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The Impact of Regional Absorptive Capacity on Spatial Knowledge Spillovers

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The Impact of Regional Absorptive Capacity on Spatial Knowledge Spillovers[1]

The Cohen and Levinthal model revisited

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Abstract

We design a conceptual framework for linking two approaches: the literature on absorptive capacity and the literature on spatial knowledge spillovers. Regions produce new knowledge, but only part of it is efficiently adopted in the economy; the share of efficiently adopted technology depends on territorial capital. Our data set is based on a panel of European regions over the period 1999-2005, combining data from EUROSTAT and the European Values Study (EVS); we test the hypothesis that insufficient levels of territorial capital hamper the capability of regions to grasp and fully exploit new knowledge. Results show that a lower regional absorptive capacity increases knowledge spillovers towards surrounding areas, hampering the regions' capability to understand, decode and efficiently exploit new knowledge, both locally produced and originating from outside.

JEL classification codes:

O33 - Technological change: choices and consequences; diffusion processes
R11 - Regional economic activity: growth, development, and changes

Keywords: Absorptive capacity, knowledge spillovers, total factor productivity, spatial econometrics

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1. Introduction

Since the Cohen and Levinthal (1990) (hereafter, CL) seminal paper on the firm's absorptive capacity regarding knowledge and innovation, much research has focused on understanding key characteristics of firms, regions and countries that make it easier to understand and decode information coming from outside in an economically efficient manner. This research has been present in the literature for more than 15 years. On 17 April 2008 JSTOR[2] listed as many as 189 articles citing CL. The fields in which this concept has been addressed include not only management science but also anthropology, industrial organization, social science, and so on.

The concept of absorptive capacity, whose foundations were originally designed in the context of firm theory, can be extended to more complex institutions, such as countries and regions. The idea that a proper knowledge base is needed to understand more and better knowledge is not new and can be partially derived from human capital-based growth models. However, in the present investigation the focus is not simply on the role of human capital in enhancing the growth capabilities of regions or countries, but rather on the role of the stock of accumulated knowledge in the capability of a region to identify and utilize proper knowledge from outside.

A few real-world cases may exemplify the scope of our research. We will take Sicily as an illustrative case. Sicily is a lagging region in the southern part of Italy. It is one of the largest and and most problematic regions in an otherwise well-developed country. Although its international image reflects sometimes old-style stereotypes, the region undoubtedly also has branches of several innovative corporations, including ST Microelectronics, a large chipmaker which consistently ranks first among the top Italian firms in terms of the number of patent requests filed

[1] JSTOR is one of the largest digital archives for academic research.

to the European Patent Office (hereafter, EPO)[3] and the United States Patent Office (henceforth, USPTO[4]).

In 2003, the last year for which EUROSTAT data were reasonably complete, Sicily ranked 148th among European NUTS2 regions for the variable Human Resources in Science and Technology, thus obtaining a middle position among the 261 regions in the EU sample, and 170th for the number of patent applications to the EPO as a ratio to total population. Its capital-labour ratio stood in a very high 27th place; its savings rate is around 10 per cent; and its GDP per capita reached € 14965 in 2004. All these results suggest that all the necessary technical factors that growth theory traditionally identifies as growth-enhancing are available in this region – not to a lesser extent as in many other European regions.

It is noteworthy, however, that productivity data (see Figure 4[5]) tell us a different story. Sicily ranks 215th among European NUTS2 regions for productivity level; it only finds a place among regions in the bottom 20 percent of the TFP distribution. Furthermore, in the years 2003-2004 TFP actually *decreased* in Sicily by 0.92 percent, which meant a 205th place in the total ranking. Although this result is partly determined by Italy's poor performance, nevertheless, even if Sicily's performance is compared only with Italian regions, it still ranks very low. How does this discrepancy come about? What drives this result, and why are physical factors not sufficient to explain Sicily's growth in efficiency? In particular, where does knowledge produced in Sicily go? Why does it not show up in Sicily's statistics on productivity? These questions form the

[3] Figure 1 depicts the number of patent requests filed to the EPO in 2004. The darker the colour, the higher the number of patents per 1,000 inhabitants requested. Sicily is in the 3rd range of the distribution, along with 103 other EU regions. The map is based on EUROSTAT data and made with Luc Anselin's Geoda. The geographical distribution of patent requests mimics the well-known European core-periphery pattern, with a marked bias towards northern regions with respect to R&D activity.

[4] ST Microeletronics ranks 1st among Italian firms by number of patents granted from the USPTO over the years 2002-2006, with a total of 950 patents, representing more than 18 per cent of the total value for Italian companies. (Data source: USPTO, available upon request).

[5] Productivity is measured here as total factor productivity (hereafter, TFP). We calculate it as the residual of a Cobb Douglas production function of the form $Y = AK^{\alpha}L^{1-\alpha}$.

background for the present paper. The answers will be sought in spatial knowledge spillovers and the absorptive capacities of regions.

The questions above are linked to Solow's paradox about the new economy, where "*We see the computer age everywhere except in the productivity statistics*" (Solow 1987). However, in the case of Sicily, the conclusion is even worse: factor accumulation does not show up in Sicily's current performance. Therefore we need a broader framework, in which relevant growth factors are taken into account. In particular, we take for granted here that knowledge produced in specific regions where regional receptivity is not sufficient spills over to surrounding areas. Hence, patenting an innovation in a region, especially in an increasingly globalized world, is no longer sufficient to retain its positive fallouts in the region itself. The area must be endowed with the capability to understand technical innovation and decode it in order to produce more efficiently.

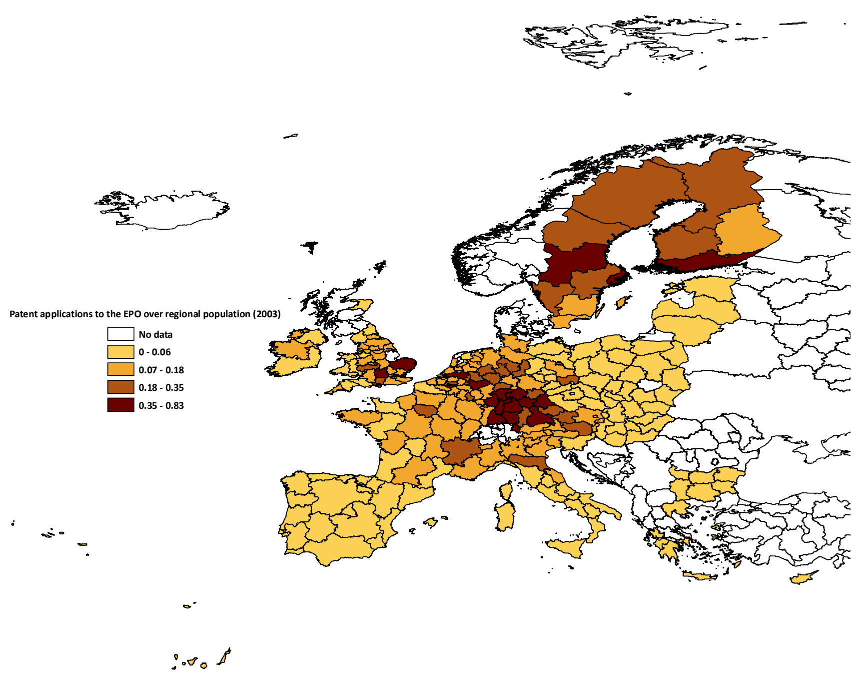

Figure 1 - Number of patents filed to the EPO by regional population (2003)

