THE RIMINI CENTRE FOR ECONOMIC ANALYSIS

WP 08-40

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THE GERMAN EAST-WEST DIVIDE IN KNOWLEDGE PRODUCTION: AN APPLICATION TO NANOMATERIAL PATENTING

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THIS VERSION: 15/08/2010

ABSTRACT

Research and development (R&D) in the field of nanomaterials is expected to be a major driver of innovation and economic growth. Consequently, it is of great interest to understand which factors facilitate the creation of new technological knowledge. The existing literature has typically addressed this question by employing a knowledge production function based on firm-, regional- or even country-level data. Estimating the effects for the entire national system of innovation, however, assumes poolability of regional data. We apply our reasoning to Germany, which has well-known regional disparities, in particular between the East and the West. Based on analyses at the NUTS-3 regional level, we find different knowledge production functions for the East and the West. Moreover, we investigate how our results are affected by the adoption of alternative aggregation levels. Overall, our findings suggest that a careful evaluation of poolability and aggregation is required before estimating knowledge production functions at the regional level.

Key words: nanomaterials; patents; poolability; Germany; spatial autocorrelation

JEL-Classification: C21, L60, O32, R11, R12

INTRODUCTION

Innovation studies frequently recognize the importance of nanotechnology as it can have a wide array of potential applications - e.g. in biotechnology, chemistry or material sciences - and it is expected to result in incremental and radical innovations (Meyer 2006), substantially contributing to economic growth and employment (Bozeman *et al.* 2007). Most of its applications are expected to result specifically from so-called 'nanomaterials'. The term refers to functional structures sized less than 100 nanometres (Youtie *et al.* 2008), which give the material specific properties, allowing them to be used in new ways and to bring about new effects in larger structures of which they are part.

In this perspective, it seems all the more important for regions to find ways of benefiting from the expected growth of nanomaterial applications. Initially, innovation systems had been referred to nation states (Edquist 1997; Lundvall 1992; Nelson 1993), but the concept has been extended to the regional level as well (Cooke *et al.* 2000; Cooke *et al.* 1997; Howells 1999). While being part of the national system of innovation, a regional system of innovation can be defined as a regional network between public and private research to adapt, generate and extend knowledge and innovations (Buesa *et al.* 2006; Howells 2005). Many regions have recognized the importance of promoting research activities in nanotechnology, which has led to the establishment of 'science parks' and 'nanoclusters', substantially supported by public policy. Moreover, as nanomaterials are still in their infancy and related products at an early phase of their life-cycles, cooperation between universities, public research institutes and private businesses seems to be critical to create the required knowledge for actually benefiting from nanomaterials research.

For these reasons it is important to examine whether different regions produce innovations in differenty ways. In this respect, it is of particular interest to investigate the innovative capabilities of regions that have been in an economical transition vis-à-vis regions with established industrial structures. For example, Germany is often studied by making a distinction between the East and the West, where different economic systems had been in place until the reunification in 1990 (Brixy & Grotz 2004; Fritsch 2004; Günther 2004). In this article we argue that institutional differences between these regions continue to influence the effectiveness of scientific knowledge production in a key technological area like nanomaterials. Hence, we apply appropriate econometric techniques to this problem, while not neglecting the issue of knowledge spillovers across regions that might produce spatial correlation and unreliable statistical inference.

So-called 'poolability' issues are not new to the study of German regions or of regional systems of innovation. In this regard, earlier empirical evidence (Bode 2001, 2002, 2004a, b) shows mixed results with regard to several poolability hypotheses. In analyses on regional innovative activities and R&D spillovers as well as on agglomeration externalities in Germany, tests carried out on the North/South of Germany or on agglomerated/peripheral regions do not suggest poolability problems, while additional tests on high/low innovativeness and labor productivity indicate that caution *should* be used in pooling regional data in the German knowledge production context. On the other hand, such issues are discussed very briefly in the above literature, and often without a informative presentation of the findings (Bode 2001). In this regard, our contribution aims at providing a more explicit treatment of poolability problems in innovation analyses.

We also tackle one further problem, that is, whether the modifiable areal unit problem (MAUP) is a relevant issue to our data and the economic relationship we analyse. In other words, we check if our results are robust to aggregation issues. This is important because inventors often do not live where the research facilities they work at are located, which may induce bias in our estimates (patents are attributed to the place of residence of the inventor). By testing regions at different aggregation levels, we aim at eliminating this mismatch.

The remainder of the article is structured as follows. We first introduce the concept of knowledge production functions and describe our dataset and the econometric estimation and testing method. Subsequently, we present our results first for the whole of Germany and afterwards for East and West Germany subsets of our data. Finally, we set out our results concerning aggregation issues and conclude with limitations of our study and avenues for further research.

THE MODEL: KNOWLEDGE PRODUCTION IN NANOMATERIALS

Today, it has almost become conventional wisdom that most developed market economies are based on knowledge. Its creation has typically been modeled in the context of knowledge production functions (Griliches 1979), for which the basic idea is that investments in knowledge, which may be embodied in people and technology, increase the productivity of capital and labor resulting in new products and processes. It is therefore important to explore the factors leading to knowledge creation in an emerging technology field. Endogenous growth theory postulates that knowledge production increases with research input, and in particular with human capital (Aghion & Howitt 1992; Romer 1990). In this article, the objective is to analyse the determinants of knowledge production by linking the observable innovative output – patents – to observable inputs. We focus on three types of inputs: private and public investments in research and development (R&D) (both in terms of personnel), as well as the technological specialization of a region which also represents the stock of knowledge scientists can draw from. This knowledge stock identifies a specific technological specialization profile which can be assumed to lead to a certain technology competence of a region (Jones 1995; Porter & Stern 2001; Romer 1990).

Patents have been frequently employed as measures of output in a knowledge production function framework (for example, Griliches 1990; Patel & Pavitt 1997) since they can be characterized as intermediary outcomes of the innovation process (see, for example, Acs *et al.* 2002). Nevertheless, several disadvantages are associated with the use of patents (Griliches 1990). First, not all inventions are patentable, and not all inventions are patented as firms may choose other protection strategies like secrecy or complexity of design. Furthermore, although a granted patent exhibits a certain level of originality and newness, research has shown that the actual value of patents is highly skewed, leading to a ‘long tail’ in the distribution of the patent value (Harhoff *et al.* 2003). As a consequence, only a few patents are economically highly valuable.

