with a clear downward pattern in  $\hat{f}_1(\ln y_0)$  only after a certain threshold of the relative level of GDP per worker in 1990 ( $\ln y_0$ ): specifically, a diverging behaviour characterizes the group of Eastern regions (45 regions), while Western regions maintain a conditional predicted convergence path. The assumption of identical speed of convergence is consequently rejected.

Nonlinearities in the effects of gross physical investment,  $\hat{f}_2(\ln s_k)$ , and of secondary school enrolment ratio,  $\hat{f}_3(\ln s_h)$ , are clearly detected. Specifically, an increase in the saving rate is associated with an increase in growth rate only when  $\ln s_k$  is above the EU average. The existence of a threshold in the effect of  $\ln s_k$

**Table 1** Nonparametric estimation results of the additive nonlinear model

Variables	Unconstrained nonlinear growth model	
	F-tests and p-values	Edf
$f_1(\ln y_0)$	14.418 [0.000]	2.543
$f_2(\ln s_k)$	16.911 [0.000]	2.424
$f_3(\ln s_h)$	3.165 [0.013]	3.649
$f_4(\ln(n + 0.05))$	5.721 [0.000]	2.607
$R^2_{adj.}$	0.533	
Deviance	55.4	
AIC	740	
GCV	1.137	
Moran's $I$	3.848 [0.000]	

Notes: Dependent variable: productivity growth rate. F test and p-value (in squared brackets) for the overall significance of smooth terms are reported in Column 2. Edf are the effective degrees of freedom. Deviance is the percentage of explained deviance. AIC is the Akaike Information Criterion. GCV is the generalized Cross Validation. Moran's  $I$  standard deviates and p-values are computed using a great-circle distance-based binary weights matrix with a threshold distance of 424 km. The number of observations in the sample is 249

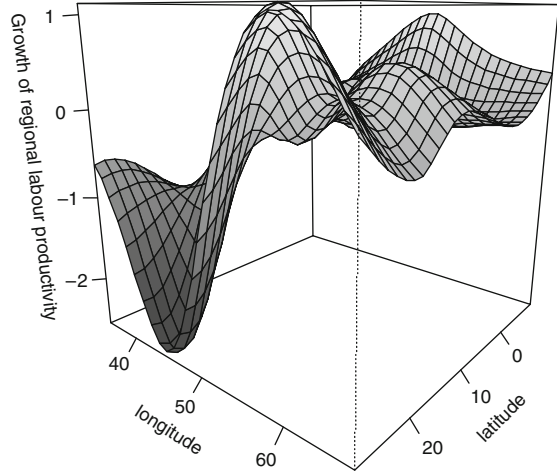


**Fig. 2** Model 2: partial effects of univariate smooth terms

(Fig. 2b) is in line with Azariadis and Drazen (1990) theoretical prediction. Quite differently, the rate of schooling has a positive effect on regional growth only up to a threshold, then a downward pattern comes out (Fig. 2c). To explain this odd result, it may be useful to observe that most of the regions with levels of  $\ln s_h$  higher than the threshold belong to Eastern countries. It is recognised that, despite the high enrolment rates in primary and secondary schooling, a decline in the quality of education is of particular concern in these countries. Finally, the influence of the employment growth rate on regional growth is monotonically negative, albeit the marginal effect is not homogenous across the sample (Fig. 2d). Finally, Fig. 3 displays the partial effect of the smooth interaction between latitude and longitude,  $f(no, e)$ .

The value of the spatial autocorrelation parameter  $\hat{\rho}_{dist}$  is equal to 0.58 and statistically significant at the 5%, confirming the role of spatial frictions in the interregional diffusion of technological spillovers. The endogeneity of the lag term  $W_{dist}\gamma_y$  is confirmed by significance of the control function  $f_I(\hat{v})$ . As pointed out

**Fig. 3** Partial effects of the smooth interaction term  $f_{10}(lat, long)$



above, the significance of the  $\hat{\rho}_{dist}$  parameter means that the exogenous terms affect the left hand side of the model through a “global multiplier effect” (“spatial diffusion with friction”) (see Anselin 2004; and Basile 2008, for a thorough discussion of these issues).