Source: EUROSTAT

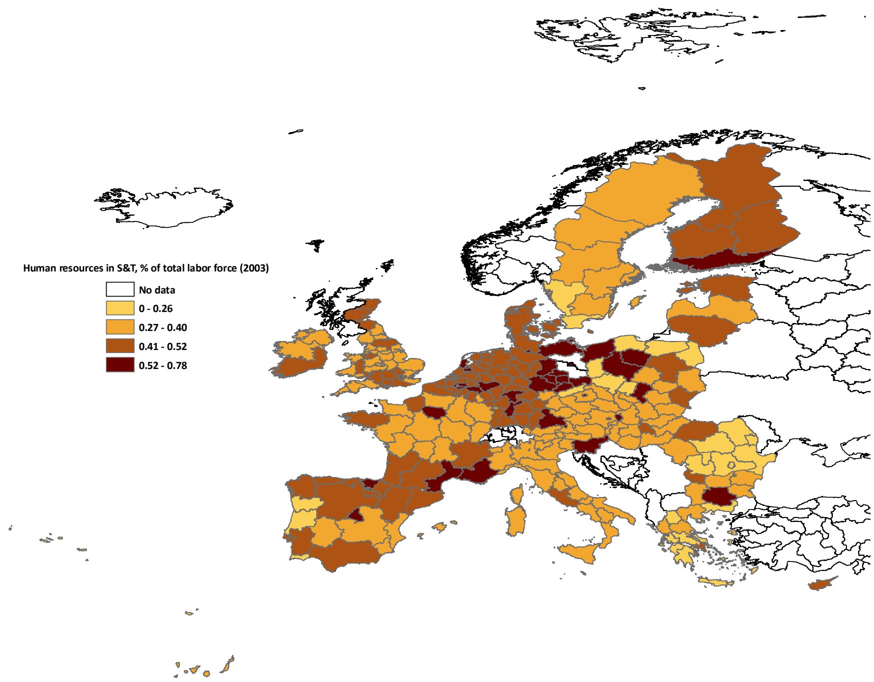

Figure 2 - Human resources in Science and Technology, as a percentage of total labor force (2003)

Source: EUROSTAT

2. Absorptive capacity and knowledge spillovers

The basic lesson on absorptive capacity is that it comes from knowledge accumulation. The basis for this statement originates from a cognitive approach. In particular, "*Research on memory development suggests that accumulated prior knowledge increases both the ability to put new knowledge into memory, what we would refer to as the acquisition of knowledge, and the ability to recall and use it*"(Cohen and Levinthal, 1990, p. 129).

The development of effective absorptive capacity requires more than a mere exposition of, and familiarization with, the relevant prior knowledge. Learning crucially depends first of all on the intensity of the effort. Moreover, the ability to assimilate information as a function of the richness of the pre-existing knowledge structure highlights two important factors:

- Learning has a cumulative pattern;
- Learning performance is greatest when the object of learning is related to what is already known.

Although this sounds easier to understand in a small and relatively less complex organization such as a firm, regions might display similar patterns. If prior knowledge is needed for a firm's staff to understand and decode new knowledge, why shouldn't regions behave similarly? Moreover, if exerting a higher effort and being culturally and socially not too distant helps employees in similar firms to understand new knowledge, why shouldn't more aggregate entities such as regions also obey these rules?

A recent attempt to link the firm's behaviour with regional innovation performance is made by Abreu et al. (2008). In their paper, they combine two British firm-level data sets to measure the role of the firms' absorptive capacity in driving regional innovation performance. In particular, they find that a larger share of R&D employees, the use of new management techniques, and collaborative behaviour are all positively associated with an increase in regional innovation performance. Their study, however, does not have the same scope as ours. In fact, technical, standardized innovation is automatically assumed to lead to growth. However, this is not always true. Regions and countries can consistently file patents, especially when the industrial structure is oriented towards large firms; but at the same time locally-produced knowledge can be more useful to firms in other regions or countries than to the local population. In fact, while patents are certainly a good and structured way to measure innovation, they mostly refer to R&D carried out in large firms.

In Abreu et al. (2004), long-run productivity growth rates at country level are linked to human capital accumulation, in a spatial panel of 73 countries over the period 1960-2000. TFP is used as a measure of aggregate technology; its rate of change over time is explained with a model that nests the Nelson and Phelps (1966) and Lucas (1988) models. The authors link up with the literature on direct and indirect effects, which forms the basis of our measure of outward knowledge spillovers (hereafter KS). Although their spatial framework resembles ours, and the TFP concept is used, our approach differs in that, in the present study, spatial econometrics techniques are used to obtain the outward KS measure.

Knowledge is a critical success factor for the economic performance of firms and regions, as it creates a competitive advantage (see Hitt et al. 2002). Knowledge needs to be produced, but also to be used or absorbed. Thus, knowledge diffusion and spillovers are important elements, so that the framing of a knowledge system – both public and private – is an important issue (see Agarwal et al. 2004; Shane and Stuart 2002). An optimal knowledge investment is thus something that cannot be handled by an individual agent if knowledge is shared with other agents (see Arrow 1962; Aghion and Howitt 1992).

New knowledge can actually take different forms. It can also be the creative adoption of existing knowledge (for instance, the use of satellite phones by Serbian troops as a device of communication device to overcome the destruction of their fixed phone lines by the opponents' coalition), new and more efficient managerial techniques (Toyota's *Just-in-time* system), the creative and artistic combination of old, traditional materials to impose non-standardized products on the market (French and Italian fashion companies). The list might be considerably longer. Clearly, patents are not the only measure of innovative activities in a country. That is why we resort to a different measure of technological change, i.e. TFP. With this statistic we can assess whether a country or a region is more efficient in combining physical factors, broadly categorized as capital and labour. Moreover, with proper frontier techniques we can also assess whether the unit of analysis is more or less close to an estimated technological possibility frontier.

The literature on absorptive capacity can be connected to the research carried out on KS and knowledge leakages. The first step to define a link entails extending the unit of analysis from the firm to the aggregate level. Next, one may wonder what happens if local absorptive capacity lacks the capability to absorb locally-produced knowledge. In other words, if local firms produce technical innovation that the local labour force cannot fully exploit, then where do the positive effects take place?

