The impact of regional absorptive capacity on spatial knowledge spillovers

The Cohen and Levinthal model revisited

Andrea Caragliu‡ - Peter Nijkamp†

Abstract

This paper on regional growth conditions and impacts builds on two strands of literature that are essentially strongly linked. The literature on absorptive capacity identifies characteristics of firms that make it easier to understand and decode information coming from outside in an economically efficient manner. The literature on spatial knowledge spillovers focuses on the channels through which knowledge spills over to surrounding regions.

This paper aims at designing a conceptual framework for linking these two literature strands. Regions produce new knowledge, but only a part of it is efficiently adopted in their real economy. What the effective share of efficiently adopted technology is depends on the local endowment in the territorial capital. The present paper aims at investigating the critical success conditions of territorial capital for regional growth.

In our study we use a new dataset based on a panel of European regions over the period 1999-2005, which combines data from Eurostat, different ESPON projects and the European Values Study in order to test the hypothesis that insufficient levels of territorial capital hamper the capability of regions to understand and fully exploit new knowledge. We develop then a total factor productivity model that also incorporates territorial capital. Spatial econometrics techniques are next used to ensure unbiased estimates of the relevant parameters.

Our 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

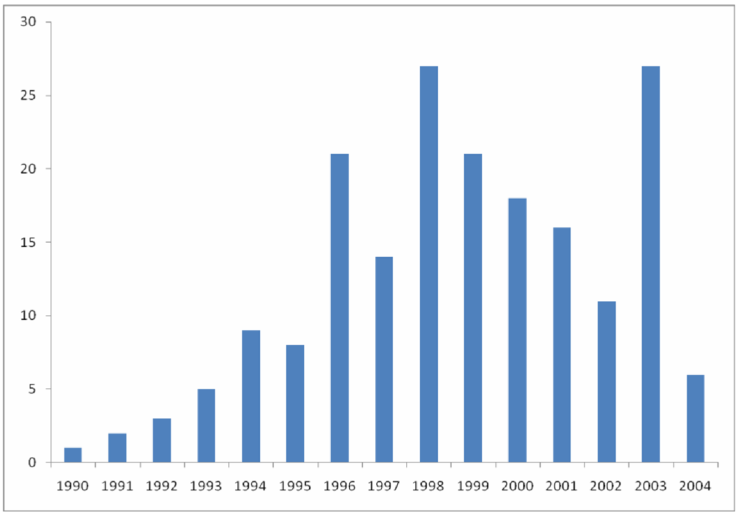
Keywords:

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

1. Introduction

Since the Cohen and Levinthal (1990) (henceforth, 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 April 17th, 2008 JSTOR listed already 189 articles citing CL. Fields in which this concept has been addressed include not only management science but also anthropology, industrial organization, social science and so on.

Figure 1 - Number of citations of Cohen and Levinthal (1990)



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 for regions or countries, but instead on the role of the stock of accumulated knowledge in the capability of a region in identifying and encapsulating 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's one of the largest and most populated regions in an otherwise well developed country. Although its international image reflects sometimes old style stereotypes, the region has undoubtedly also branches of several innovative corporations, including ST Microelectronics, a large chipmaker which

consistently ranks first among the top Italian firms patent in terms of number of patents requests filed to the European Patent Office (henceforth, EPO)[1] and the USPTO[2].

In 2003, the last year for which Eurostat data were reasonably complete, Sicily ranked 148th among European NUTS2 regions for the ratio of Human Resources in Science and Technology, thus obtaining a middle position among the 267 regions in the EU sample, and 170th for the number of patent applications to the EPO as a ratio to total population. Its capital-labor ratio stands at a very high 27th place, its saving rate is around 10%, while its GDP per capita reaches 14965 euro in 2004. All these results suggest that all necessary technical factors that growth theory traditionally identifies as growth enhancing are available in this region, at least not in a lesser extent as in many other European regions.

It is noteworthy, however, that productivity data (see figure 3)[3] 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% of the TFP distribution. Furthermore, in the years 2003-2004 TFP actually *decreased* in Sicily by .92%, which equals a 205th place in the total ranking. Although this result is co-determined by Italy's poor performance, nevertheless even if Sicily's performance is compared only to 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? The questions form the background for the present paper. The answer will be sought in spatial knowledge spillovers and absorptive capacities of regions.

The above questions are linked to Solow's paradox on the new economy, where "*We see the computer age everywhere except in the productivity statistics*"[4]. However, in the case of Sicily the conclusion is even worse: factor accumulation does not show up in Sicily's current performance.

---

[1] Figure 2 depicts the number of patent requests filed to the EPO in 2004. The darker the color, the higher the number of patents per 1,000 inhabitants requested. Sicily is the 3rd range of the distribution, along with other 103 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 of the R&D activity.

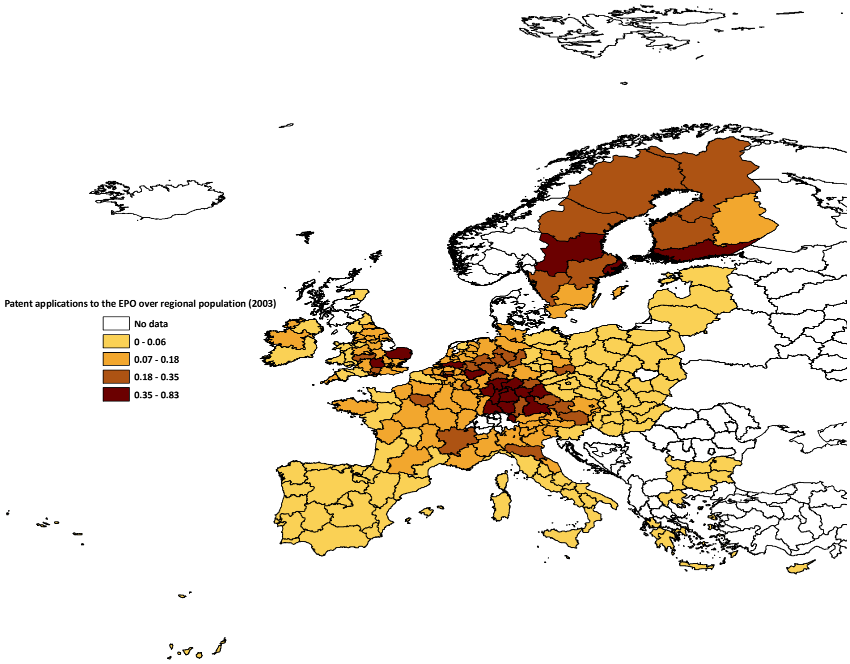
[2] ST Microeletronics ranks first among Italian firms by number of patents granted from the USPTO over the years 2002-2006, with a total of 950 patents, representing more than 18% of the total value for Italian companies. Data source: USPTO, available upon request.