Hence, our knowledge production function can be written as follows:

$$y_i = \alpha x_i + \beta z_i + \chi a_i + \varepsilon_i, \tag{1}$$

where: y_i is the output of the knowledge production function in region i, x_i is the research input; z_i is the stock of knowledge of the region; a_i includes other variables affecting innovation output; ε_i is the error term assumed to be i.i.d. with a zero mean and constant variance; α, β and χ are the parameters to be estimated.

DESCRIPTION OF THE EMPIRICAL APPLICATION

Description of the data – Due to the cross-cutting nature of nanomaterials and their use in a variety of scientific fields, the identification of nanomaterial patents is not trivial. Several different search strategies have been developed by bibliometricians and patent analysts to single out the field of nanomaterials (Hullman & Meyer 2003; Schummer 2004; Zitt & Bassecoulard 2006). We make use of the results of a search strategy that evolved from a collaborative project with a major European chemicals company, which is one of the largest patent applicants in nanomaterials with a specialized department for patent information research. Our analysis focuses on patent applications at the European Patent Office as these patents are typically assumed to have a higher quality in contrast to patent applications at national patent offices. For these European patent applications the costs of filing the application are much higher which should presumably discourage poor quality patent applications. Besides the nanomaterial patent data which are used as dependent variable, all explanatory variables are obtained from the German National Statistical Office and the European Statistical Office (Eurostat) at the German district (*kreise*) level (NUTS-3). There are 439 NUTS-3 regions in Germany.

When employing patent data, patent applicant and inventor should be carefully distinguished. The applicant is the holder of the patent rights while the document itself also shows the name(s) of the inventor(s). Differences between the applicant and the inventor are relevant when it comes to the spatial assignment of a patent as they are typically not located in the same place. In this respect, inventors tend to be geographically dispersed around the applicant's location. Taking this location as the focal point would, however, lead to a substantial bias as most large firms maintain several R&D units while all patents are applied for from the firm's headquarter. We therefore focus on the inventor's location. Moreover, as there could be several inventors on a patent document, we apply a fractional counting approach to assign every inventor mentioned the respective share of the nanomaterial patent.

Building on our knowledge production function framework, we regress the number of nanomaterial patents on private and public investments in R&D, on the regional specialization, as well as on control variables and a spatial filter which takes into account the spatial autocorrelation in our data. Regarding the explanatory variables, we use the number of industrial and public sector R&D employees as a proxy for human capital inputs. To take the technological specialization of a region into account, we analyse the patent applications in other technology fields like mechanics, electronics, chemicals and pharmaceuticals. Patent applications in further technology fields are left out of the estimation as a reference group. As nanomaterials have a cross-cutting nature, our specialization patterns can also be assumed to reflect the stock of technological knowledge available to the scientists. We compute the shares of the number of patent applications in each field over the total number of patent applications to yield our regional specialization pattern excluding any potential size effect. Finally, we control for several other regional characteristics. First, we include the shares of employees working in the manufacturing and services sector, as well as the GDP per capita in logs (also included as a squared and as a cubic term). While the sector shares should give an insight on the economic orientation of a region, the GDP per capita should map its level of economic development. Moreover, we add three dummy variables indicating the centrality, urbanization and agglomeration patterns of a region.[1] Our measures account for time lags in the knowledge production function by using the sum of nanomaterial patents applied for in the years from 2000 to 2004, while all explanatory variables are based on the year 2000.[2]

Figure 1 provides a map of the number of nanomaterial patents in each German district. On the one hand, there is not a smooth geographical distribution of patents in Germany. On the other hand, the spatial distribution of the patent applications cannot be considered random. A prevalence of high values for the Western regions of Germany can be highlighted. Most of the patents appear to be located in the major German cities and in specialized regions. Inversely, the East German *kreise* are characterized, with few exceptions, by low patenting activities.

In the following, we will argue that (i) spatial econometric adjustments are necessary but that (ii) poolability of the 439 regions is questionable.

Estimation Method – On the basis of the model and data presented above, we follow Grimpe and Patuelli (2010) and propose the estimation of negative binomial regressions. In addition, we stick to Grimpe and Patuelli's estimation framework by employing, when necessary, spatial filters (Griffith 2003) in order to account for spatial autocorrelation. The main characteristics and advantages of our estimation strategy are summarized below.

Our model explains the output of the knowledge production function, which is measured here as a count of patent applications. This variable does not have values smaller than 0, and is an integer. Log-linear or Poisson regressions are commonly used for estimating models with count data as a dependent variable. Further, data over- or under-dispersion with respect to the underlying statistical distribution are observed in economics, in which case, simple log-linear or Poisson estimators are inefficient. This problem is often tackled by using negative binomial estimations, which assume, as a data-generating function, a two-stage model including an unobserved variable E (gamma-distributed) with mean 1 and variance $1/\theta$, and a discrete variable (the dependent) Poisson-distributed conditionally to E with mean μ and variance $\mu + \mu2/\theta$ (see, for example, Venables & Ripley 2002). The dispersion parameter θ is fitted iteratively (by maximum likelihood or by means of a moment estimator).