KS theory, which laid its foundations in the empirical industrial organization in the 1980s, assumes that, although knowledge is a public good, appropriability may be imperfect. In Michael Spence's words: *"Imperfect appropriability means that a fraction of each firm's research leaks out" (Spence 1984)*

Thus, KS theory has properly described how, in the absence of sufficient local absorptive capacity, new knowledge spills over to surrounding areas. But what exactly is a KS? Through which mechanisms and vehicles does knowledge travel, and how far does it go? This issue calls for a more profound analysis. There is apparently an abundance of under-exploited knowledge (see Arrow 1962). Several definitions of KS have been given in the literature. An appropriate definition was given by Grossman and Helpman (1992). They define KS by two main characteristics: *"By technological spillovers, we mean that (1) firms can acquire information created by others without paying for that information in a market transaction, and (2) the creators (or current owners) of the information have no effective recourse, under prevailing laws, if other firms utilize information so acquired"* (Grossman and Helpman 1992, p. 16). Hence, KS require the passage of knowledge in a non-marketed form, so that somebody using knowledge created elsewhere or by somebody else cannot be subject to legal procedures. Given this difficult definition, it comes as no surprise that KS turn out to be difficult to measure, and subject to a certain degree of subjectivity.

Usually the measure of KS entails a link between the productivity growth of an organization j and a measure of the innovative activity of some other organization i, which has some type of relationship with j. Studies differ on the way knowledge can be carried across borders. Usually this happens by standardized categorization (i.e. patenting). Patent-flows between firms (or industries) involved in the same vertical relationship (Nadiri 1993) bring knowledge from firm to firm, and hence across administrative and political boundaries. Alternative technology and knowledge carriers include input-output mechanisms, multinational companies, labour force pooling, and (attracting only recent attention) migrations.

Among patent measures, Bernstein and Nadiri (1988) devised a measure of the pool of research activity available to a firm compared with the (unweighted) sum of R&D expenditures of other firms in the same industry; Jaffe (1986, 1989) used patent applications to construct a measure of similarity of research activities, and then calculated the external R&D pool available to each firm.

For the focus of the present paper, patents might be partially misleading. This is because, if the methodology were to resemble that of Jaffe et al. (1993), we would need to construct complex and cumbersome data sets with citations classified according not only to industry or patent class, but also to regional origin. This way the added value of such a paper would mainly lie in trying an already established estimation procedure on a different data set on an alternative scale.

Another possible drawback of using patent data is that they reflect only a part of real innovation and knowledge, i.e. what can be standardized and can be technically described on a document and revised by peers[6]. Knowledge is actually a more complex phenomenon, assuming different forms

[6] The relevant reference here is Griliches (1990).

and being spread by alternative carriers. Blumentritt and Johnston (1999), for example, define knowledge according to four categories. Table 1 shows their conceptual scheme.

Table 1 - A taxonomy of knowledge

Codified knowledge Effectively information of all kinds facts and figures	**Common knowledge** Knowledge that is accepted as standard without being made formally codified	**Social knowledge** Knowledge of social links and shared values	**Embodied knowledge** Knowledge that is rooted in experience, background and skill of a person. It is strongly related to the person that holds it.
Knowledge of things and objects **Knowledge of sentences and propositions** *Musgrave* **Know what** **Know why** *Lundvall* **Explanatory knowledge** Know why Knowledge of information. *Millar* **Catalogue knowledge** Know what Knowledge of information. *Millar* **Symbolic knowledge** Information. *Collins* **Encoded knowledge** Information conveyed by signs and symbols Books, manuals… *Blackler*	**Embedded knowledge** Knowledge that resides in systemic routines *Blackler* **Embrained knowledge** Knowledge that is dependent on conceptual skills and cognitive Abilities Knowledge that or knowledge about *Blackler* **Experiental knowledge** what was Context dependent knowledge Informal knowledge *Fleck*	**Know who** *Lundvall* Social knowledge Know who Context dependent knowledge. *Millar* **Encultured knowledge** Other word social knowledge that reflects certain common experiences. *Collins* **Encultured knowledge** Share understanding of social links *Blackler*	**Embodied knowledge** Knowledge of playing golf (feeling that it is right) *Collins* **Embodied knowledge** Depends on cobining sentient or sensory info and physical cues Knowledge how or knowledge by acquaintaince (craft skills) only partyl explicit: *Blackler* **Tacit knowledge** **Instrumentalities** *Fleck* **Tacit knowledge** *Polanyi* **Know how** *Lundvall*
Formal knowledge **Contingent knowledge** *Fleck* **Explicit knowledge** *Polanyi*	**Knowledge of how to do things** *Musgrave* Process knowledge Know how Context dependent knowledge. *Millar*		These concepts might contribute to either process knowledge or embedded knowledge depending on their contents

Source: Blumentritt and Johnston (1999)

Patents fall into the category of codified knowledge. However, as evidenced by this taxonomy, as well as by everyday life, knowledge goes well beyond codified schemes. Managerial skills, tacit knowledge, relational and social capital are all elements which play a crucial role in explaining why certain areas are more productive than others, by shaping their cultural context. This is a possible strong point of the present paper. We do not refer to any specific form of knowledge, but instead try to capture all possible spillover effects of local skills towards surrounding areas.

3. A framework for knowledge spillovers

The research question to be answered in the present study is the following: *Does lower absorptive capacity cause higher knowledge leakages to surrounding areas?* This question can be linked to our previous work on the topic of territorial capital. In particular, in Capello et al. (2008), we inspect the role of territorial capital in generating increasing returns to regional growth. A simplified version of this process is presented in the following flow chart (Figure 3).

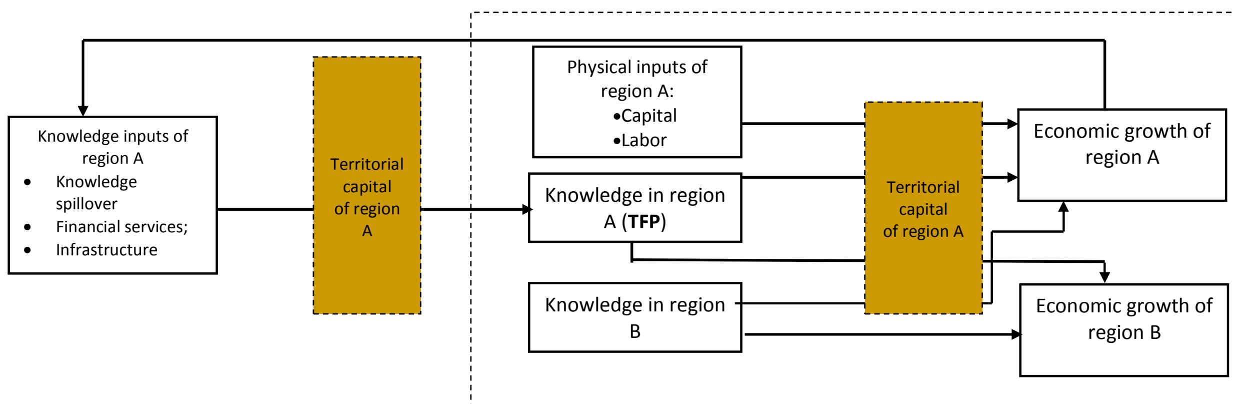

Figure 3 - Theoretical flow chart underlying Capello et al. (2008)

In this paper, we want instead to assess whether the lack of local absorptive capacity causes locally produced knowledge to spill over to surrounding areas. But, in the literature on KS, the focus is usually on the determinants of positive (incoming) KS. In our study, however, we reverse the question: *Does the lack of local capabilities cause outward KS?*

The established literature usually finds that KS are facilitated by geographic proximity and by human capital endowment of the areas under consideration. But what happens if we reverse the reasoning? Knowledge leakages might be determined again by geographical proximity, but also by the lack of absorptive capacity, and of course by the absorptive capacity of surrounding areas. A more complex and comprehensive concept of proximity is needed in this case. Socio-economic proximity, for example, or cultural and relational proximity make the spatial component of this problem more complex to represent and interesting to investigate. This is where the concept of territorial capital enters: as a comprehensive measure of local territorial elements, it encompasses all previous measures of local endowments, from social to human capital, that determine the capability of a region in understanding and decoding knowledge not only coming from outside but also locally produced.