[3] Productivity is measured here as total factor productivity (henceforth, TFP). We calculate it as the residual of a Cobb Douglas production function of the form

$$Y = AK^{\alpha}L^{1-\alpha} \quad (1.)$$

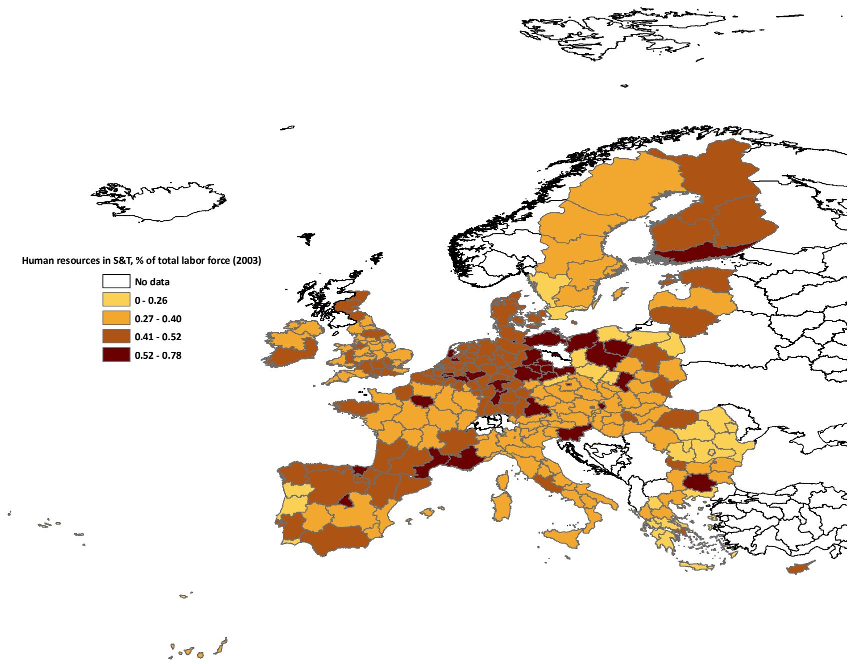
[4] See Solow (1987).

Figure 2 - Number of patents filed to the EPO by regional population (2003)



Source: Eurostat

Figure 3 - Human resources in Science and technology, as percentage of total labor force (2003)



Source: Eurostat

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 a more and more globalized world, is not sufficient anymore 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.

In turn, this capability depends clearly on the area's endowment with territorial capital. Territorial capital is the set of all local, spatially bounded characteristics that determine an area's capability to grow. In particular, it encompasses all "soft" components (social, relational and human capital above all) that determine a society's quality, and the density and efficiency of its members' interactions[5]. It seems plausible that Sicily's (and with it, that of several other European areas) insufficient endowment of territorial capital causes locally produced knowledge to spill over to surrounding competing areas. To provide evidence supporting this proposition we will develop here a simple econometric model and test it on a sample of 267 European regions.

The paper is structured as follows. In the second section we review highlights from the main literature on the topic. In section 3 we will present a conceptual and theoretical framework. In the fourth section we show empirical results from a modeling experiment. Finally, we draw conclusions and suggest some relevant policy implications.

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*"[6].

Development of effective absorptive capacity requires more than a mere exposition to and familiarization with the relevant prior knowledge. Learning crucially depends first of all on the

[5] Camagni (2008) provides a comprehensive overview on the theoretical framework behind the concept of territorial capital. In Capello et al. (2008) the role of this concept as a determinant of increasing returns in local knowledge is tested.
[6] Cohen and Levinthal (1990), p. 129.

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 more aggregate entities such as regions should not 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 authors combine two British firm-level datasets 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 behaviours are all positively associated with an increase in regional innovation performance. Their study, however, is still lacking part of our scope. 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 useful to firms in other regions or countries, more 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) model. The authors reconnect to the literature on direct and indirect effects, which forms the basis of our measure of outward spillovers. Although both 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 optima l knowledge investment is thus an issue 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 as well be creative adoption of existing knowledge (for instance, the use of satellite phones by Serbian troops as a device of communication overcoming the destruction of their fixed phone lines by the opponents' coalition), new and more efficient managerial techniques (Toyota's *Just in time* system), 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 way longer. Clearly, patents are not the only measure of innovative activities in a country. That's why we resort to a different measure of technological change, i.e. Total Factor Productivity (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 labor; 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 knowledge spillovers (henceforth, 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 local labor force cannot fully exploit, where do the positive effects take place?

The KS theory, which laid its foundations in the empirical industrial organization in the '80s, assumes that, although knowledge is a public good, appropriability may be imperfect. In Michael Spence's words (See Spence 1984): *"imperfect appropriability means that a fraction of each firm's research leaks out"*

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 knowledge spillover? 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 has been 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, pag. 16). Hence, KS require the passage of knowledge in non-marketed form so that somebody using knowledge created elsewhere or by somebody else cannot be subject to trial. 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 knowledge spillovers entails a link between the productivity growth of an organization j and a measure of the innovative activity of some other organization i, having with j some type of relationship. 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, labor force pooling and (drawing only recent attention) migrations.

Among patent measures, Bernstein and Nadiri (1988) devise a measure of the pool of research activity available to a firm with the (unweighted) sum of R&D expenditures of other firms in the same industry; Jaffe (1986, 1989) uses patent applications to construct a measure of similarity of research activities and then calculates 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 would resemble that of Jaffe et al. (1993), we would need to construct complex and cumbersome datasets with citations classified according 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 dataset on an alternative scale.

Another possible drawback from 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[7]. Knowledge is actually a more complex phenomenon, assuming different forms and being spread with alternative carriers. Blumentritt and Johnston (1999), for example, define knowledge according to four categories. Table 1 shows their conceptual scheme.

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

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 statements 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 knowing about *Blackler* **Experiential knowledge** what was Context dependent knowledge *Millar* **Informal knowledge** **Meta 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 combining sentient or sensory info and physical cues Knowledge how or knowledge by acquaintance (craft skills) only partly 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 embodied knowledge depending on their content

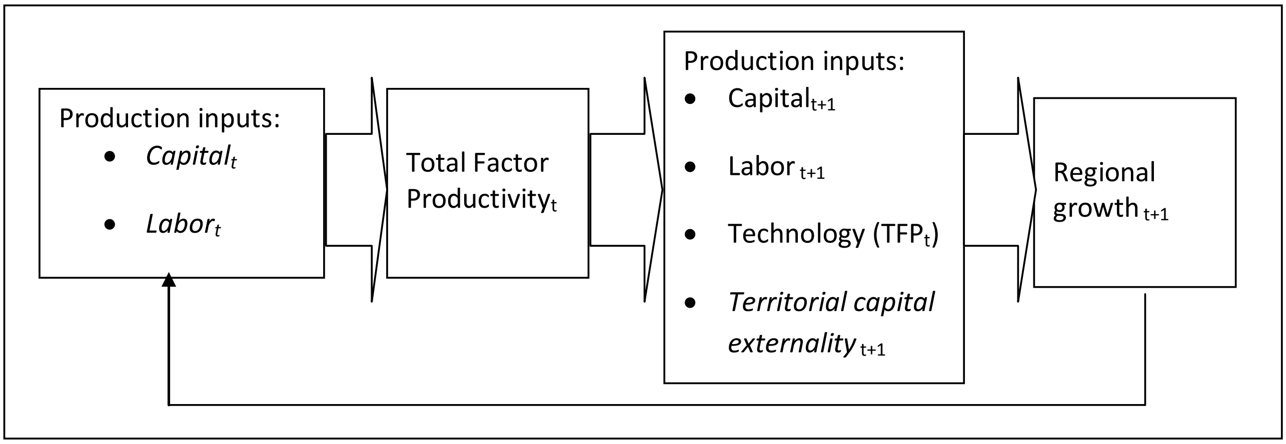
Source: Blumentritt and Johnston (1999)

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, all these elements 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 don't refer to any specific form of knowledge, but instead try to capture all possible spillover effects of local (lack of) skills towards surrounding areas.