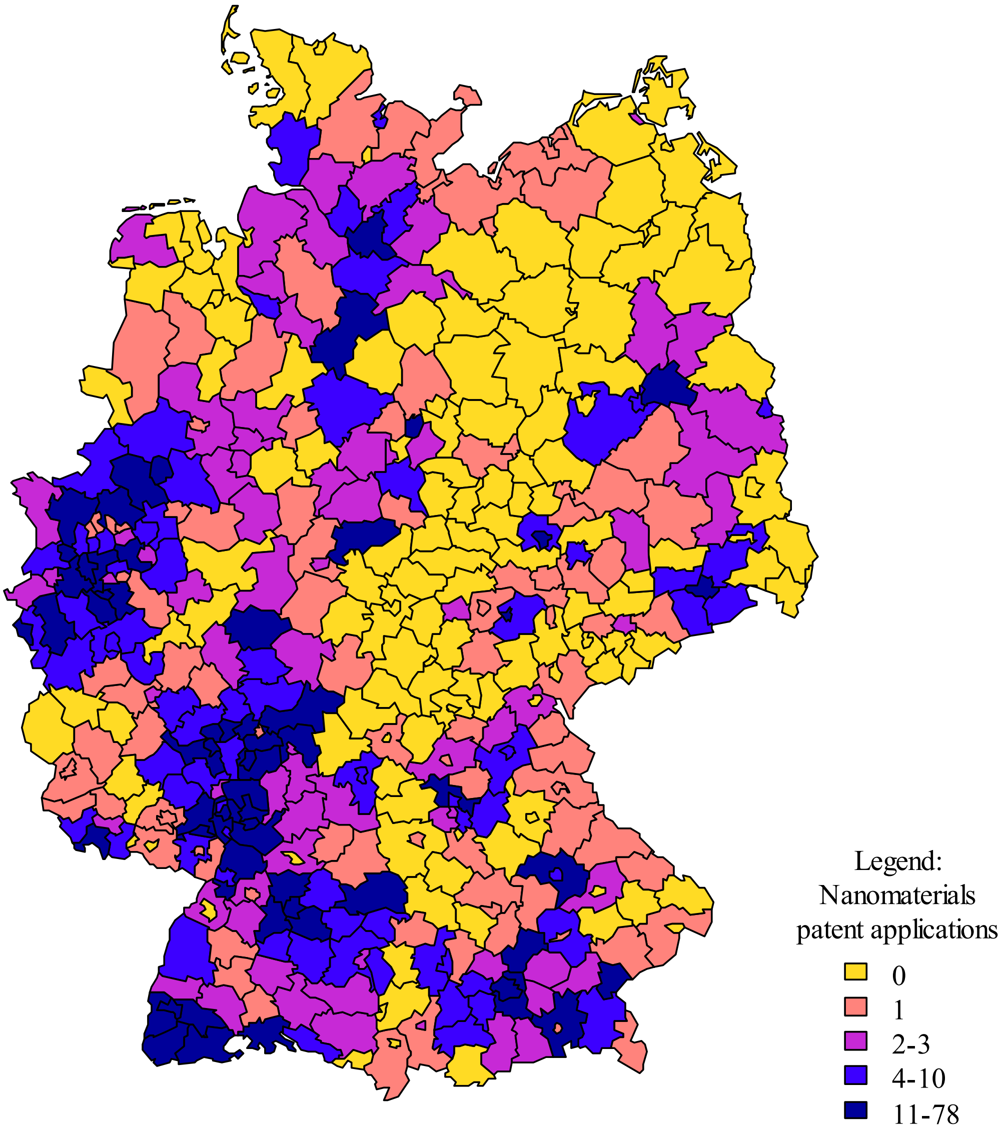

Figure 1: Geographic distribution of patent applications in nanomaterials

The above estimation framework is augmented with the use of spatial filtering methods in the case of spatial autocorrelation. Spatial autocorrelation (Cliff & Ord 1981) refers to the correlation between the values of a georeferenced variable to be attributed to the proximity of the georeferenced objects (regions, point patterns, and so on). It is most commonly measured by means of Moran's I (MI, Moran 1948). This statistic is computed as

$I = \left[N \sum_i \sum_j w_{i,j} (x_i - \bar{x})(x_j - \bar{x}) \right] \Big/ \left[\left(\sum_i \sum_j w_{i,j} \right) \sum_i (x_i - \bar{x})^2 \right]$, where: N is the number of georeferenced units; x_i is the value of the variable X for unit i; and $w_{i,j}$ is the value of cell (i, j) of a spatial weights matrix **W** (defined below). Positive values of Moran's I imply positive spatial autocorrelation, and vice versa. The computation of the Moran's I requires the use of a spatial weights matrix **W**, which defines the relations of proximity between georeferenced units. Binary spatial weights matrices are often used, where a value of 1 for the generic cell (i, j) implies that the two units i and j are neighbors, while the opposite applies for the value 0.[3]

It has been shown that, when regression residuals are spatially correlated, the regression coefficients may be biased and/or have inefficient standard errors (depending on whether spatial dependence or a spatial error process is present; Anselin & Griffith 1988). Several econometric techniques have been developed over the last two decades to control for spatial autocorrelation (see, for example, Anselin 1988; Griffith 1988), but they are based – with few exceptions – on the assumption of normality. We employ an eigenvector-decomposition-based spatial filtering technique (Griffith 2003, 2006), which allows to relax the normality assumption and can therefore be applied to regressions with any underlying statistical distribution. The spatial filtering technique used is related to the computational formula of the Moran's I. It extracts orthogonal and uncorrelated numerical components (eigenvectors) from a given (N x N) spatial weights matrix (Tiefelsdorf & Boots 1995), therefore drawing comparisons to principal components analysis. The extracted eigenvectors represent the latent spatial autocorrelation – to be looked for in a georeferenced variable – which is due to the chosen spatial weights matrix. Formally, we extract the eigenvectors of the following modified spatial weights matrix:

$$(\mathbf{I} - \mathbf{1}\mathbf{1}^{\mathrm{T}}/N)\mathbf{W}(\mathbf{I} - \mathbf{1}\mathbf{1}^{\mathrm{T}}/N), \tag{2}$$

where: **W** is the given geographic weights matrix; **I** is an (N x N) identity matrix; and **1** is an (N x 1) vector containing only ones. The sequence in which the eigenvectors are extracted maximizes the residual Moran's I values. Consequently, the first extracted eigenvector, e_1, is the one which shows the greatest Moran's I value among all eigenvectors of the modified matrix. The second extracted eigenvector, e_2, is the one which shows the greatest Moran's I value while being uncorrelated to e_1. The process continues with the final extraction of $(N - 1)$ eigenvectors. The resulting set of vectors is the complete set of all possible (mutually) orthogonal and uncorrelated map patterns (Getis & Griffith 2002).

After selection on the basis of a Moran's I threshold value,[4] stepwise regression and manual backward elimination (see Grimpe & Patuelli 2010), a subset of the above eigenvectors – all statistically significant at least at the 5 per cent level – is employed as additional regressors in the estimation of our model. From a spatial dependence point of view, these eigenvectors – their linear combination being hereforth referred to as our 'spatial filter' – account for the residual spatial autocorrelation resulting from the regression analysis.

Poolability – Testing for poolability is equivalent to testing for sub-sample stability of the estimated regression coefficients. The question underlying the econometric procedures labeled as 'poolability tests' is whether a single model can fit all the data we are analysing or it is better to specify different models for different subsets of the dataset.

For sake of simplicity, suppose the observations of a dataset can be grouped in two groups. For instance, we might wish to investigate a dataset of either different individuals or regions or sectors over time. Another example might be a sectoral/regional dataset across different countries or wider regions, as in our case.

Our target is to model the conditional expectation of a dependent variable, y, given a set of independent variables x, $E(y_{ig} \mid x_{ig})$, where i = 1, …, I and g = 1, …, G are two indices identifying each observation according to the groups they belong to. Suppose we specify a linear model of $E(y_{ig} \mid x_{ig})$ and we want to test if β, the vector of the coefficients, is the same for all i or not. Our restricted model will be:

$$y_{ig} = x_{ig}\beta + u_{ig}, \tag{3}$$

while our unrestricted model will be:

$$y_{ig} = x_{ig}\beta_i + u_{ig}, \tag{4}$$

where u_{ig} is the error. In other words, our null hypothesis is $H_0 : \beta_i = \beta$.