Traditional management science studies find that more human capital leads to a greater capability of firms to understand and decode new knowledge. In this context the above-mentioned study by CL (1990) is important, as they argue that: *"The ability to evaluate and utilize outside knowledge is largely a function of the level of prior related knowledge".*

Hence, accumulated prior knowledge may actually increase the ability of firms to correctly evaluate new information, assimilate it, and apply it for commercial purposes. CL build, in turn, on psychology studies where individuals are shown to be more able to absorb and understand new skills when better endowed with previous knowledge. The passage from the individual to the organizational level is done through aggregation. Similarly, we believe that, if organizations and companies in a region are better endowed with absorptive capacity, they also have higher chances to decode new knowledge themselves, thus preventing outward KS. Its seems therefore plausible that we may formulate a general framework model of the following nature:

$$\text{Outward spillovers}_i = f\,(\text{Innovation}_i\,,\ \text{Innovation}_i * \text{territorial capital}_i\,,\ \text{territorial capital}_j), \qquad (1)$$

where region i is the region under consideration, while regions j, with j≠i, are all other regions. We may expect eq. (2.) to meet the following reasonable expectations:

- A positive sign for the first variable: more innovation in a region provides scope for outward KS. This is in line with similar studies on technology and knowledge transfer, which find that higher investment in knowledge production leads to a stronger likelihood of this new knowledge spilling over to the surrounding areas (Landry et al. 2007).

- A negative sign for the second variable: more local capacity (in terms of territorial characteristics and capabilities of understanding and translating knowledge) should make it easier for the area to retain the positive effects of local innovation within its boundaries. *Cognitive proximity* helps economic agents (firms as well as individuals) in mutual understanding each other. The *economic value* of new knowledge is thus more likely to be fully exploited locally when people own high stocks of cognitive elements within the territorial capital domain.

- A positive sign for surrounding areas' endowments of cognitive capital, in line with what the absorptive capacity literature suggests. In a way, this last expectation is the reverse of the previous point: when neighbouring regions own large stocks of cognitive capital, they tend exert a pull effect on locally produced knowledge. Their socio-economic soil is more fertile and ready to reap the positive effects of externally produced knowledge, through commuting patterns, input output mechanisms, and formal and informal exchange of new ideas. Finally, this last sign is expected to be positive for one more reason. Knowledge spillovers happen through several different channels, one of which is trade: through reverse engineering, firms can acquire technology embedded in traded goods (MacGarvie 2005, Padilla-Pérez 2008). Trade is a negative function of geographical, technological and cognitive distance: thus, when neighbouring regions own a consistent stock of cognitive capital, they are better suited to understand and exploit externally-produced knowledge.

Empirical estimation can be carried out with standard linear regression, as well as with spatial econometrics techniques. In our application we use the NUTS2 level for European regional data.

4. The measure of outward knowledge spillovers and the data set

4.1 Measuring outward knowledge spillovers

To test our model a first step is required: finding a good proxy for *outward* KS. Doing so also requires an *ex ante* definition of knowledge. The definition of the proper measure of knowledge and KS would ideally be based on three broad theoretical quantities:

- Patents;
- Total Factor Productivity (TFP);
- Efficiency scores.

Patents are a common and much utilized measure of technical change. Furthermore, patent citations are the most successful measure of knowledge transfer; they have been used to assess spatial decay effects that knowledge faces in the transfer process. Among several qualities of patents (from the point of view of a researcher), we can mention three:

- They certainly measure knowledge, be it strictly or ill-defined, limited to technically created know-how, concentrated in large firms, and so on[7];
- They are standardized;
- They must pass novelty inspection by peers[8].

Nevertheless, they represent a skewed measure, as patenting is mostly carried out in large firms. Hence patent statistics tend to be higher in regions where firm structure is biased towards large dimensions.

TFP is more reliable as a measure of the type of knowledge we want to consider. As a residual to a production function, it encompasses everything that is not measured by physical factors. As such, its difference over time also captures the change in non-technical efficiency, i.e. creativity, managerial skills, and all the non-technical knowledge factors that might arise from a global time-improvement of general regional knowledge. If spatially-lagged, it can also measure the extent to which regions are influenced by surrounding areas; hence an inverse function of this spatial lag might represent a good measure of outward knowledge spillovers. How this new measure is constructed is explained below.

Finally, efficiency scores can be obtained by applying the non-parametric technique of the efficiency frontier, and then used as a measure of relative efficiency. They can be used as a dependent variable, with a method similar to the one mentioned above, to measure outward KS.

[7] We thank Henri de Groot for this remark which he gave us in a common discussion.

[8] For a comprehensive review of the pros and cons of using patent data, including our second and third point, see Griliches (1990).

TFP has been criticized on the basis of its very nature[9]. Its shortcomings include the following issues:

1. GDP-related measures, including TFP, would dramatically *understate* quality improvements. This critique, however, has unacceptable implications. Quality adjustments implied by intertemporal comparisons between similar objects, for instance tallow candles and energy-saving bulbs, would imply estimating implausibly low productivity levels for periods before the Industrial Revolution.

2. GDP-related measures would actually *overestimate* real productivity improvements, by ignoring the environmental fallouts of modern intensive economies and their required exploitation of natural resources. Then, in the light of this critique[10], the question is "What is the real situation?" In other words, are real productivity gains over- or understated?

3. Residual measures would include not only productivity gains but also measurement errors, the extent of the black market, noise in the data, and so on.

This last critique is well grounded. However, it is clear that it cannot explain the whole variation in productivity levels. Therefore, TFP must capture at least part of the real gains in productivity.

We calculate TFP levels as in Capello et al. (2008). TFP here is the residual in an OLS regression over the function:

$$\ln(y) = \alpha \ln(k), \tag{2}$$

[9] Hulten (2000) is a good introduction to this measure, at the same time summarizing its qualities and shortcomings.

[10] The *Atlantic Monthly* once had a cover with the title "*The Gross Domestic Product is such a crazy mismeasure of the economy that it portrays disaster as gain*". This citation and the first two points are from Hulten (2000). See also Cobb (1995).

where lower-case letters indicate, as usual, variables divided by the labour force[11]. Figure 4 depicts spatial variations of the Solow residual in 2005. It is evident that productivity levels display strong core-periphery patterns, with top values being recorded in Germany, the Nordic countries and in metropolitan/urban areas (Greater London, Madrid, Lazio, Ile de France, Stockholm). Spatial autocorrelation is also evident from the map. This assumption is strengthened by Moran's I global autocorrelation index, which equals 0.43 for the 2005 TFP data[12.]