3. A framework for knowledge spillovers

The question to be searched 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. This can be simplified as in the following scheme (figure 2).

Figure 4 - Theoretical flow chart underlying Capello and Caragliu (2008)



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

The established literature usually finds that knowledge spillovers are facilitated by geographic proximity and by human capital endowment of areas under consideration. 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 in this case needed. Socio-economic proximity, for example, or cultural and relational proximity make the spatial component of this problem more complex to represent and interesting to inspect. 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 coming not only from outside, but also locally produced.

Traditional management science studies find that higher human capital leads to a higher capability of firms to understand and decode new knowledge. In this context the abovementioned study by Cohen and Levinthal (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 explained 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 knowledge spillovers. Its seems therefore plausible that we may formulate a general framework model of the following nature:

$$\text{Outward spillovers}_i = f\,(\text{Innovation}_i\,,\ \text{Innovation}_i * \text{territorial capital}_i\,,\ \text{territorial capital}_j) \qquad (2.)$$

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 certainly gives scope for outward spillovers;
- 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 inside the positive effects of local innovation;
- A positive sign for surrounding areas endowments, in line with what the absorptive capacity literature suggests.

Empirical estimation can be carried out with spatial panel techniques. We will use in our application the NUTS2 level for European regional data.

4. The measure of outward knowledge spillovers and the dataset

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;
- Efficiency scores.

Patents are a common and much utilized measure of technical change. Also, 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 patents' several qualities (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[8];
- They are standardized;
- They must pass novelty inspection by peers[9].

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 gauged 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 to this spatial lag might represent a good measure of outward knowledge spillovers. How this new measure is built is explained below.

Finally, efficiency scores can be obtained by applying the nonparametric technique of the efficient 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 above mentioned, to measure outward spillovers.

TFP has been criticized on the basis of its very nature[10]. Its shortcomings include the following issues:

1. GDP–related measures, including TFP, would dramatically *understate* quality improvements. This critique is nevertheless inconsistent with its own implications. Quality adjustments implied by intertemporal comparisons between similar objects, for

[8] We thank Henri De Groot for this remark he gave us in a common discussion.
[9] For a comprehensive review of pros and cons of using patent data, including our second and third point, see Griliches (1990).
[10] Hulten (2000) represents a good introduction to this measure, at the same time summarizing its qualities and shortcomings.

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 environmental fallouts of modern intensive economies and their required natural resources exploitation. Then the question, having this critique reached a consistent climax[11], is "Where does the real situation lie?" 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

$$\ln(y) = \alpha \ln(k) \qquad (3.)$$

where lowercase letters indicate as usual variables divided by the labor force[12]. Figure 5 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, 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 .43 for the 2005 TFP data[13],[14].

The innovative component of this database is our measure of outward knowledge spillovers.

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. Total Factor Productivity, on the contrary, shows the efficiency with which physical factors are combined. As

[11] The Atlantic Monthly once showed 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 due to Hulten (2000). See Cobb (1995).

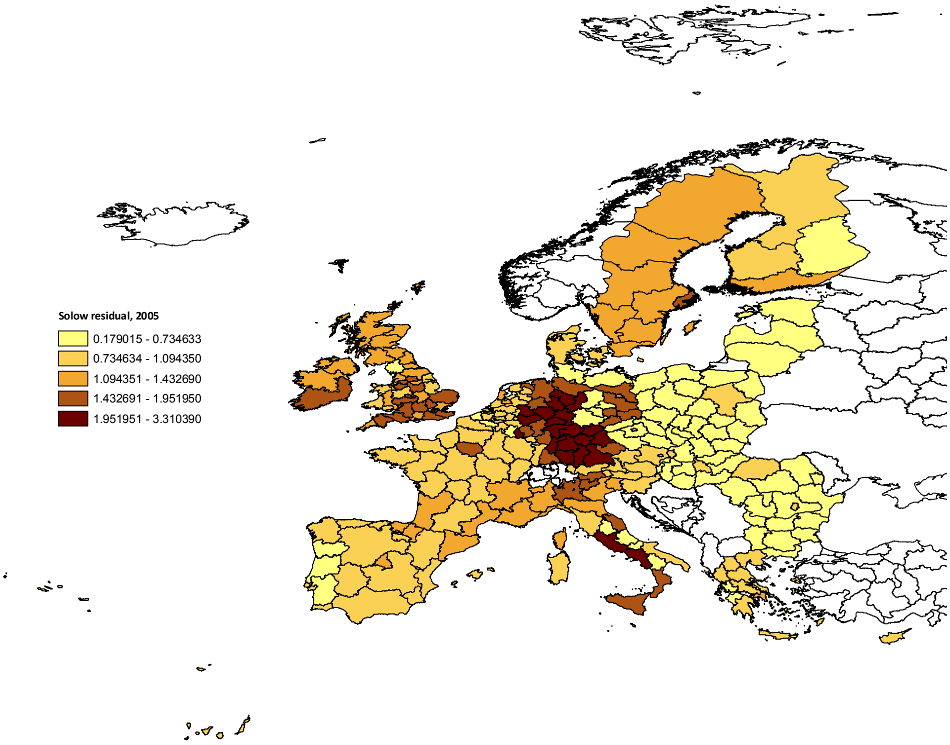
[12] The log-linear transformation allows us to estimate a Cobb-Douglas production function of the form $Y = AK^{\alpha}L^{1-\alpha}$

[13] Randomization with the GeoDA application yields a pseudo p-value of .001. 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.

[14] More details on spatial patterns in productivity levels can be found in appendix.

such, it measures not only the outcome of the R&D production process, but also improvements in managerial and organisational techniques, creativity, growth of tacit knowledge and all non-technical change factors that contribute to improved economic efficiency.

Figure 5 - Total factor productivity in NUTS2 regions, 2005



Productivity in turn can be explained by a set of determinants. This approach is typically referred to as "knowledge production function"[15]: it usually entails studying the relationship between R&D inputs and output (measured with 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 to building our measure of outward knowledge spillover.

In this study we TFP actually proxies for generic regional knowledge. Here TFP is used as a measure of 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

[15] See Griliches (1979) and Pakes and Griliches (1984) for basic reference on this approach.

$$Y = X\beta + \varepsilon \qquad (4.)$$

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[16]. This can be done with two main models: the spatial lag and the spatial error model. In this case the first can be preferred: it is reasonable to assume that productivity levels are correlated across space, as input-output mechanisms, labor force pooling, educational attainments, human and social capital, (all of which can be embodied in the new concept of territorial capital) determine final productivity and can be demonstrated to clustered in space. Eq. (4.) then reads as follows:

$$Y = \rho WY + X\beta + \varepsilon \qquad (5.)$$

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 one in absolute terms implies that spatial correlation becomes bigger and bigger the longer the distance.