## 4.2 Relational Proximity and Knowledge Spillover Effects

In this section we present the results of an econometric analysis aimed at testing the two hypotheses illustrated in Sect. 2 (statements *H1* and *H2*). We first analyze proposition *H1*, according to which knowledge spillovers depend on the presence of both geographical and relational proximity. This assumption is tested by including on the right-hand side of the growth regression model a linear term measuring the relational spillover variable,  $W_{rel}\gamma_y$ , along with the linear term measuring the spatial spillover effect,  $W_{dist}\gamma_y$ , while all other variables are treated as nonlinear smooth terms:

$$\begin{aligned} \gamma_y = & \beta_0 + f_1(\ln y_0) + f_2(\ln s_k) + f_3(\ln s_h) + f_4(\ln(n + g + \delta)) \\ & + f_5(lat, long) + \rho_{dist}W_{dist}\gamma_y + \rho_{rel}W_{rel}\gamma_y + f_6(\hat{v}_{dist}) + f_7(\hat{v}_{rel}) + \varepsilon \end{aligned} \quad (4)$$

Spatial interactions are based on the inverse distance weights matrix, while relational interactions are modelled with the relational inverse distance matrix  $W_{rel}$  illustrated in Sect. 3. A control function approach is adopted in order to control for the endogeneity of both variables. “Relational lags” of the exogenous explanatory variables are therefore considered as further instruments. The smooth

interaction between latitude and longitude,  $f(lat, long)$ , accounts for spatial trends in the DGP.<sup>12</sup>

Estimation results of model (4) are shown in Table 2. The  $\rho_{dist}$  and the  $\rho_{rel}$  parameters measure the degree of spatial spillovers and of relational spillovers, respectively. The magnitude of  $\hat{\rho}_{dist}$  is rather high (0.788) but in line with that reported in previous analyses (Basile 2009), while the coefficient  $\hat{\rho}_{rel}$  is equal to 0.219 and significant at the 1% level. Apparently, a relevant role for geographical distance is maintained when the effect of relational distance is accounted for. The economic interpretation of a significant  $\hat{\rho}_{rel}$  parameter is similar to the one usually adopted with respect to the  $\hat{\rho}_{dist}$  parameter. Thus, we can say that a random shock in regions  $i$  as well as a change in the level of an exogenous variable (such as human or physical capital investments) in regions  $i$  influence not only the growth outcome of that region, but also the growth outcome of all other regions with a strength decreasing with the relational distance between the regions (along with the geographical distance between regions).

While the control function associated to the geographical lag –  $f_6(v_{dist})$  – is highly significant, confirming the endogeneity of this process, trust lag does not turn out to be endogenous. We interpret this result as a further demonstration of the slow pace at which soft forms of capital accumulate over time (Putnam 2000). Trust capital is as easy to spoil as difficult to accumulate. Synergies among local actors crucially depend on mutual understanding, which in turn thrives on high education levels, cultural homogeneity and sharing similar values.

As mentioned above, all other terms enter the model nonlinearly. Nonlinearities in economic growth regression usually come out from three possible reasons (1) the existence of multiple steady-states in the DGP, (2) the omission of relevant growth determinants, (3) nonlinearity in the production function. The number of effective degrees of freedom (*edf*) associated to each smooth term is always higher than one suggesting that in fact the relationship between regional growth and its determinants is far from being linear. Specifically, the estimation results suggest that an increase in the saving rate is associated with an increase in growth rate only when  $\ln s_k$  is above the EU average. Quite differently, the rate of schooling has a positive effect on regional growth only up to a threshold, then a downward pattern comes out. Finally, the influence of the employment growth rate on regional growth is monotonically negative, albeit the marginal effect is not homogenous across the sample.<sup>13</sup>

<sup>12</sup>Prior to the main tested hypotheses, we adopted a from-particular-to-general specification strategy to choose the most suitable specification. The first step entails estimating a basic human-capital augmented neoclassical model *à la* Mankiw et al. (1992). Next, the hypothesis of linearity and of spatial independence is relaxed, as residuals of the first OLS estimates display spatial autocorrelation. We therefore estimated a spatial Durbin model (and a spatial lag) model, *à la* Ertur and Koch (2005, 2007) and Basile (2008, 2009). Finally, we augment the spatial lag specification by incorporating social proximity effects. This section presents the econometric results of the preliminary two steps, while the effect of social proximity is analyzed in Sect. 4.2.

<sup>13</sup>The plots of these smooth terms are not reported in the paper, but they are available upon request.

Finally, although the effect of the other variables remains qualitatively similar to those obtained in a linear setting, the inclusion of relational knowledge spillovers consistently improves all relevant fit statistics and choice criteria: the adjusted  $R^2$  is equal to 0.733 (it is equal to 0.37 in a linear setting), the percentage of explained deviance and the Generalized Cross Validation (GCV) score are equal respectively to 76.9 and to 0.719, while the Akaike criterion decreases with respect to linear estimates to 621. The Moran's I statistics are not statistically significant.