Two tests for poolability can be distinguished according to the assumptions regarding the distribution of the errors. The Chow test assumes that $u_{ig} \sim N(0, \sigma^2)$, whereas the Roy-Zellner test assumes $u \sim N(0, \Sigma)$, with

$$Cov(u_{ig}, u_{jh}) = \sigma_\mu^2 + \sigma_v^2, \text{ for } i = j \text{ and } g = h; \tag{5}$$

$$Cov(u_{ig}, u_{jh}) = \sigma_{\mu}^{2}, \text{ for } i = j \text{ and } g \neq h, \tag{6}$$

where j = 1, …, I, h = 1, …, G and Σ is the IG x IG variance-covariance matrix of the error term (Baltagi 2001). Of course, it would also be possible to test the hypothesis $\beta_g = \beta$[5].

The tests and criteria above, however, rely on the assumptions of linearity of the model for $E(y_{ig} \mid x_{ig})$, and of normality of the errors. However, both these assumptions do not suit our setting. Since we adopted a maximum likelihood estimator, we follow Watson and Westin (1975) and we use a likelihood ratio test for poolability:

$$\lambda = 2(\log L_u - \log L_r), \tag{7}$$

where log L_u is the log of the likelihood of the unrestricted model, and log L_r is the one of the restricted model. λ is asymptotically distributed as a χ^2 with a number of degrees of freedom equal to the number of restrictions.

There is a rich empirical literature on poolability testing. For example, Vaona (2008) and Vaona and Patuelli (2008) show that the finance-growth nexus does not display statistically significant heterogeneity at the regional level in Italy. Schiavo and Vaona (2008) tackled the same issue across countries. Nunziata (2005) focused on the poolability of the unemployment effect of labor market institutions across different OECD countries. Van den Berg et al. (2008) used poolability tests to assess whether financial crises are caused by the same factors homogenously across different countries. Hahn (2008) adopted a Roy-Zellner test for poolability while studying profitability and contestability in the Austrian banking sector. Vaona and Pianta (2008) applied poolability tests to the determinants of innovation across different economic sectors and firm-size classes. Additionally, Baltagi and Griffin (1983) studied the demand for gasoline in OECD countries by means of poolability tests.

Our poolability analysis, which focuses on the German East and West divide, is presented in the next section.

POOLABILITY OF GERMAN INNOVATION DATA

Baseline Model for Germany – In the first step, we estimate the baseline model for all German NUTS-3 regions including the spatial filter (SF). Table 1 shows the results.

Table 1: Baseline negative binomial model results for nanomaterial patenting (439 NUTS-3 regions)

	Baseline model (SF) Coefficients
Human capital inputs	
Industry-funded R&D employees (in logs)	0.272 (0.051)***
Government-funded R&D employees (in logs)	0.051 (0.022)**
Regional specialization	
Share of mechanics patents	–1.148 (0.881)
Share of electronics patents	1.465 (0.854)*
Share of chemicals patents	3.684 (0.885)***
Share of pharmaceuticals patents	0.971 (1.057)
Controls	
Share of employees in manufacturing	–0.013 (0.007)**
Share of employees in services	0.032 (0.018)*
GDP per capita (in logs)	227.496 (124.194)*
GDP per capita (in logs)^2	–22.134 (12.118)*
GDP per capita (in logs)^3	0.717 (0.394)*
Population (in logs)	0.097 (0.047)**
Central city dummy	–0.541 (0.131)***
Urbanization dummy	0.448 (0.137)***
Agglomeration dummy	0.369 (0.115)***
Spatial filter	1.000 (0.056)***
Intercept	–781.14 (423.743)***
θ	4.745
Observations	439
Null deviance (dof)	2,128.302 (438)
Residual deviance (dof)	420.120 (382)
AIC	1,703.897
MI	–0.099**

***, ** and * denote significance at the 1, 5 and 10 per cent levels. Robust standard errors in parentheses.

Our results indicate that knowledge production in nanomaterials is in fact mainly driven by both the government- and industry-funded R&D personnel. This supports the predictions of our model that inputs to the R&D process in terms of qualified R&D employees support the creation of new knowledge in an emerging field of technology. The importance of government-funded R&D personnel confirms that nanomaterials are in a rather early stage of commercialization, as universities and public research institutes mainly focus on basic research and technology development in contrast to the more application-driven research of private firms.

Regarding the technological specialization of the stock of knowledge available in a region, our results show a high importance of chemicals and electronics patents. Moreover, nanomaterials patenting also tends to be facilitated by a rather modern economic structure of a region as pointed out by the coefficients for the manufacturing and services sectors. Finally, our results further show that the number of inhabitants of a region matters considerably, and that agglomeration and urbanization foster the creation of nanomaterials patents.

In the following section, we will focus on the test of the poolability hypothesis and conduct separate analyses for the resulting regions.

Poolability of West and East German Districts – The empirical findings set out in Table 1 indicate that it is possible to clearly identify, for the German NUTS-3 regions, a knowledge-production function in the field of nanomaterials.

However, inference from the above results would imply that the production function found is common to all German districts - a highly desirable assumption whose soundness, though, could be challenged. In fact, the regional economic literature on Germany is rich in examples where a distinction is made between more and less developed areas of the country, primarily along the former border between West and East Germany (see, amongst others, Brixy & Grotz 2004; Fritsch 2004; Günther 2004). In particular, Fritsch (2004) shows that West and East Germany have dramatically different regional growth regimes. In the innovation field, Günther (2004) finds that, while both West and East German firms are involved in innovation cooperation, the better productivity advantages experienced in West Germany are due to different economic structures.

As a consequence, we propose to test for the poolability of our model with respect to the West/East subdivision. Formally, we test the hypothesis:

$$H_0 : \beta_{\mathrm{W}} = \beta_{\mathrm{E}} = \beta, \tag{8}$$

where β_{W} and β_{E} are the vectors of the regression coefficients computed over the West and East German subsamples, respectively, while β is the vector of the regression coefficients computed for the baseline model (see Table 1).

Therefore, we compare the restricted model estimated (under H_0) in the preceding section and the unrestricted model, which is obtained by interacting all explanatory variables with two dummies, identifying West and East German districts, respectively.[6] The likelihood ratio test for the two models (see Equation (7)), under 16 restrictions, returns a value of 89.18, which rejects H_0 with a 99.9 per cent probability, and confirms that our model cannot be pooled for West and East German districts. Consequently, separate models will be estimated for the two macro-areas.