Eq. (5.) cannot be estimated: the dependent variable is also in the right-hand side. To obtain an estimable function we must rearrange terms in the usual way, i.e. bring move 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:

$$\begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ 0 & \dots & \dots & 0 \\ 0 & 0 & \dots & 1 \end{pmatrix} - \hat{\rho} \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \dots & \dots & \dots & \dots \\ w_{n1} & \dots & \dots & w_{nn} \end{pmatrix} \qquad (6.)$$

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

where $\hat{\rho}$ is the (estimated) autocorrelation parameter[17] and w_{ij} represent distance values among European regions. Eq. (6) shows that the result of this calculation is a (nXn) matrix[18]. This matrix, after being inverted, transforms each variable in the X matrix into the contribution to and from each region towards the dependent variable. In other words, it can be interpreted asd a sort of input-output matrix, where each element shows the weight to be associated to each observation in the vectors stacked in the X matrix 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 uppercase letter B from the word meaning "weight", takes on the form

$$(I-\hat{\rho}W)^{-1} = \mathrm{B} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & \dots & \dots & a_{nn} \end{pmatrix} \qquad (7.)$$

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

$$TFP_{r,t} = \beta_0 + \beta_1 HRST_{r,t} + \beta_2 H_{r,t} \beta_3 FD_{r,t} \beta_4 INST_{r,t} \qquad (8.)$$

In eq. (8.) variables are respectively Human Resources in Science and Technology, Human Capital, Financial Development and Quality of Institutions (all measured in 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, entries in rows represent contributions of HRST in each region to the analyzed region's TFP.

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 surrounding regions' productivity or the extent to which each region's productivity spills over neighbors.

---

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

[18] Provided that the weight matrix is constant over time, an assumption which seems reasonable over a 7 years time span as this dataset.

4.2 The dataset

Our dataset comprises data on 260 European NUTS2 regions. Data have been collected from three main sources:

1. Eurostat (NUTS2 data on regional GDP, population, labor force, gross fixed capital formation);
2. ESPON database (detailed information on transport infrastructure in European regions);
3. European Values Study (Comprehensive survey on Europeans and their beliefs about broad life categories, including trust, religion, politics, society and so on).

The dataset comprises the following variables (Table 2):

Table 2 - The dataset

Variable	Raw data	Source
Outward knowledge spillovers	Y: regional GDP in constant prices	Eurostat
	K: stock of capital estimated with the perpetual inventory method	Eurostat
	L: regional labor force	Eurostat
R&D intensity	Patent applications to the European Patent Office per 1,000 inhabitants	Eurostat
Territorial capital	PCA on the following five components[19]:	Eurostat; European Values Study; ESPON project 1.2.1
	1. Collective goods/landscape: percentage of arable land (proxy of the intensity of agricultural soil use and quality of maintenance)	Eurostat
	2. Transfer of R&D results: spatial lags of patent applications to the European Patent Office	Eurostat (spatial lags: own calculations)

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

	over regional population	
	3. Governance: average regional percentage of tax evasion (proxy to the quality of regional management)	European Values Study
	4. Agglomeration and district economies: population density	Eurostat
	5. Relational capital: average regional availability to help own neighbors or fellow region's citizens	European Values Study

This study uses the concept of territorial capital as a novel way through which space is modeled. 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 knowledge spillovers to surrounding areas.

Our ex ante choice of the determinants of outward knowledge spillovers can be related to the literature on economic growth. Traditional neoclassical economics has oftentimes focused on the role of factor accumulation in explaining long run economic performance (Solow 1956 and 1957; Swan 1956; Mankiw, Romer and Weil 1992). Only at later stages the literature on human capital has started to stress the role of soft elements in explaining how efficiently hard components (capital, labor, land, and infrastructure) are combined[20]. More recently endogenous growth theorists found a way to incorporate externalities in constant returns to scale growth models. Theoretically speaking, these externalities are conceived as the mechanisms magnifying the effects of factor accumulation. Practically, they have been identified, among many cases, in aggregate human capital (for example, Lucas 1988) and R&D (Romer 1990).

We believe these to be only partial explanations to 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

[20] see Becker 1964 for a comprehensive summary of the research on the role of human capital in economic interactions

collective goods, district economies in shaping the chances that regions have to retain within themselves the positive effects of new knowledge.

5. Empirical results

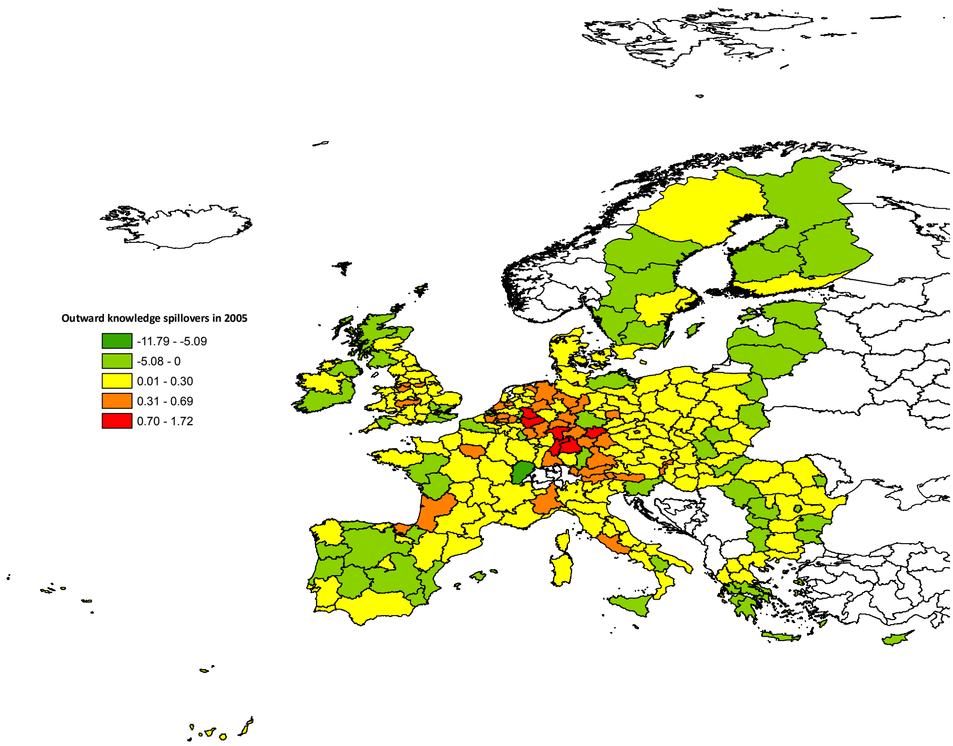
Outward knowledge spillovers in our opinion depend on a set of variables, as pointed out in Section 3. However, not all of them are expected to have the same impact on the final outcome. Knowledge spillovers are expected to heavily depend on regional innovation inputs. The higher the expenditure and 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 neighbors being highly committed to R&D. Their proximity represents a positive externality and should translate into higher productivity levels even in neighboring regions. This variable is expected to have the strongest effect on outward spillovers.