However, one point in this relationship is not yet fully clear. How do geographical and relational distance interact with each other? The answer to this question is the object of the next section.

### 4.3 *Geographical and Relational Proximity: Synergies in Knowledge Spillover Effects*

The growth model presented in (4) can be further adapted in order to take possible (nonlinear) interactions between the two global spillover effects into account. Column 2 in Table 1 reports the estimates of a fully nonlinear econometric model, where the extent to which knowledge spills over surrounding regions is accounted for by a smooth term. In this case non linear structure is ex ante imposed for the distribution of geographical and relational frictions among European regions in the emergence of knowledge spillovers.

This statement corresponds to testing the second research question (H2) presented in Sect. 2. This translates in the following testable nonlinear equation:

$$\begin{aligned} \gamma_y = & \beta_0 + f_1(\ln y_0) + f_2(\ln s_k) + f_3(\ln s_h) + f_4(\ln(n + g + \delta)) \\ & + f_5(lat, long) + f_6(W_{dist}\gamma_y, W_{rel}\gamma_y) + f_7(\hat{v}_{dist}) + f_8(\hat{v}_{rel}) + \varepsilon \end{aligned} \quad (5)$$

Results of estimating (5) are shown in Table 2. The smooth term is highly significant at all conventional levels. From this analysis and provided estimates for relevant controls that do not differ consistently from similar linear models, we can infer that indeed not only geographical distance plays a role in mitigating the extent to which knowledge spillovers travel. Also, relational distance co-determines the geography of knowledge spillovers.

This statement can also be seen graphically. Figure 4 plots the joined effect of  $W_{dist}\gamma_y$  and  $W_{rel}\gamma_y$  from two different perspectives. The vertical axis displays the scale of the expected values of regional growth, while the two axes of the horizontal plane report the scale of  $W_{dist}\gamma_y$  and  $W_{rel}\gamma_y$ .

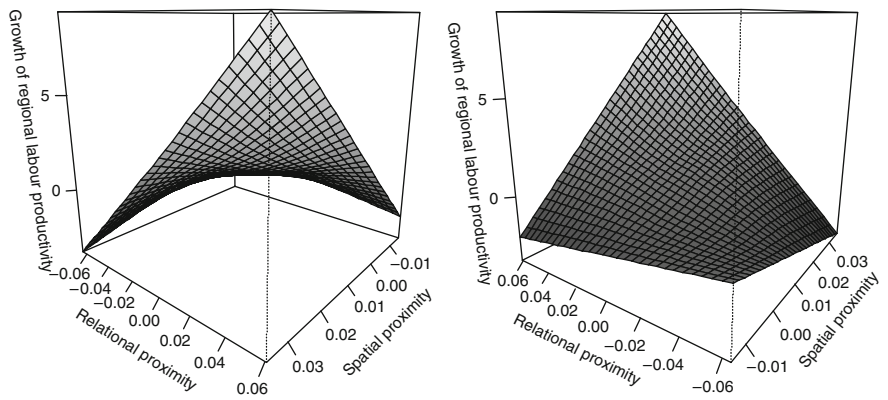
Not only does a smaller distance – both in terms of geographical and relational space – increases the magnitude of estimated knowledge spillovers; but also the effects of the two measures of proximity mutually reinforce. We can therefore infer that knowledge flows more easily between regions that are not too distant either from a geographical or a relational point of view. We can conclude that, *ceteris*



**Table 2** Spatial and relational spillovers

Variables	Linear externalities		Nonlinear interaction between spatial and relational externalities	
	F-tests and p-values	Edf	F-tests and p-values	Edf
$f_1(\ln y_0)$	6.002 [0.000]	3.028	10.718 [0.000]	3.259
$f_3(\ln s_k)$	18.912 [0.000]	2.483	19.239 [0.000]	2.079
$f_5(\ln s_h)$	7.505 [0.000]	3.942	9.528 [0.000]	3.938
$f_4(\ln(n + 0.05))$	3.022 [0.038]	2.555	5.572 [0.019]	1.000
$f_5(lat, long)$	2.387 [0.002]	15.649	3.068 [0.010]	4.988
$f_6(v_{dist})$	23.797 [0.000]	2.894	37.230 [0.000]	2.847
$f_7(v_{soc})$	1.175 [0.279]	1.000	0.187 [0.665]	1.000
$\rho_{dist}$	0.788			
	(0.245) [0.001]			
$\rho_{soc}$	0.219			
	(0.067) [0.001]			
$f_8(W_{dist}\gamma_y, W_{soc}\gamma_y)$			17.823 [0.000]	4.567
$R^2_{adj.}$	0.733		0.747	
Deviance	76.9		77.1	
GCV	0.719		0.650	
AIC	621		599	
Moran's $I$	-0.229 [0.590]		0.199 [0.421]	