Following the estimation strategy outlined above, we compute two new sets of candidate eigenvectors for the two new contiguity matrices related to West and East Germany. These eigenvectors will be employed for the computation of spatial filters, when required by autocorrelated regression residuals.

Table 2It follows that our pooled results hold for West Germany, as both private and public research institutions significantly and positively affect nanomaterials research, while in East Germany nanomaterial patenting is predominantly driven by industry. This finding is interesting when keeping in mind that, since reunification, the East German economy has been typically lagging behind the West German one.

Table 2 presents the coefficient estimates obtained for West and East Germany. The estimation carried out for the 326 West German districts supports the results obtained for the baseline model, carrying consistent signs and significance levels. We can again identify significant effects of privately- and government-funded R&D employees and, consistently with the baseline results, for a regional specialization in electronics, chemicals and pharmaceuticals. Regarding the control variables, we see positive size, urbanization and agglomeration effects, as well as an effect of a service-oriented economic structure of the region.

With regard to the estimates obtained for the 113 East German districts, our results change dramatically. We now find a significant effect only for the share of employees in industry-funded R&D. Almost no other significant effect can be identified, aside from a (complex) effect of per capita GDP, and a positive effect of agglomeration, which is consistent with the West German and the baseline estimations. No spatial filter is necessary, since the regression residuals are spatially uncorrelated.

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Table 2: Unpooled negative binomial model results for nanomaterial patenting (West and East German NUTS-3 regions)

	West/East Germany unpooled models	
	West Germany	East Germany
Human capital inputs		
Industry-funded R&D employees (in logs)	0.251 (0.060)***	0.606 (0.178)***
Government-funded R&D employees (in logs)	0.088 (0.023)***	0.010 (0.057)
Regional specialization		
Share of mechanics patents	–0.435 (0.896)	–4.389 (2.986)
Share of electronics patents	2.267 (0.811)***	0.372 (2.542)
Share of chemicals patents	4.774 (0.887)***	0.257 (2.769)
Share of pharmaceuticals patents	2.229 (1.043)**	0.211 (2.685)
Controls		
Share of employees in manufacturing	0.004 (0.008)	–0.027 (0.040)
Share of employees in services	0.063 (0.023)***	0.056 (0.074)
GDP per capita (in logs)	102.673 (145.243)	7005.964 (3,167.495)**
GDP per capita (in logs)^2	–10.513 (14.030)	–705.083 (320.675)**
GDP per capita (in logs)^3	0.356 (0.451)	23.642 (10.818)**
Population (in logs)	0.115 (0.062)*	–0.088 (0.133)
Central city dummy	–0.591 (0.155)**	–0.306 (0.692)
Urbanization dummy	0.473 (0.165)***	0.406 (0.395)
Agglomeration dummy	0.367 (0.137)***	1.024 (0.292)***
Spatial filter	1.000 (0.092)***	–
Intercept	–335.234 (500.378)	–23,194.329 (10,425.958)**
θ	3.476	1.863
Observations	326	113
Null deviance (dof)	1,250.619 (325)	350.422 (112)
Residual deviance (dof)	340.524 (295)	91.446 (97)
AIC	1,460.688	297.167
MI	–0.013	0.043

***, ** and * denote significance at the 1, 5 and 10 per cent levels. Robust standard errors in parentheses.

Table 3 provides some guidance on the interpretation of the industry human capital coefficients found for East and West Germany. Once regressing the number of industry R&D employees on the remaining explanatory variables of our knowledge production function model, we find that, in West Germany, it is strongly correlated to the local stock of knowledge, while, in East Germany, no significant correlation shows up. Consequently, firms in the West appear to choose the location of their research facilities in order to exploit the preexisting stock of knowledge. Inversely, in the East, because of its poor stock of knowledge, the R&D activities of firms are mostly based on qualified human resources. From a policy perspective, it seems sensible to particularly foster the development of a ‘critical mass’ of specialized competence in East German locations and also to favor specialization and accumulation of knowledge.

Table 3: Relationship between the number of industry-funded R&D employees (dependent variable, in logs) and other innovation indicators

	West Germany	East Germany
Share of mechanics patents	2.820 (1.098)**	–0.193 (1.163)
Share of electronics patents	3.929 (0.937)***	0.261 (1.414)
Share of chemicals patents	2.297 (1.142)**	–0.544 (1.087)
Share of pharmaceuticals patents	4.136 (1.361)***	1.628 (1.791)

*** and ** denote significance at the 1 and 5 per cent level, respectively. Robust standard errors in parentheses. Regressors include an intercept and the control variables shown in Table 2.

GEOGRAPHICAL AGGREGATION AND THE INVENTOR’S LOCATION

This section is devoted to the analysis of the findings presented above for different levels of spatial aggregation. The potential problem that we will try to address is pointed out by Grimpe and Patuelli (2010), who note that patent application data do not refer unambiguously to the location of where the research was actually performed. Instead the applicant’s address – typically the firm’s headquarter – and the residence address of the inventor(s) are given. Consequently, if the inventors tend to live in districts surrounding the ones in which the research facilities are located, a distortion in the data could emerge, generating, for example, artificial spatial autocorrelation. Such issue can be included in the framework of the modifiable areal unit problem (MAUP, Openshaw 1984), which refers to the possibility of observing varying levels of correlation between aggregate variables depending on the given choice of geographical boundaries.

In order to verify if the inventor’s location problem is of any significance to our case study, we re-estimate our baseline model for different geographical aggregation levels. Since the main factor involved in the potential mismatch between the location of the research facilities and of the inventor’s residence is commuting choices, we use, as our alternative geographical aggregation levels, functional regions. Functional regions (see, for example, OECD 2002) are often defined as areas which include an inner 'core' (often a city's central business district), and a surrounding area which has a high degree of interaction internally and with the core. Practically, functional regions are made up to represent homogeneous regional labor markets, and usually defined by aggregating smaller areas/regions in order to minimize the share of inter-regional commuting. It should be noted, however, that higher aggregation levels may not lead to improved estimates, if the newly-formed areas are too wide to capture the variance of the economic process being studied (Haining 1990).[7]

For our analysis, we define functional regions in four different ways: (i) 271 labor market regions ('*Arbeitsmarktregionen*' of the '*Gemeinschaftsaufgabe Verbesserung der regionalen Wirtschaftsstruktur*', which we will refer to as 'Aggregation 1') which are intended mostly for public subsidy policies, and are viewed as quasi-functional regions; (ii) 150 functional regions defined in Eckey et al. (2006) by means of factor analysis based on commuting flows ('Aggregation 2'); (iii) 97 planning regions ('*Raumordnungsregionen*'; 'Aggregation 3'), which always include a central business district and its surrounding areas; and (iv) 52 functional regions defined in Kropp and Schwengler (2008) through hierarchical clustering ('Aggregation 4'). Hence, we analyse increasingly aggregated data. Before estimating our knowledge production function model for the new aggregation levels, we decide to exclude the dummy variable for central cities from all new analyses, since it would not anymore single out central business district regions. With regard to the urbanization and agglomeration dummies, we reclassify the regions according to the predominant feature (the modal score) within each aggregated region.