The innovative component of this database is our measure of outward KS. Industrial economists traditionally identify patent citations as the best measure for technological transfer. However, as mentioned in the previous paragraph, patents only capture a part of technological transfer, in particular what can be universally codified. TFP, on the other hand, shows the efficiency with which physical factors are combined. As such, it measures not only the outcome of the R&D production process, but also improvements in managerial and organizational techniques, creativity, growth of tacit knowledge, and all non-technical change factors that contribute to improved economic efficiency.

Productivity, in turn, can be explained by a set of determinants. This approach is typically referred to as the "knowledge production function"[13]: it usually entails studying the relationship between R&D inputs and output (measured by some form of benefit from the invention activity such as GDP growth, firm profits or turnover, productivity, or the stock market value of the firm). This approach is only functional for building our measure of outward KS.

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[11] The log-linear transformation allows us to estimate a Cobb-Douglas production function of the form $Y = AK^{\alpha}L^{1-\alpha}$.

[12] Randomization with the GeoDA application yields a pseudo p-value of .001. This evidence strongly suggests the existence of positive and significant spatial autocorrelation of productivity levels across EU regions, which could be explained by diffusion processes. In Luc Anselin's words, positive spatial autocorrelation "is compatible with a notion of contagion or diffusion". See Anselin (2001) for further details on the interpretation of this statistic.

[13] See Griliches (1979) and Pakes and Griliches (1984) as the basic references on this approach.

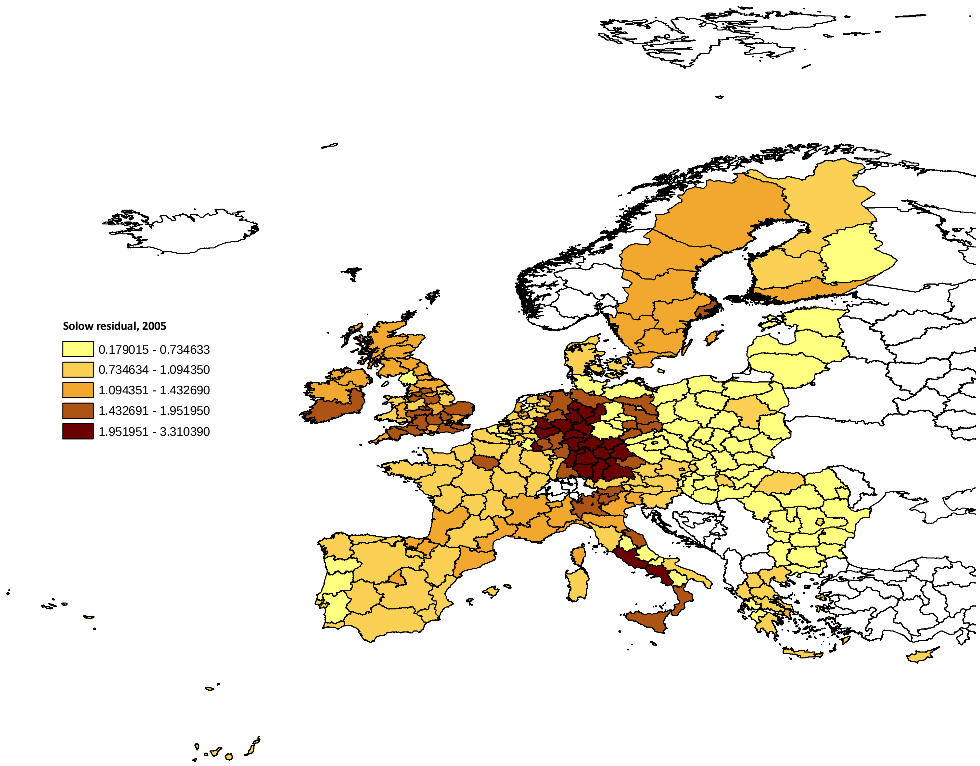

Figure 4 - Total factor productivity in NUTS2 regions, 2005

In this study, TFP actually proxies for generic regional knowledge. In a simple linear framework, if we indicate TFP as Y and the set of its determinants as X,we can write the knowledge production function as:

$$Y = X\beta + \varepsilon . \qquad (3)$$

Suppose then that productivity levels are correlated across space. Estimating the β coefficients with pooled least squares would yield biased estimates. Spatial econometrics makes it possible to wipe out spatial autocorrelation[14]. This can be done with two main models: the spatial lag and the spatial error model. In this case, the first is preferred: it is reasonable to assume that productivity levels are correlated across space, as input-output mechanisms, labour force pooling, educational attainments, human and social capital (all of which can be embodied in the new concept of

[14] Though the source of this phenomenon is not identified.

territorial capital) determine final productivity and can be demonstrated to cluster in space. Eq. (3) then reads as follows:

$$Y = \rho WY + X\beta + \varepsilon \,, \tag{4}$$

where W is the spatial weight matrix, and ρ is the spatial autocorrelation coefficient. The latter can be interpreted in a way similar to the time-autocorrelation coefficient in the time series literature. It also displays similar features: in particular, a value of ρ bigger than 1 in absolute terms implies that spatial correlation becomes larger, the longer the distance.

Eq. (5.) cannot be estimated: the dependent variable is also on the right-hand side. To obtain an estimable function, we must rearrange terms in the usual way, i.e. bring the ρWY term to the left-hand side, isolate Y and premultiply the matrix $(I-\rho W)^{-1}$ to the X matrix and the ε vector.

The (I-ρW) matrix, however, has an interesting interpretation. It is, in fact, obtained as follows:

$$\begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ 0 & \dots & \dots & 0 \\ 0 & 0 & \dots & 1 \end{pmatrix} - \hat{\rho} \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \dots & \dots & \dots & \dots \\ w_{n1} & \dots & \dots & w_{nn} \end{pmatrix}, \tag{5}$$

where $\hat{\rho}$ is the (estimated) autocorrelation parameter[15], and w_{ij} represent distance values between European regions. Eq. (6) shows that the result of this calculation is an (nXn) matrix[16]. This matrix, after being inverted, transforms each variable in the X matrix into its contribution to and from each region to the dependent variable. In other words, it can be interpreted as a sort of input-output matrix, where each element shows the weight to be assigned to each observation in

[15] In our case $\hat{\rho}$=1.28.

[16] Provided that the weight matrix is constant over time, an assumption which seems reasonable over a 7-year time span like this data set.

the vectors stacked in the X matrix in order to obtain inward and outward flows of these elements to the region observed.

Suppose, in fact, that the matrix $(I-\rho W)^{-1}$ (which we will denote with the Greek upper-case letter B from the word meaning "weight") takes on the form:

$$(I-\hat{\rho}W)^{-1} = \mathrm{B} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & \dots & \dots & a_{nn} \end{pmatrix}. \tag{6}$$

Suppose then that the knowledge production function in our case has the linear function form:

$$TFP_{r,t} = \beta_0 + \beta_1 HRST_{r,t} + \beta_2 H_{r,t} + \beta_3 FD_{r,t} + \beta_4 INST_{r,t}\,. \tag{7}$$

In eq. (7) variables are respectively Human Resources in Science and Technology (HRST), Human Capital, measured as the percentage of people holding a degree from an upper secondary education institution (according to the ISCED[17] system), Financial Development (here measured as the share of people in the workforce employed in the finance and banking industry) and Quality of Institutions (measured, as in Capello et al. (2008), as the percentage of arable land). All variables are measured in logs for each region r at time t. Premultiplying, for instance, vector "HRST" by B yields an input-output matrix, where entries in each column represent the contribution of each region's TFP to the allocation of human resources to science and technology in other regions and, vice versa; and the entries in the rows represent contributions of HRST in each region to the analysed region's TFP.