Notes: Dependent variable: productivity growth rate. F test and p-value (in squared brackets) for the overall significance of smooth terms are reported in Column 2. Edf are the effective degrees of freedom. Deviance is the percentage of explained deviance. AIC is the Akaike Information Criterion. GCV is the generalized Cross Validation. Moran's  $I$  standard deviates and p-values are computed using a great-circle distance-based binary weights matrix with a threshold distance of 424 km. The number of observations in the sample is 249



**Fig. 4** Partial effects of the smooth interaction term

*paribus*, both spatial and relational proximity co-determine knowledge spillovers and their impact is maximized when regions are both physically as well as relationally proximate.

A final improvement in our estimates entails a richer semi-nonlinear econometric model, where we also control for selected growth-enhancing factors that have been previously found to be relevant in the regional growth literature. This is done in the next sub-section.

#### 4.4 Robustness Checks

To test the robustness of our results, we control for the omission of possibly relevant growth determinants. Specifically, we take agglomeration and Jacobs externalities as well as sectoral composition and R&D intensity as controls entering the model linearly whereas we allow the other variables to make up the nonlinear component of the semiparametric model:

$$\begin{aligned} \gamma_y = & \beta_0 + f_1(\ln y_0) + f_2(\ln s_k) + f_3(\ln s_h) + f_4(\ln(n + g + \delta)) \\ & + f_5(lat, long) + f_6(W_{dist}\gamma_y, W_{rel}\gamma_y) + f_7(\hat{v}_{dist}) + f_8(\hat{v}_{rel}) \\ & + \beta_1 \ln sh(agr) + \beta_2 \ln(dens) + \beta_3 \ln(Jacobs) + \beta_4 \ln(R\&D) + \varepsilon \end{aligned} \quad (6)$$

Results of estimating (6) are shown in Table 3.

The addition of the above mentioned control variables does not substantially change the main conclusions of this paper on the role of relational spillovers. Spatial and relational distance both mediate in the ease with which knowledge

**Table 3** Robustness checks

Variables	Coefficients, std.err., F-tests and p-values	Edf
$f_1(\ln y_0)$	16.456 [0.000]	3.414
$f_3(\ln s_k)$	30.990 [0.000]	1.850
$f_5(\ln s_h)$	7.879 [0.000]	3.851
$f_4(\ln(n + 0.05))$	5.389 [0.021]	1.000
$f_5(lat, long)$	1.050 [0.379]	3.699
$f_6(v_{dist})$	35.523 [0.000]	2.727
$f_7(v_{soc})$	0.913 [0.423]	2.556
$f_8(W_{dist}\gamma_y, W_{soc}\gamma_y)$	14.613 [0.000]	5.484
$\ln Sh(agr)$	-0.263 (0.093) [0.005]	
$\ln dens$	0.056 (0.074) [0.447]	
$\ln Jacobs$	-0.461 (0.259) [0.076]	
$\ln r\&d$	0.208 (0.083) [0.013]	
$R^2_{adj.}$	0.767	
Deviance	79.3	
GCV	0.610	
AIC	582	
Moran's I	-0.800 [0.782]	

Notes: see Table 1

spreads. Also, their effect is higher when regions are proximate both spatially as well as relationally.

Nevertheless, with the inclusion of these important control variables, the nonlinear spatial trend  $-f_5(lat, long)$  – loses its significance. We can therefore conclude that unobserved spatial heterogeneity in growth behaviour displays no more relevant patterns. Moreover, with the inclusion of additional control variables, the precision of our estimates increases further: the  $R^2$  and the percentage of explained deviance increase respectively to 0.767 and 79.3, the GCV score abates to 0.610 and the Akaike criterion decreases to 582. The significance level associated to Moran's I statistics also further reduces.