Our starting assumption is that the aggregation level used in our baseline model is well suited. If it is not so, we can expect our empirical findings at higher aggregation levels to be more meaningful (or to show higher significance levels). If instead the maximum level of disaggregation (NUTS-3) is a necessary condition for identifying significant effects of our variables of interest, then we may expect our results to deteriorate as aggregation increases. Table 4 shows the results obtained, which require careful interpretation.

Table 4: Negative binomial model results for nanomaterial patenting (aggregated regional data)

	Models for aggregated regions			
	Aggregation 1 (271 regions)	Aggregation 2 (150 regions)	Aggregation 3 (97 regions)	Aggregation 4 (52 regions)
Human capital inputs				
Industry-funded R&D employees (in logs)	2.000 (0.066)***	1.845E–5 (1.655E–5)	1.875E–5 (1.015E–5)*	–2.649E–5 (1.926E–5)
Government-funded R&D employees (in logs)	–0.001 (0.021)	5.149E–5 (5.290E–5)	2.472E–5 (5.133E–5)	7.935E–5 (4.318E–5)*
Regional specialization				
Share of mechanics patents	–1.144 (1.063)	0.341 (1.483)	–0.628 (1.980)	–0.276 (2.917)
Share of electronics patents	1.327 (1.136)	3.266 (1.406)**	1.616 (1.713)	2.864 (2.553)
Share of chemicals patents	4.628 (1.086)***	5.463 (1.429)***	4.858 (1.944)*	5.527 (3.057)*
Share of pharmaceuticals patents	–0.059 (1.273)	2.120 (1.609)	0.810 (2.347)	3.134 (4.265)
Controls				
Share of employees in manufacturing	0.001 (0.009)	0.010 (0.014)	0.026 (0.022)	0.083 (0.023)***
Share of employees in services	0.052 (0.027)*	0.021 (0.056)	–0.011 (0.088)	0.107 (0.074)
GDP per capita (in logs)	998.208 (477.026)**	1,472.033 (989.858)	838.434 (1,031.149)	7,083.400 (3,692.120)*
GDP per capita (in logs)^2	–96.004 (47.138)**	–140.904 (98.241)	–80.032 (101.376)	–706.792 (369.325)*
GDP per capita (in logs)^3	3.073 (1.552)**	4.494 (3.249)	2.546 (3.320)	23.506 (12.311)*
Population (in logs)	0.732 (0.129)***	0.720 (0.145)***	0.960 (0.272)***	0.939 (0.186)***
Urbanization dummy	0.309 (0.149)**	0.628 (0.211)***	0.316 (0.193)	0.208 (0.230)
Agglomeration dummy	0.081 (0.143)	0.306 (0.234)	0.340 (0.234)	–0.222 (0.363)
Spatial filter	1.000 (0.079)***	–	–	–
Intercept	–3,464.616 (1,607.918)**	–5,133.743 (3,322.998)	–2,938.620 (3,493.369)	–23,675.371 (12,299.678)*
θ	5.824	3.072	3.390	4.789
Observations	271	150	97	52
Null deviance (dof)	2123.461 (270)	926.236 (149)	492.116 (96)	573.427 (51)
Residual deviance (dof)	250.170 (234)	148.832 (135)	103.486 (82)	52.347 (37)
AIC	1,109.689	783.846	659.640	358.458
MI	–0.027	0.029	0.095*	0.003

***, ** and * denote significance at the 1, 5 and 10 per cent levels. Robust standard errors.

In the case of Aggregation 1 (271 regions), only industry R&D is significant, while, for Aggregations 2, 3 and 4 (150, 97 and 52 regions), neither private or public R&D are more than just marginally significant (i.e., below our chosen minimum level of significance of 5 per cent). Clearly, the effect of population (size of the regions) remains significant in all estimations, while specialization in chemicals shows diminishing levels of significance as aggregation increases. Overall, we note a moderate variation of coefficient estimates and significance levels. From a comparison with the results of Table 1, it is evident that aggregating the initial NUTS-3 regions does not provide better information on the estimated knowledge production function and the related regression parameters. It is noteworthy that, when estimating the knowledge production function for higher levels of aggregation (2, 3 and 4), no significant residual spatial autocorrelation is left, and consequently a spatial filter is not necessary (larger regions appear to capture better industrial agglomerations), probably as an effect of the chosen aggregation criteria.

Our results suggest that the aggregation level of the baseline model is the most appropriate (among the ones considered) for our analysis, since the estimates appear to deteriorate as we move towards higher aggregation levels. This is presumably due to the considerable loss of information and variation in the data, and to the different objectives and underlying criteria of the aggregation levels adopted. For example, functional regions, differently from NUTS-3 districts, are *not* real administrative entities, and therefore cannot put in place policies aiming to foster innovation. On the other hand, the tendency of industry-R&D to remain significant at finer levels of aggregation might be explained by firms contrasting the diffusion of their expertise.

CONCLUSIONS

This article has focused on two issues. First we checked whether different regions can be pooled within the same sample when estimating a knowledge production function for nanomaterial patents in Germany. Secondly, we tackled the issue whether estimating a knowledge production function at different levels of regional aggregation has an impact on econometric results. This analysis has been performed in order to account for the fact that there is typically a geographical mismatch between the location of the inventor and the actual location of the research facility where the inventive work was carried out.

Regarding poolability, we have found that East Germany has a statistically different knowledge production function from West Germany. We found that in East Germany innovation in nanomaterials is positively correlated with the number of industry-funded R&D employees but no role is played by government-funded R&D employees and by the stock of accumulated knowledge represented by the share of mechanics, electronics, chemicals and pharmaceutical patents. On the contrary, in West Germany the opposite turns out to be true. This is rather worrying, as it would seem that in a field like nanomaterials, where basic research (still) plays an important role, East Germany seems to rely only on the private sector without having an adequate level of knowledge and effective government-funded R&D activities to successfully support this engine of growth. On the other hand, in West Germany, firms tend to locate their research facilities so to exploit spillovers from public research facilities and the existing stock of knowledge.