[17] *"The International Standard Classification of Education (ISCED) was designed by UNESCO in the early 1970's to serve 'as an instrument suitable for assembling, compiling and presenting statistics of education both within individual countries and internationally'. It was approved by the International Conference on Education (Geneva, 1975), and was subsequently endorsed by UNESCO's General Conference when it adopted the Revised Recommendation concerning the International Standardization of Educational Statistics at its twentieth session (Paris, 1978)*". (from unesco.org)

Hence, we can operate both row and column sums to inspect, respectively, TFP outward and inward spillovers. It suffices to premultiply the TFP vector by the B matrix to obtain a weighted sum of TFP spillovers to surrounding regions. In other words, we can assess the average outward productivity spillover of the *i-th* region which contributes to the surrounding regions' productivity, or the extent to which each region's productivity spills over to its neighbours.

We might interpret this new approach in terms of *economic value*. While paper track (i.e. patents) KS imply the passage of standardized knowledge, spillovers of productivity imply the imitative, creative resonance process through which people of neighbouring regions, by commuting to the workplace where better work processes can be learnt, by trading, reverse engineering and buying semi manufactured products from commercial partners, can learn and add economic value to he knowledge embedded in economic processes[18].

4.2 The data set

Our data set comprises data on 261 European NUTS2 regions. Data have been collected from two main sources:

1. EUROSTAT (NUTS2 data on regional GDP, population, labour force, gross fixed capital formation);
2. European Values Study (EVS), a comprehensive survey on Europeans and their beliefs about broad life categories, including trust, religion, politics, society, and so on.

The data set comprises the following variables (Table 2):

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[18] We thank Roberto Camagni for this useful comment.

Table 2 - The dataset

Variable	Raw data	Source
Outward KS	Y: regional GDP in constant prices K: stock of capital estimated with the perpetual inventory method[19] L: regional labor force	EUROSTAT EUROSTAT EUROSTAT
R&D intensity	Patent applications to the European Patent Office per 1,000 inhabitants	EUROSTAT
Territorial capital	Principal Components Analysis (PCA) on five territorial capital components[20]	EUROSTAT; EVS.

This study uses the concept of territorial capital as a novel way to model space. Regions are endowed with a set of spatially-bounded resources, which contribute to their capability to understand, decode, and creatively adopt new technologies. These resources, both hard (physical and human capital, infrastructure) and soft (social and relational capital, knowledge transfer mechanisms, governance), define the notion of territorial capital. Regions with insufficient levels of territorial capital are less prone to use new knowledge in an efficient manner. This causes higher KS to surrounding areas.

Our *ex ante* choice of the determinants of outward KS can be related to the literature on economic growth. Traditional neoclassical economics has often focused on the role of factor accumulation in explaining long-run economic performance (Solow 1956, 1957; Swan 1956; Mankiw et al. 1992). The literature on human capital has only recently started to stress the role of soft elements in

[19] Here we assume, as in Capello et al. (2008), an annual 2.5% depreciation rate.

[20] Details on the performed principal components analysis are given in the Appendix.

explaining how efficiently hard components (capital, labour, land, and infrastructure) are combined[21]. More recently, endogenous growth theorists have found a way to incorporate externalities in constant returns to scale growth models. Theoretically speaking, these externalities are conceived as the mechanisms which magnify the effects of factor accumulation. Practically, they have been identified, from among many cases, in aggregate human capital (for example, Lucas 1988) and R&D (Romer 1990).

We believe these to be only partial explanations of the formation of increasing returns. Cognitive elements also play a major role in explaining economic mechanisms. In this research, we focus on the role of governance, R&D transfer agencies, relational capital, management of collective goods, and district economies in shaping the chances that regions have to retain the positive effects of new knowledge within their own boundaries.

5. Empirical results

In our opinion, outward KS depend on a set of variables, as pointed out in Section 3. However, not all of them are expected to have the same impact on the final outcome. KS are expected to heavily depend on regional innovation inputs. The higher the expenditure and commitment to R&D, the higher the chances that produced knowledge spills over its positive effects to surrounding areas. Thus, for example, regions bordering Oberbayern or Stuggart in Germany are expected to gain from their neighbours being highly committed to R&D. Their proximity represents a positive externality and should translate into higher productivity levels even in neighbouring regions. This variable is expected to have the strongest effect on outward spillovers.

[21] For a comprehensive summary of the research on the role of human capital in economic interactions, see Becker 1964.

However a minor, but not negligible, role might be played by cognitive elements. New knowledge, although locally produced, might not be understood by agents in the real economy (Capello et al. 2008). Lack of human and social capital, in particular of its *trust* component, might be detrimental to the efficient understanding and exploitation of this knowledge (La Porta et al. 1999). Thinness of social networks might provide disincentives to the fluid and efficient transfer of knowledge, and limit the capability of countries and regions to fully achieve their long-run growth potential (Beugelsdijk and van Schaik 2005). Lack of R&D transcoding agencies might hamper the likelihood that knowledge is fully exploited, even by firms who did not take part in the knowledge production process (Camagni 2008). This can be summarized by a generalized lack of *territorial capital*. Local lack or insufficient endowment of territorial capital, and in particular of its cognitive elements, might cause increased outward KS. By the same token, a high endowment of territorial capital cognitive elements might help regions to retain the positive effects of R&D activity in the local economy. This effect is expected to be of a smaller magnitude than that of R&D expenditure.

Territorial capital might also work as a force contrary to the local retention of knowledge: if neighbouring regions have a higher endowment of territorial capital, provided that space imposes less impedance to knowledge transfer, they might be more capable of understanding and decoding new local knowledge. Hence, neighbours' territorial capital is expected to exert a positive influence (pull effect) on outward KS.

Our measure is a weighted sum of the region's relative TFP contributions to and from its neighbours. As such, it can also take on negative values. The last observation is interesting: what we claim is that we can actually represent the relative net balance of inward and outward KS. If the variable is negative, the region should be a net knowledge recipient. Figure 5 represents this measure for the last available year (2005).