Additional controls are significant in three out of four cases. Signs associated to the additional controls are all in line with the literature. In particular, there is evidence of *negative* Jacobs externalities, which may be linked to the level of spatial aggregation of our data. Jacobs externalities were deemed to play a major role in large, diversified and creative cities (in regions at the EU NUTS3 level definition) (Jacobs 1969; Beaudry and Schifffauerova 2009), while sectoral specialization may actually foster productivity growth at the NUTS2 level. However, more research may shed light on this highly debated issue.

## 5 Conclusions

Regional spillovers are growth enhancing elements of a region which, as pure public goods, exert positive (negative) effects on other regions, with remarkable distance-decay effects. The reasons behind the spatially-bounded nature of spillovers may be found in spatial proximity (following a pure spatial-geographical approach) as well as in other notions of proximity. In this paper, we test the hypothesis that relational proximity, intended as the proximity between pairs of regions in developing collective learning processes, co-determines knowledge spillovers. Specifically, we test the hypothesis that both geographical and relational proximity explain the mechanisms behind knowledge spillovers. Space here is therefore defined along two axes: a relational space, where functional, hierarchical, economic and relational interactions take place, and the geographical space in which these relations are embedded.

We test the role of relational proximity as determinant of knowledge spillovers using a sample of 249 EU27 NUTS2 regions over the period 1990–2004. The evidence strongly supports the idea that relational space adds information on the way agents interact and on how knowledge spillovers are generated. Thus, relational as well as physical proximity are found to be key determinants for knowledge spillover exploitation. Also, we find that the effects of geographical and relational proximity on knowledge spillovers reinforce each other; data clearly show that, *ceteris paribus*, regions closer in spatial terms exchange knowledge more easily when their levels of trust is similar. These two main results are robust both to different choices of models, allowing for spatial heterogeneity of the estimated

parameters and controlling for endogeneity of the processes explained by the model, as well as to the inclusion of other relevant growth determinants.

Our results call for further research on the topic. Only recently attention has been paid to the different definitions of space that might determine the extent to which knowledge travels. Empirical assessments of these theories are quite rare and more empirical research, supported by strong theories, might help in accounting for more complex and satisfactory definitions of space.

This paper has also relevant policy implications. EUs DG Regio, i.e. the European Regional Authority, is in charge of regional policy for the EU27 Member States, and explicitly focuses mainly on territorial cohesion,<sup>14</sup> with a clear commitment to reducing spatial disparities between European regions, in terms of economic wealth, and, consequentially, of future opportunities (European Commission 1996, 1999; European Council 1999a, b). Soft policies are part of the policy bundle for this Authority; however, seldom have more comprehensive context policies been attempted.

In fact, there is evidence that social capital can be accumulated, thus enhancing relational proximity. Books like Putnam (2000) are replete with examples of local US communities feeding their wealth of social values, trust and norms, laying the basis for future socio-economic improvements. Investing in social and relational capital is costly and expensive. Rules and norms, trust and values have typically long accumulation time, while also presenting very short spoiling periods. Social capital, therefore, seems to accumulate at a slow pace and risks to dissipate at a fast rate. However, regions may significantly benefit from such investment.

The propensity to cooperate is for instance the object of some cooperation-enhancing research policies. A few recent examples include the voucher issued by the province of Limburg (Netherlands) and that released by the region of Lombardy. In the first case, Limburg started a pilot project in 1998, randomly assigning vouchers to 20 SMEs in order to foster cooperative behaviour aiming at R&D activities. Similarly, in 2005 Lombardy released R&D cooperation vouchers to firms and Technology Transfer Centres for improving technical contents of an innovation or for patenting. Target firms included SMEs, on the premise that this is the segment of the market that faces the biggest constraints to cooperative behaviour in research and patenting. In both cases, evidence suggests that cooperative behaviour indeed increased among SMEs after the introduction of the vouchers.

These examples present the case for similar policies, for instance in the form of tax reductions or rebates, for firms and institutions lacking, fully or partially, the capability to cooperate. In presence of a typical market failure, these measures may actually build up the stock of trust needed to foster cooperation between distant areas, thus causing faster and more efficient growth spillovers between regions, and therefore an increase in the long run equilibrium growth rate for EU areas.

<sup>14</sup>Keywords on DG Regios' website as of May 5, 2010 include the following terms: "Beneficiaries", "Future of Cohesion Policy", "Territorial Cohesion", "Territorial Co-operation", "Closure 2006", "RegioStars", "Economic crisis", "Cohesion reports", "Danube strategy", and "Ex Post Evaluation 2000–2006".

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