However a minor, albeit 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 detriment the efficient understanding and exploiting of this knowledge (La Porta et al. 1997). Thinness of social networks might provide disincentives to fluid and efficient transfer of knowledge, and hamper 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 didn’t 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 knowledge spillovers. By the same token, a high endowment of territorial capital cognitive elements might help regions in retaining positive effects of R&D activity in the local economy. This effect is expected to be of a smaller magnitude than R&D expenditure.

Territorial capital might also work as a force contrary to locally retaining knowledge: if neighboring regions have a higher endowment of territorial capital, provided that space imposes a lesser impedance to knowledge transfer, they might be more apt in understanding and decoding new local knowledge. Hence, neighbors’ territorial capital is expected to exert a positive influence (pull effect) on outward knowledge spillovers.

Our measure is a weighted sum of the regions' relative TFP contributions to and from neighbors. 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 knowledge spillovers. If the variable is negative the region should be a net knowledge recipient. Map 4 represents this measure for the last available year (2005).

Figure 6 – Outward knowledge spillovers in 2005



The map shows OKS divided into five subclasses, zero being represented with a yellow color. From yellow to red regions are net knowledge exporters: this again shows a clear core-periphery pattern, with peripheric regions tending to "import" knowledge from outside and central regions, in particular in the Pentagon area, displaying darker red (among the top net knowledge exporters, 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 knowledge spillovers?

The first equation tested is a simple linear functional form

$$OKS_{r,t} = \alpha + \beta R \& D_{r,t} + \gamma TC_{r,t} * R \& D_{r,t} + \delta TC_{j,t} + \varepsilon_{r,t} \quad (9.)$$

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

Outward Knowledge Spillovers 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 with the PCA-built measure indicated in Table 2 and territorial capital in neighboring regions is measured with its spatial lags. The results of this first test are shown in Table 3:

Table 3 - Estimates on equation (9.)

Variable	OLS estimates	FE estimates
R&D intensity	.34 (***)	.03
Territorial capital*R&D intensity	-.36 (***)	-.15
Territorial capital in neighboring regions	.18 (***)	.14 (**)
Constant term	.10 (***)	.13 (***)
R^2	*.0541*	*within = 0.0014* *between = 0.0282* *overall = 0.0281*
Number of obs.	*477*	*477*

*NB: * = 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 and significant, 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 OKS, while the higher the endowment of local territorial capital, and in particular of its soft, interaction components, the lower outward knowledge spillovers are.

However a first caveat arises from the third column in Table 3. Although the magnitude and sign of the coefficients does not vary, the estimated parameters for R&D intensity and the interacted term (Territorial capital*R&D intensity) become insignificant (the p-value is respectively 0.259 and 0.335). This failure of fixed effects to improve estimation precision might

be due either to the lack of region-specific effects (which might have been wiped out by including territorial capital elements in the regression[21]) or on the contrary to the presence of *strong* region-specific effects that have not been correctly modeled. 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[22]. R^2 is quite low in both estimates, which might reveal some underlying omitted variable bias, a suspicion that might be reconnected to the previous issue. Finally, observations are clearly only partially representing the whole sample[23]. This should come as no surprise: the original data are unevenly available 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) due to the lack of investments data for these two countries.

6. Conclusions and policy implications

This paper aimed at offering a bridge between two different, but complementary, approaches: absorptive capacity and knowledge spillovers.

By identifying a new measure of knowledge spillover we have tested the assumption that local territorial characteristics help retaining locally the positive effects of knowledge creation. The relatively low endowment of territorial capital is found to be associated with higher outward knowledge spillovers. Time processes are found to be insignificant in the dataset, 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, a wise management of collective goods) in exploiting knowledge is quite strong. However, from the policymaker's perspective this may not be sufficient. If territorial capital, and in particular elements pertaining to the trust and governance domains, would 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.

[21] Computed Moran's I for the outward knowledge spillovers measure is -.0041.

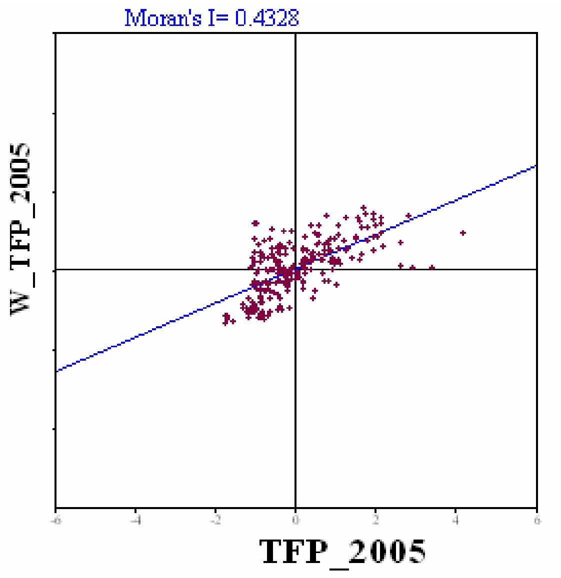
[22] We thank Henri De Groot for this remark.

[23] The total number of observations in the dataset is 2088=261 regions times 8 years: thus the estimates in table 3 exploit only about ¼ of the dataset.

Appendix A – Spatial autocorrelation issues in the dataset

A graphical inspection of maps figures 2, 3 and 5 suggests the clear presence of spatial autocorrelation in the data. This statement is supported by the values of the Moran's I statistic (figure 8).

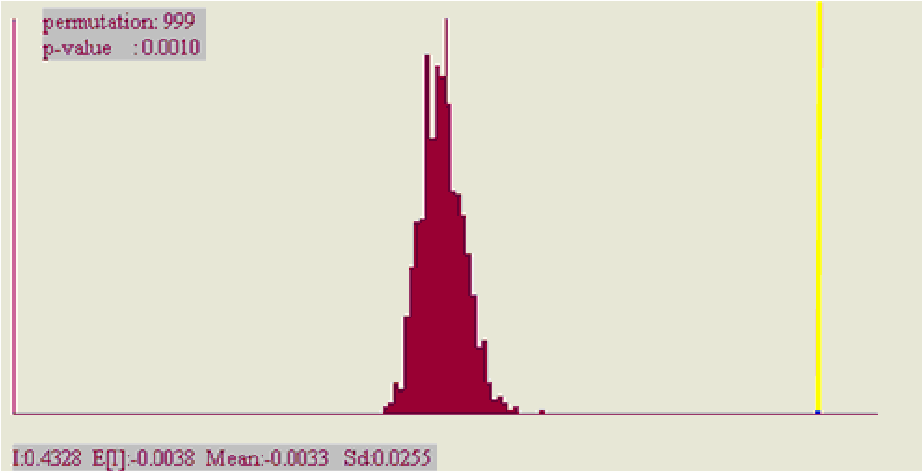
Figure 7 - Moran's I scatterplot on 2005 TFP levels in EU27 NUTS2 regions



Inference for Moran's I is based on a permutation approach, in which a reference distribution is calculated for spatially random layouts with the same data as we observe[24]. The randomization uses an algorithm to generate spatially random simulated data sets first described in Anselin (1986). The observed Moran's I is shown as a yellow bar, while the pseudo-significance level (0.001) is computed as the ratio of the number of statistics for the randomly generated data sets that are equal to or exceed the observed statistic plus one, over the number of permutations used plus one. Hence, the value of 0.001 in figure 9 indicates that none of the simulated values were larger than the observed .43.