Finally, we found that the level of aggregation at which we analyse our sample matters, as estimates performed at higher aggregation levels eventually lead to less reliable results. Moreover, our findings suggest that the NUTS-3 aggregation level chosen in our baseline model is most appropriate, since it is the only one at which, after accounting for spatial autocorrelation, it is possible to identify significant effects of our variables of interest, and to suggest policy actions, because of the administrative nature of the NUTS-3 districts.

Acknowledgements

We would like to thank Melanie Arntz (ZEW, Germany) for providing the data concerning the German labor market classifications; Harald Bathelt (University of Toronto, Canada) for supplying information on industrial development in Germany; Roger Bivand (NHH, Norway) for creating an `R` script essential to the article; Hans-Friedrich Eckey (University of Kassel, Germany) and Per Kropp (IAB, Germany) for sharing their results on district aggregation; Ulrich Blum (IWH, Germany), Jason P. Brown (Purdue University, USA), Francesco Crespi (Roma Tre University, Italy), Rico Maggi (University of Lugano, Switzerland) and Christian Rammer (ZEW, Germany), as well as participants to the BRICK-GREDEG Workshop on 'The Dynamics of Knowledge and Innovation in Knowledge Intensive Industries' (Moncalieri), the 12th Uddevalla Symposium 2009 (Bari), the FIRB-RISC conference 'Research and Entrepreneurship in the Knowledge-Based Economy' (Milan), for useful suggestions. We are grateful to two anonymous referees for insightful comments on an earlier version of the article.

REFERENCES

ACS, Z.J., L. ANSELIN & A. VARGA (2002), Patents and Innovation Counts as Measures of Regional Production of New Knowledge. *Research Policy* 31, pp. 1069-1085.

AGHION, P. & P. HOWITT (1992), A Model of Growth through Creative Destruction. *Econometrica* 60, pp. 323-351.

ANSELIN, L. (1988), *Spatial Econometrics: Methods and Models*. Dordrecht Boston: Kluwer Academic Publishers.

ANSELIN, L. & D.A. GRIFFITH (1988), Do Spatial Effects Really Matter in Regression Analysis? *Papers in Regional Science* 65, pp. 11-34.

BALTAGI, B.H. (2001), *Econometric Analysis of Panel Data,* 2nd edition. Chichester New York: Wiley.

BALTAGI, B.H. & J.M. GRIFFIN (1983), Gasoline Demand in the OECD: An Application of Pooling and Testing Procedures. *European Economic Review* 22, pp. 117-137.

VAN DEN BERG, J., B. CANDELON & J.-P. URBAIN (2008), A Cautious Note on the Use of Panel Models to Predict Financial Crises. *Economics Letters* 101, pp. 80-83.

BODE, E. (2001), Is Regional Innovative Activity Path-Dependent? An Empirical Analysis for Germany (Kiel Working Paper No. 1058). Kiel: Kiel Institute of World Economics

BODE, E. (2002), R&D, Localised Knowledge Spillovers and Endogenous Regional Growth: Evidence from Germany. *In* L. SCHÄTZL & J. REVILLA DIEZ, eds., *Technological Change and Regional Development in Europe.* pp. 28-42. Heidelberg New York: Physica-Verlag.

BODE, E. (2004a), Agglomeration Externalities in Germany. *44th Congress of the European Regional Science Association.* Porto.

BODE, E. (2004b), The Spatial Pattern of Localized R&D Spillovers: An Empirical Investigation for Germany. *Journal of Economic Geography* 4, pp. 43-64.

BOZEMAN, B., P. LAREDO & V. MANGEMATIN (2007), Understanding the Emergence and Deployment of "Nano" S&T. *Research Policy* 36, pp. 807-812.

BRIXY, U. & R. GROTZ (2004), Entry-Rates, the Share of Surviving Businesses and Employment Growth: Differences of the Economic Performance of Newly Founded Firms in West and East Germany. *In* M. DOWNLING, J. SCHMUDE & D. KNYPHAUSEN-AUFSESS, eds., *Advances in Interdisciplinary European Entrepreneurship Research.* pp. 141-152. Muenster: Lit.

BUESA, M., J. HEIJS, M. MARTÍNEZ PELLITERO & T. BAUMERT (2006), Regional Systems of Innovation and the Knowledge Production Function: The Spanish Case. *Technovation* 26, pp. 463-472.

CLIFF, A.D. & J.K. ORD (1981), *Spatial Processes: Models & Applications*. London: Pion.

COOKE, P., P. BOEKHOLT & F. TOEDTLING (2000), *The Governance of Innovation in Europe: Regional Perspectives on Global Competitiveness*. London New York: Pinter.

COOKE, P., M. GOMEZ URANGA & G. ETXEBARRIA (1997), Regional Innovation Systems: Institutional and Organisational Dimensions. *Research Policy* 26, pp. 475-491.

ECKEY, H.-F., R. KOSFELD & M. TÜRCK (2006), Abgrenzung Deutscher Arbeitsmarktregionen. *Raumforschung und Raumordnung* 64, pp. 299-309.

EDQUIST, C. (1997), *Systems of Innovation: Technologies, Institutions, and Organizations*. London Washington: Pinter.

FRITSCH, M. (2004), Entrepreneurship, Entry and Performance of New Business Compared in Two Growth Regimes: East and West Germany. *Journal of Evolutionary Economics* 14, pp. 525-542.