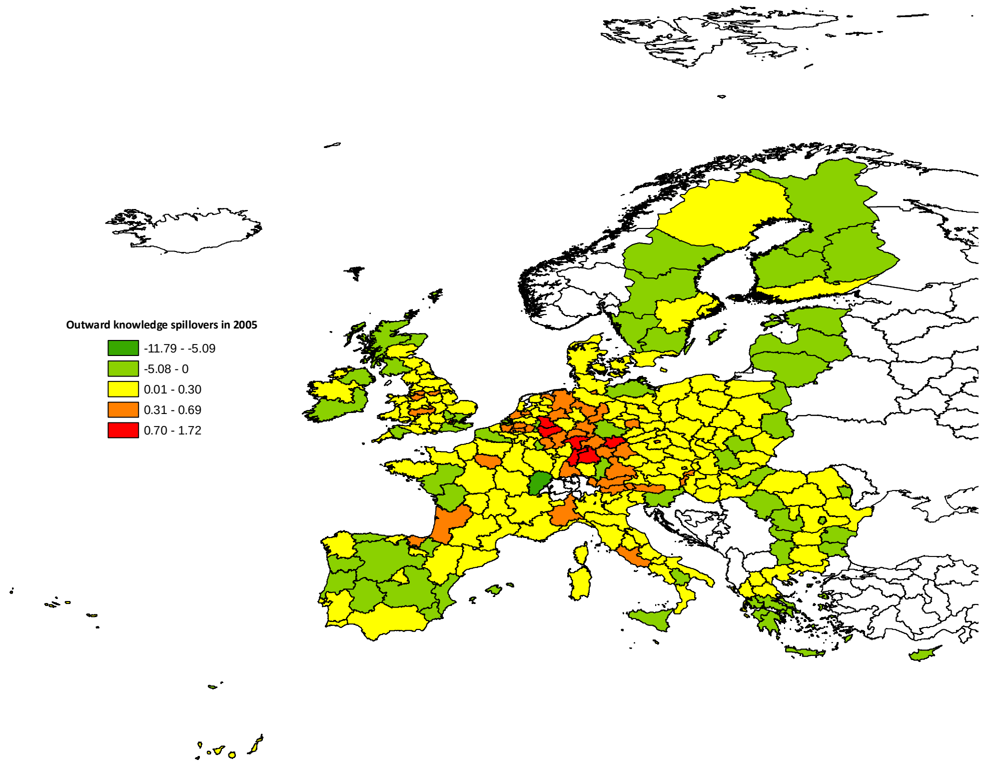

Figure 5 – Outward knowledge spillovers in 2005

The map shows outward KS divided into five subclasses. The first category with values above zero (0.01-0.30) is shown in yellow. The yellow and light red, regions which are net knowledge exporters: this again shows a clear core-periphery pattern, with peripheral regions tending to "import" knowledge from outside, and central regions, in particular the Pentagon area[22], shown in dark red (among the top net knowledge exporters are Ile De France, Oberbayern, Piemonte, Southern Netherlands regions and South Austria).

After this conceptual and empirical exposition, we are now ready to test our main hypothesis. Does higher territorial capital lead to lower outward KS?

[22] The area comprising London, Paris, Milan, Munich and Hamburg. In this core region, productivity and GDP growth are on average the highest among EU regions. It is considered the engine for European growth.

The first equation tested is a simple linear functional form:

$$OKS_{r,t} = \alpha + \beta R\&D_{r,t} + \gamma TC_{r,t} * R\&D_{r,t} + \delta TC_{j,t} + \varepsilon_{r,t}\ , \tag{8}$$

where r =(1…261), j=(all regions: j≠r), t=(1999,…,2006).

Outward KS are measured as described above; R&D intensity is measured by the number of patent applications to the EPO per 1,000 inhabitants; Territorial Capital is proxied by the PCA-built measure indicated in Table 2; and territorial capital in neighbouring regions is measured by its spatial lags. The results of this first test are shown in Table 3:

Table 3 - Estimates on equation (8)

Variable	OLS estimates	
R&D intensity	0.03	0.03(*)
Territorial capital*R&D intensity	-0.02(***)	-0.02(***)
Territorial capital in neighboring regions	0.03(*)	0.03(***)
Constant term	0.001	-
R^2	*0.01*	*0.02*
Number of obs.	*1756*	*1756*

*Notes: * = significant at the 90% level; ** = significant at the 95% level; *** = significant at the 99% level*

At a first glance, this table meets our expectations. With OLS estimates, both the R&D intensity and spatially-lagged territorial capital elements are positive, while the interaction between local cognitive elements in the territorial capital domain is negative. Hence these results suggest that R&D intensity and external territorial capital do exert a positive pull effect on outward KS, while the higher the endowment of local territorial capital, and in particular of its soft, interaction components, the lower outward KS are. Significance associated with the R&D intensity term varies with the exclusion of the constant term, which is also rejected in the larger model. Thus, it is possible that large nonlinearities may determine the optimality of dropping the constant term from the regression.

Fixed effects do not improve estimation precision[23]: this might be caused either by the lack of region-specific effects (which might have been wiped out by including territorial capital elements in the regression) or by the presence of *strong* region-specific effects that have not been correctly modelled. Moreover, an even more natural interpretation might be that most of the variance in the sample is cross-sectional. In this case, most cross-sectional variance would be wiped out by regional dummies, resulting in poor panel estimates[24]. R^2 is low in both estimates, which might reveal some underlying omitted variable bias, an explanation that might be linked to the previous issue. Finally, it is clear that the observations imperfectly represent the whole sample[25]. This should come as no surprise: the original data are available only patchily across regions and countries. The territorial capital measure reflects its determinants, which in turn are based on EVS questions that were unevenly administered in European regions. And, finally, data on the capital stock could not be retrieved on New Member States (namely, Bulgaria and Romania) because of the lack of investment data for these two countries.

Similarly, further use of spatial econometric techniques is no longer needed. By construction, our measure of outward KS takes care of the spatial autocorrelation patterns in the data: hence all

[23] Results are available upon request.

[24] We thank Henri de Groot for this remark.

[25] The total number of observations in the data set is 1827=261 regions times 7 years. When data were missing, linear interpolation has been carried out, when meaningful. More details are explained in the Appendix .

usual tests for the presence of spatial autocorrelation in the dependent variable have a negative outcome[26].

The results are consistent with different choices of the weight matrix. In particular, the first and second coefficient tend to have the same sign and significance when distance is defined according to a queen and rook contiguity criterion, a threshold criterion with respectively, a 500, 1500, and 3,000 kilometre threshold, and a nearest neighbours criterion, k, being set at 4, 30, and 50. Thus, we can safely rely on the consistency of our construction: geographical distance does play a major role in our framework, but is not sufficient *per se* to explain outward KS. On the contrary, the coefficient associated with the interaction term remains remarkably stable. This consistency is not perfect though. The significance of the third coefficient varies with different definitions of distance, which might suggest the need for further inspection of this topic[27]. In particular, we could assess which is the threshold beyond which external cognitive capital fails to exert a pull effect on each region.

6. Conclusions and policy implications

This paper has aimed to provide a bridge between two different, but complementary, approaches: absorptive capacity, and knowledge spillovers (KS).

By identifying a new measure of KS we have tested the assumption that local territorial characteristics help in retaining locally the positive effects of knowledge creation. The relatively low endowment of territorial capital is found to be associated with higher outward KS. Time

[26] For example, the computed Moran's I for the outward KS measure is -.0041.

[27] We thank Laura Resmini for her useful remark on the role of different distance measures in our analysis.

processes are found to be insignificant in the data set, but this last result may crucially depend on the short time span we can observe.