[24] This section is based on Anselin (2003).

Figure 8 - Permutations and pseudo-significance of the Moran's I statistic on 2005 TFP levels



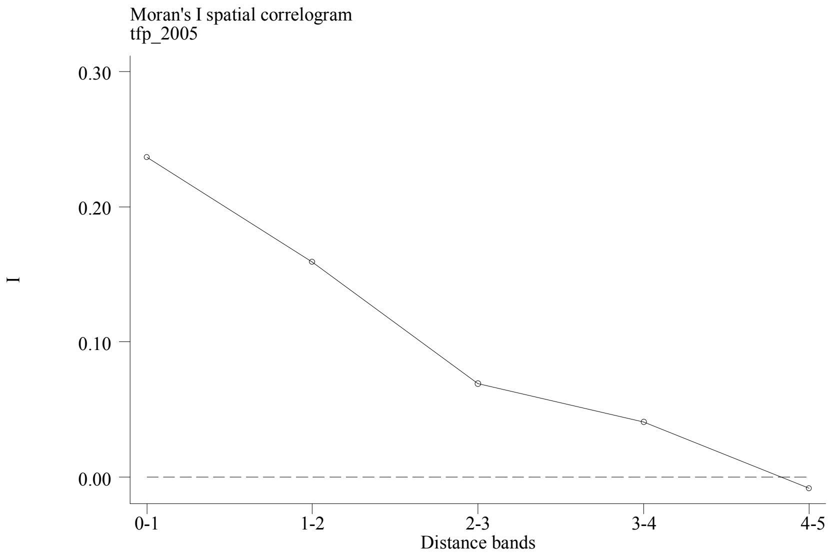
The calculated Moran's I is based on a queen second order weight matrix. Data are based on 2005 productivity levels; however, results do not vary significantly if we perform similar calculations in the previous years (Table 4).

Table 4 - Global Moran's I for productivity levels in 1999-2005

Year of TFP calculation	Global Moran's I
1999	0.3676
2000	0.4102
2001	0.4155
2002	0.5331
2003	0.4736
2004	0.4588
2005	0.4328

The Stata spatial package described in Pisati (2001) allows further inquiries into spatial issues of our dataset; in particular we can assess how much of our conclusions depend on the choice of the distance. The choice of the distance measure is not always self-evident. Here we assume that a second-order distance measure represents the (average) distance decay effect that productivity levels have. With Pisati's toolbox we can test the consistency of our conclusions by changing the definition of distance and then performing again the calculation of the Moran's I statistic.

Figure 9 - Values of the Moran's I with different definitions of distance



We can actually plot the values of the Moran's I statistic when different thresholds are used in defining the weight matrix. As a result (Figure 10) we obtain a downward sloping graph which shows that up to the 4th order contiguity definition data are characterized by positive spatial autocorrelation (this is based again on 2005 data, but similar results have been obtained on the rest of the dataset). Table 5 shows calculated values for the Moran's I statistic as the distance threshold varies. Slight differences when the statistic is calculated with Stata instead of GeoDA depend on the use of different routines in defining the weight matrix.

Table 5 - Moran's I statistics with different distance thresholds

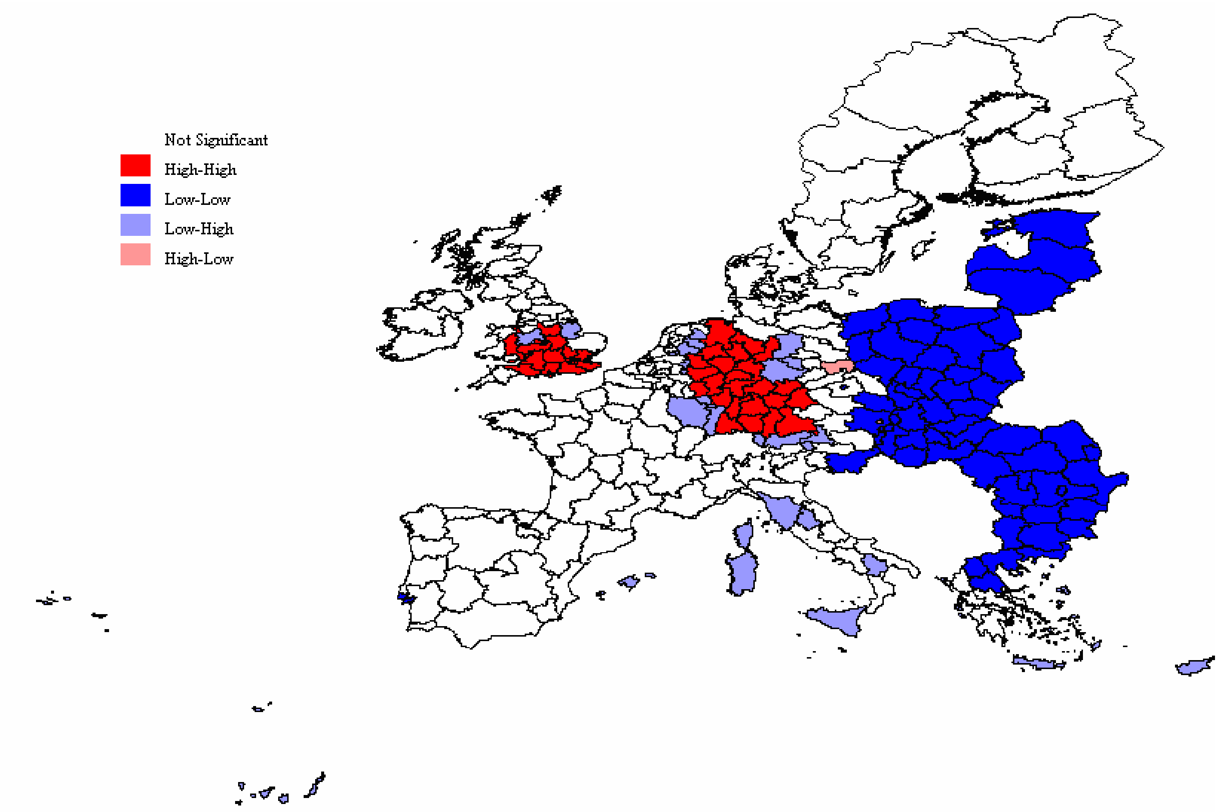
Distance bands	I	E(I)	sd(I)	z	p-value
(0-1]	0.236	-0.004	0.034	6.983	0
(1-2]	0.159	-0.004	0.029	5.634	0
(2-3]	0.069	-0.004	0.023	3.11	0.001
(3-4]	0.041	-0.004	0.025	1.794	0.036
(4-5]	-0.008	-0.004	0.021	-0.201	0.42

Table 5 shows that up to the (3-4] interval positive and significant spatial autocorrelation affects productivity levels.

So far we just demonstrated that spatial autocorrelation is positive and statistically significant. However, we still can't state where productivity clusters (be they positive or negative) are. Anselin (1995) introduces Local Indicators of Spatial Autocorrelations (henceforth, LISA). This technique can be used to identify spatial clusters of the underlying variable. Map 5 shows the result of this analysis performed on 2005 TFP levels.

Results show quite clearly that positive clusters of high productivity (i.e. regions with high TFP levels surrounded by regions with similarly high TFP levels) can be found in the heart of Germany and in South East England, in this latter case probably driven by the outstanding values of the London region. On the contrary, most new member states regions form a cluster of low productivity levels

Figure 10 - LISA on 2005 productivity levels



Although this situation might look troublesome from the policymaker's perspective: under a regime of social cohesion objectives, wide productivity differentials across space are not welcome. However, a more careful look in the data shows that this issue might be less relevant in perspective than what Figure 10 currently shows.

Figure 11 - Productivity levels convergence: TFP 2004-2005 vs 1999 levels

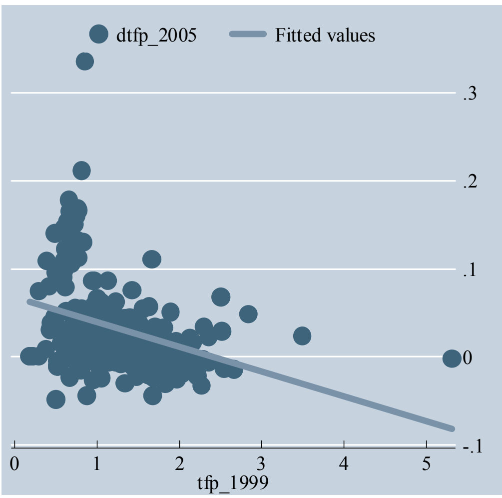
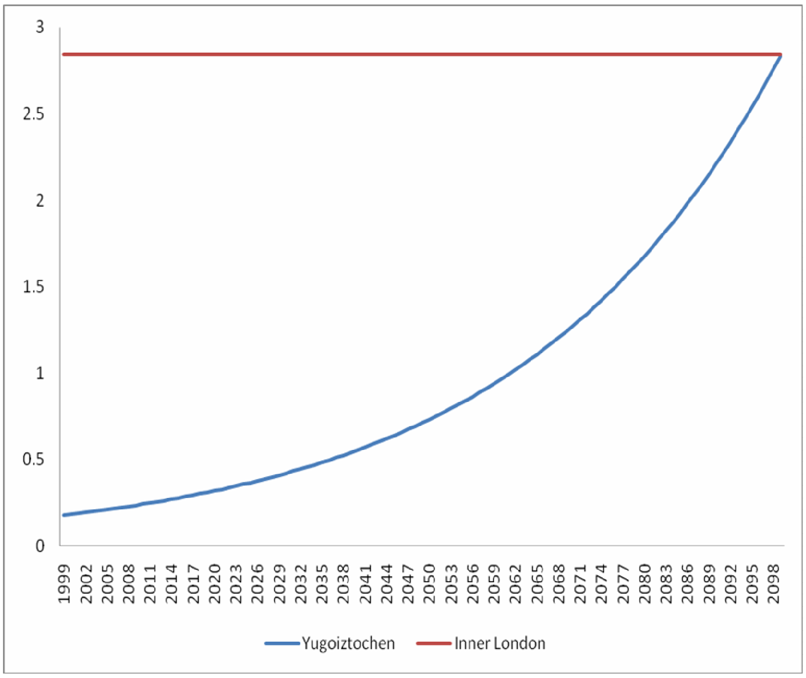


Figure 11 plots the change in productivity levels in 2004-2005 (calculated as the log difference) against the initial (1999) TFP level. A convergence process is clear: least productive regions (most notably eastern EU regions) display a higher productivity change over the sample period, the convergence coefficient being quite big, and around 2.8% per year. If this rate would be carried on indefinitely, the least productive region in the sample, Yugoiztochen in Bulgaria, would catch up with the most productive region, Inner London in UK, by the end of the century. This process is shown

in Figure 12.

Figure 12 - Productivity convergence: the catch up is complete before 2100[25]



Appendix 2[26] – Results from Principal Components Analysis

Data on soft elements are obtained by the European Values Study[27], a survey conducted across European countries, with the same questions. Our datasets is based on averaging across regions answers to the following questions (Table 6):

Table 6 - Selected questions from the EVS

Variable	Question	Scale
v244	According to you, how many of your compatriots cheat on taxes?	1-4
v277	Would you be prepared to actually do something to improve conditions of people living in your neighborhood/community?	1-5

[25] Data show that actually the Campania region is the highest productivity region of the sample. However we dismiss its value due to likely problems of capital stock and labor measurements, in turn due to the extent of the black labor market.

[26] Our measure of the territorial capital cognitive elements is the same as in Capello et al. (2008).

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

The indicator of cognitive elements within the territorial capital domain is obtained by running a principal component analysis to the above questions and the three variables from the Eurostat database that have already been defined in Table 2. Table 7 shows the results of the PCA.

Table 7 - Principal components /correlation

Number of observations = 103

Number of comp. = 5

Trace = 5

Rotation: unrotated principal

Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.52141	0.413137	0.3043	0.3043
Comp2	1.10827	0.0790951	0.2217	0.5259
Comp3	1.02918	0.205002	0.2058	0.7318
Comp4	0.824174	0.307202	0.1648	0.8966
Comp5	0.516972	.	0.1034	1

Table 8 shows instead the relative scores for the components in the eigenvectors we use to measure territorial capital's cognitive elements.

Table 8 – Eigenvectors in the PCA

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Percentage of arable land	-0.6181	0.1546	-0.2237	0.4401	0.5919	0
Spatial lags of patent applications to the EPO	0.4063	0.4552	-0.3828	0.6239	-0.3031	0
Average regional cheating on taxes (As perceived by interviewed people in the EVS)	0.1684	0.1786	0.8737	0.3815	0.1758	0
Population density	0.6488	-0.2584	-0.2002	-0.0233	0.6867	0
Average regional interest in fellow region's citizens as stated by people interviewed in the EVS	0.0589	0.8187	0.0013	-0.5206	0.2352	0

Principal component analysis must be performed on a strongly balanced dataset (each gap in a single vector 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 preferred temporally to spatially close observations when both were available.

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 relatively spatially homogeneous.

Reference

Abreu, M., Grinevich, Vadim., Kitson M. and Savona M. "**Absorptive capacity and regional patterns of innovation**", *DIUS RR-08-11*, 2008.

Abreu, M., De Groot, H., and Florax, R.J.G.M. "**Spatial patterns of technology diffusion: an empirical analysis using TFP**", *Tinbergen Discussion Paper 04-079/3*, Amsterdam-Rotterdam (2004).