This last observation introduces a crucial issue in our conclusions. We believe that the evidence demonstrating the role of territorial characteristics (including cognitive proximity, relational capital, and a wise management of collective goods) in exploiting knowledge is quite strong. However, from the policy maker's perspective this may not be sufficient. If territorial capital, and, in particular those elements pertaining to the trust and governance domains, only accumulate at a slow pace, investment in such capital may require a long-run perspective which may be at odds with the short-run political cycle.

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Appendix[28] – Results from Principal Components Analysis

Data on soft elements are obtained through the European Values Study[29], a survey conducted across (among others) European countries, with the same questions. As our theory is based on the cognitive approach, we formed a measure of cognitive elements which is based on the conceptual framework described in Camagni (2008). This has been slightly modified to stress the role of cognitive elements in the soft domain of the territorial capital definition. The choice of which social capital measures to include is based on Putnam (2000)[30]. His definition of social capital includes four domains. Each domain is described by questions asked in different surveys and polls administered in US states. Table A1 shows the four domains in Putnam's definition and the questions used to measure social capital.

Our theoretical framework adds to social capital components the variables described in section 3 (Collective goods, transfer of R&D results, governance on land and cultural resources, district economies). To prevent the PCA techniques from skewed (towards social capital components) results, the dataset is built with one single question for each of the four Putnam domains, along with Eurostat data on the other territorial capital variables. Questions from the EVS have been selected to cover all domains. Where data were missing, reasonable substitutions have been carried out. Each question had a scale: as we were interested on strong social capital measures, we calculated the percentage of top answers for each question in each region. Principal component analysis must be performed on a strongly balanced dataset (each gap in a single vector

[28] Our measure of the territorial capital cognitive elements is similar to the one we used in Capello et al. (2008).

[29] Information on this appendix summarizes the content of the EVS website at http://www.europeanvalues.nl.

[30] Putnam (2000), pag. 291.

causing a missing value in the final scores): to obtain a full dataset, therefore, we filled in the missing value for each single vector on which we performed the PCA with the closest (in time or space) data. For example, we substituted the value of the percentage of Units of Arable Land in the Greek island of Kriti (GR43 in the NUTS codification) for 2003 with the 2002 data (which is the most recent available in this case). As an example for spatial proximity, we substituted the value of the patent applications to the EPO in Lincolnshire, UK (NUTS2 code: UKF3) with the neighboring county of Leicestershire, Rutland and Northants (whose NUTS code is UKF2). We chose temporally to spatially close observations when both were available.

Table A1 - Selected questions in the EVS dataset

Domain	Question	Scale	Var. name
Community organizational life	How often spend time in clubs and voluntary associations?	1 every week	**clubmeet**
-		2 once or twice a month	
-		3 a few times a year	
-		4 not at all	
Engagement in public affairs	Participation in any social activity	0-1	**perc_comm**
Community volunteerism	Voluntary work in any community activity	0-1	**volwork**
Informal sociability	Agree that “Most people can be trusted”	1 trust them completely	**trust**
		2 trust them a little	
		3 neither trust nor distrust them	
		4 do not trust them very much	
		5 do not trust them at all	

When neither spatially nor temporally close observations were available we tried some educated guess. Regionalized data on patent applications for Bulgaria and Romania are for example missing:

in that case our variable normalized on regional population comes from averaging patent applications per population in Eastern countries, on the assumption that patenting activity is spatially homogeneous. Table A2 summarizes the questions and the respective scales.

The indicator of cognitive elements within the territorial capital domain is obtained by running a principal component analysis to the above questions, along with the Eurostat data which have been described in Table 2. Table A3 shows the main results for the performed PCA. The first component explains 37% of total variance, which is a good result, given the markedly different indicators that measure the variables in our theoretical framework.

Table A2 - Putnam's measures of social capital in US states

Domain	Putnam
Measures of community organizational life	Served on committee of local organization last year (%)
	Served as an officer of some club or organization in last year (%)
	Civic and social organization per 1,000 population
	Mean number of club meetings attended last year
	Mean number of group membership
Measures of engagement in public affairs	
	Turnout in presidential elections, 1988 and 1992
	Attended public meeting on town or school affairs in last year (%)
Measures of community volunteerism	
	Mean number of times did volunteer work in last year
Measures of informal sociability	
	Agree that "I spend a lot of time visiting friends"
	Mean number of times entertained at home in last year
	Agree that "Most people can be trusted"
	Agree that "Most people are honest"

Source: Putnam (2000)

Table A3 - Principal components /correlation

Component	Eigenvalue	Difference	Proportion	Cumulative
1	2.58855	1.51861	0.3698	0.3698
2	1.06994	0.05727	0.1528	0.5226
3	1.01267	0.04675	0.1447	0.6673
4	0.96592	0.28127	0.138	0.8053
5	0.68465	0.2445	0.0978	0.9031
6	0.44016	0.20205	0.0629	0.966
7	0.23811	.	0.034	1

Table A4 shows instead the relative scores for the components in the eigenvectors we use to measure territorial capital's cognitive elements for the first three components.

Table A4 – Eigenvectors in the PCA

Variable	1	2	3
clubmeet	0.31276	-0.68811	-0.05502
perc_comm	0.52907	0.3186	-0.12205
volwork	0.43161	0.39085	-0.05227
trust	0.44008	0.19671	0.10651
peruaa_	-0.13878	0.33601	-0.04823
wepop_	0.47024	-0.34659	0.0162
popdens_	0.04393	0.02272	0.98255

The three components indicate a marked pattern in our data.

1. Vector one scores high in cognitive elements: frequency of club meetings, engagement in public affairs, trust and our measure of cognitive receptivity (the spatial lags of patent applications to the EPO, here named "wepop_2005"; therefore, we name this vector

"social capital (socap)";

2. The second vector can be characterized by the attention to local areas and governance of natural resources. It shows high values associated again to voluntary work and the percentage of arable land, which is our measure of the attention to the landscape and natural resources[31]. We name this component "rural governance (rurgov)";
3. Finally, the third vector is substantially dependent on our measure of district economies (population density). Therefore our name for the variable is simply "density (dens)".

Spatial patterns of original variables mimic the spatial distribution of our measure of social and relational capital, providing evidence that the choice of the name of the PCA vector was correct. This statement can be supported by inspecting a correlation table with the four components and the questions underlying the PCA (Table A5). All variables are highly correlated with the PCA vector; correlation is between .45 and .85, which justifies our choice of the definition of this vector.

Table A 5 - Linear correlations among social capital measures and the first PCA vector

	clubmeet	perc_comm	volwork	trust	socap_
clubmeet	1				
perc_comm	0.1822	1			
volwork	0.1722	0.6438	1		
trust	0.1718	0.5784	0.3108	1	
socap_	0.4754	0.8546	0.7037	0.715	1

[31] The variable might reflect both this aspect and the productive vocation of the region, i.e. the relevance of the primary sector in the overall regional GDP. However, this is not the whole story. An increasingly smaller share of European regions' GDP comes from agricultural products; also, the percentage of arable land is almost perfectly orthogonal to population density – linear correlation between the two variables equaled -0.0076 in 2005.