Agarwal, R., Echambadi, R., April, F. and Sarkar, M.B. "**Knowledge transfer through Inheritance: spin-out generation, development and performance**", *Academy of Management Journal*, Vol. 47(4): 501-522 (2004).

Aghion, P. and Howitt, P. "**A model of growth through creative destruction**", *Econometrica*, Vol. 60, No. 2 (Mar., 1992), pp. 323-351.

Anselin, L. "**GeoDa™ 0.9 user's guide**", Spatial Analysis Laboratory, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign: 2003.

Anselin, L. "**Inteprpretation of the Moran's I**", Interuniversity Consortium for Political and Social Research video excerpt from the ICPSR workshop "*Introduction to spatial data analysis"*, July 2001. Retrieved on June 5th, 2008 at the URL http://www.csiss.org/streaming_video/icpsr.htm.

Anselin, L.. "**Local indicators of spatial association — LISA**", *Geographical Analysis* 27: 93–115 (1995).

Anselin, L. "**MicroQAP: a microcomputer implementation of generalized measures of spatial association**", *Working Paper, Department of Geography*, University of California, Santa Barbara (1986).

Arrow, K. J. "**Economic welfare and allocation of resources for invention**", in National Bureau Committee foe Economic Research, "*The rate and direction of inventive activity: economic and social factors*", Princeton, NJ: Princeton University Press (for the NBER), 1962.

Becker, G. S. "**Human capital: a theoretical and empirical analysis, with special reference to education**", Chicago: University of Chicago Press (1964).

Bernstein, J. I. and Nadiri, M.I. "**Investment, depreciation, and capital utilization**", *Working Paper 2571* (1988), National Bureau of Economic Research, Cambridge, Massachusetts.

Beugelsdijk, S. and van Schaik, A.B.T.M. "**Social capital and growth in European regions: an empirical test**", *European Journal of Political Economy* 21.2, p. 301-324 (2005).

Blumentrit, R. and Johnston, R. **"Towards a strategy for knowledge management",** *Technology Analysis & Strategic Management;* Sep 1999; Vol. 11- 3, pp. 287-300.

Camagni, R., "**Regional specificities: towards a theory of territorial capital**", in "*Modelling regional scenarios for the enlarged Europe: European competitiveness and global strategies*", Capello,-Camagni-Chizzolini-Fratesi (eds.), Springer –Verlag, Berlin 2008.

Capello, R., Caragliu, A. and Nijkamp, P. "**Territorial capital and regional growth: increasing returns in local knowledge**", paper presented at the International workshop on "*Human capital, social capital and creative capital as sources of regional growth*", Tinbergen institute, 30 June-1 July, 2008.

Cobb, C., Halstead, T. and Rowe, J. "**If the GDP is up, why is America down?**", *The Atlantic Monthly*, 276, 4,

October 1995, 59-78.
Cohen W., and Levinthal, D. "**Absorptive capacity: a new perspective on learning and innovation**" *Administrative Science Quarterly* 35(1) pp 128-152.
Easterly, W. and Levine, R. "**It's not factor accumulation: stylized facts and growth models**", *World Bank Economic Review*, Volume 15, Number 2, 2001.
Griliches, Z.. "**Patent statistics as economic indicators: a survey**", *Journal of Economic Literature*, Vol. 28, No. 4. (Dec., 1990), pp. 1661-1707.
Griliches, Z.. "**Issues in assessing the contribution of research and development to productivity growth",** *The Bell Journal of Economics*, Vol. 10, No. 1. (Spring, 1979), pp. 92-116.
Grossman, G.M. and Helpman E. **"Innovation and growth in the global economy**", MIT Press: Cambridge (MA), 1992.
Hitt, M. , Ireland, D. , Camp, M. and Sexton, D. (eds), "**Strategic entrepreneurship**: **creating a new mindset**", Blackwell: Oxford, 2002.
Hulten, C. "**Total factor productivity: a short biography**", *Working Paper 7471* (2000), National Bureau of Economic Research, Cambridge, Massachusetts.
Jaffe, A.B. **"Real effects of academic research**" *The American Economic Review*, Vol. 79, No. 5 (Dec., 1989), pp. 957-970.
Jaffe, A.B. **"Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value",** *Working Paper 1815* (1986), National Bureau of Economic Research, Cambridge, Massachusetts.
Jaffe, A.B. and Trajtenberg, M. "**International knowledge flows: evidence from patent citations**", *Working Paper 6507* (1998), National Bureau of Economic Research, Cambridge, Massachusetts.
Jaffe, A. B. , Trajtenberg, M. and Henderson, R. "**Geographic localization of knowledge spillovers as evidenced by patent citations**" *The Quarterly Journal of Economics*, Vol. 108, No. 3, (Aug., 1993), pp. 577-598.
La Porta, R., López-de-Silanes, F., Shleifer, A. and Vishny, R. "**Trust in large organizations**", *American Economic Review Papers and Proceedings*, May 1997. Reprinted in P. Dasgupta and I. Serageldin, eds. *Social capital: a multifaceted perspective*, Washington, DC: The World Bank, 1999.
Lucas, R. "**On the mechanics of economic development**", *Journal of Monetary Economics* 22, 3—24 (1988).
Mankiw, N. G., Romer, D. and Weil, D. N. "**A contribution to the empirics of economic growth**", *The Quarterly Journal of Economics*, Vol. 107, No. 2 (May, 1992), pp. 407-437 (1992).
Moran, P.A.P. "**Notes on continuous stochastic phenomena**", *Biometrika*, 37, 17-33 (1950).
Nadiri, M.I. "**Innovations and technological spillovers**", *Working Paper 4423* (1993), National Bureau of Economic Research, Cambridge, Massachusetts.
Nelson, R. and Phelps, E. "**Investment in humans, technological diffusion, and economic growth**", *American Economic Review* 56(1/2), 65—75 (1966).
Pakes, A. and Griliches, Z. "**Patents and R&D at the firm level: a first look**". In Griliches (ed.), "*R & D, patents, and productivity*", National Bureau of Economic Research, pp. 55-72, Chicago: Chicago university Press 1984.
Pisati, M. "**sg162: tools for spatial data analysis**." *Stata Technical Bulletin* 60: 21-37 (2001).
Romer, P. M. "**Endogenous technological change**", *Journal of Political Economy*, vol. 98, nº 5, part II, pp. S71-S102 (1990).
Shane, S. and Stuart, T. "**Organizational endowments and the performance of university start-ups**", *Management Science,* 48 (1), 154-170 (2002).
Solow, R.M. "**We'd better watch out**," *New York Times Book Review*, July 12: 36 (1987).
Solow, R.M. "**Technical change and the aggregate production function**" *Review of Economics and Statistics*, **39**:312-320 (1957).
Solow, R.M. "**A contribution to the theory of economic growth**," *Quarterly Journal of Economics* 70: 65-94 (1956).
Swan, T.W. "**Economic growth and capital accumulation**", *Economic Record* (November 1956) 32: 343-61.

Spence, A. M. "**Cost reduction, competition, and industry performance**" *Econometrica*,Vol. 52, No. 1 (Jan., 1984), pp. 101-121