GETIS, A. & J. ALDSTADT (2004), Constructing the Spatial Weights Matrix Using a Local Statistic. *Geographical Analysis* 36, pp. 90-104.
GETIS, A. & D.A. GRIFFITH (2002), Comparative Spatial Filtering in Regression Analysis. *Geographical Analysis* 34, pp. 130-140.
GRIFFITH, D.A. (1988), *Advanced Spatial Statistics*. Dordrecht: Kluwer Academic Publishers.
GRIFFITH, D.A. (2003), *Spatial Autocorrelation and Spatial Filtering: Gaining Understanding through Theory and Scientific Visualization*. Berlin New York: Springer.
GRIFFITH, D.A. (2006), Assessing Spatial Dependence in Count Data: Winsorized and Spatial Filter Specification Alternatives to the Auto-Poisson Model. *Geographical Analysis* 38, pp. 160-179.
GRILICHES, Z. (1979), Issues in Assessing the Contribution of Research and Development to Productivity Growth. *Bell Journal of Economics* 10, pp. 92-116.
GRILICHES, Z. (1990), Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature* 28, pp. 1661-1707.
GRIMPE, C. & R. PATUELLI (2010), Regional Knowledge Production in Nanomaterials: A Spatial Filtering Approach. *The Annals of Regional Science* (forthcoming).
GÜNTHER, J. (2004), Innovation Cooperation: Experiences from East and West Germany. *Science and Public Policy* 31, pp. 151-158.
HAHN, F.R. (2008), Testing for Profitability and Contestability in Banking: Evidence from Austria. *International Review of Applied Economics* 22, pp. 639-653.
HAINING, R. (1990), *Spatial Data Analysis in the Social and Environmental Sciences*. Cambridge: Cambridge University Press.
HARHOFF, D., F.M. SCHERER & K. VOPEL (2003), Citations, Family Size, Opposition and the Value of Patent Rights. *Research Policy* 32, pp. 1343-1363.
HOWELLS, J. (1999), Regional Systems of Innovation? *In* D. ARCHIBUGI, J. HOWELLS & J. MICHIE, eds., *Innovation Policy in a Global Economy.* Cambridge New York: Cambridge University Press.
HOWELLS, J. (2005), Innovation and Regional Economic Development: A Matter of Perspective? *Research Policy* 34, pp. 1220-1234.
HULLMAN, A. & M. MEYER (2003), Publications and Patents in Nanotechnology. An Overview of Previous Studies and the State of the Art. *Scientometrics* 58, pp. 507-527.
JONES, C. (1995), R&D Based Models of Economic Growth. *Journal of Political Economy* 103, pp. 739-784.
KROPP, P. & B. SCHWENGLER (2008), Abgrenzung von Wirtschaftsräumen auf der Grundlage von Pendlerverflechtungen. Ein Methodenvergleich (IAB Discussion Paper No. 41/2008). Nuremberg: IAB
LUNDVALL, B.-A. (1992), *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*. London: Pinter.
MEYER, M. (2006), Are Patenting Scientists the Better Scholars? An Exploratory Comparison of Inventor-Authors with their Non-Inventing Peers in Nano-Science and Technology. *Research Policy* 35, pp. 1646-1662.
MORAN, P. (1948), The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society B* 10, pp. 243-251.
NELSON, R.R. (1993), National Innovation Systems : A Comparative Analysis. New York: Oxford University Press.
NUNZIATA, L. (2005), Institutions and Wage Determination: A Multy-Country Approach. *Oxford Bulletin of Economics and Statistics* 67, pp. 435-466.
OECD (2002), *Redefining Territories: The Functional Regions*. Paris: Organisation for Economic Co-operation and Development.
OPENSHAW, S. (1984), *The Modifiable Areal Unit Problem*. Norwich: Geo Books.

PATEL, P. & K. PAVITT (1997), The Technological Competencies of the World' S Largest Firms: Complex and Path-Dependent, but Not Much Variety. *Research Policy* 26**,** pp. 141-156.
PATUELLI, R., D.A. GRIFFITH, M. TIEFELSDORF & P. NIJKAMP (2010a), Spatial Filtering and Eigenvector Stability: Space-Time Models for German Unemployment Data. *International Regional Science Review* (forthcoming).
PATUELLI, R., D.A. GRIFFITH, M. TIEFELSDORF & P. NIJKAMP (2010b), Spatial Filtering Methods For Tracing Space-Time Developments In An Open Regional System: Experiments with German Unemployment Data. *In* A. FRENKEL, P. NIJKAMP & P. MCCANN, eds., *Societies in Motion: Regional Development, Industrial Innovation and Spatial Mobility.* Cheltenham Northampton: Edward Elgar.
PORTER, M.E. & S. STERN (2001), Measuring the 'Ideas' Production Function: Evidence from International Output (Harvard Business School Working Paper No. 00-073). Cambridge: Harvard Business School
ROMER, P.M. (1990), Endogenous Technological Change. *Journal of Political Economy* 98**,** pp. S71-S102.
SCHIAVO, S. & A. VAONA (2008), Poolability and the Finance-Growth Nexus: A Cautionary Note. *Economics Letters* 98**,** pp. 144-147.
SCHUMMER, J. (2004), Multidisciplinarity, Interdisciplinarity, and Patterns of Research Collaboration in Nanoscience and Nanotechnology. *Scientometrics* 59**,** pp. 425-465.
TIEFELSDORF, M. & B. BOOTS (1995), The Exact Distribution of Moran's *I. Environment and Planning A* 27**,** pp. 985-999.
TIEFELSDORF, M., D.A. GRIFFITH & B.N. BOOTS (1999), A Variance Stabilizing Coding Scheme for Spatial Link Matrices. *Environment and Planning A* 31**,** pp. 165-180.
VAONA, A. (2008), Regional Evidence on Financial Development, Finance Term Structure and Growth. *Empirical Economics* 34**,** pp. 185-201.
VAONA, A. & R. PATUELLI (2008), New Empirical Evidence on Local Financial Development and Growth. *Letters in Spatial and Resource Sciences* 1**,** pp. 147-157.
VAONA, A. & M. PIANTA (2008), Firm Size and Innovation in European Manufacturing. *Small Business Economics* 30**,** pp. 283-299.
VENABLES, W.N. & B.D. RIPLEY (2002), *Modern Applied Statistics with S,* 4th edition. New York: Springer.
WATSON, P.L. & R.B. WESTIN (1975), Transferability of Disaggregate Mode Choice Models. *Regional Science and Urban Economics* 5**,** pp. 227-249.
YOUTIE, J., M. IACOPETTA & S. GRAHAM (2008), Assessing the Nature of Nanotechnology: Can We Uncover an Emerging General Purpose Technology? *The Journal of Technology Transfer* 33**,** pp. 315-329.
ZITT, M. & E. BASSECOULARD (2006), Delineating Complex Scientific Fields by a Hybrid Lexical-Citation Method: An Application to Nanosciences. *Information Processing and Management* 42**,** pp. 1513-1531.

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[1] While the centrality and urbanization dummy variables are partially exclusive (in the source nine-point index districts could be central, urbanized or rural), agglomeration levels concern all districts, making the related dummy variable independent from the previous two.
[2] This choice shelters us from a possible endogeneity bias, as innovation takes time to spread and to have an impact on local economies.
[3] For a discussion of different approaches to the definition of proximity, as well as of standardization schemes, see, for example, Tiefelsdorf *et al.* (1999), Getis and Aldstadt (2004) and Patuelli *et al.* (2010a, b).

[4] We choose a threshold of $MI(e_n) / \max_n[MI(e_n)] > 0.25$, where $MI(e_n)$ is the MI computed on a generic eigenvector e_n. According to Griffith (2003), this threshold roughly corresponds to a 95 per cent explained variance in a regression of a generic georeferenced variable **Z** on **WZ**.

[5] There exist other tests as well. A review is offered in Baltagi (2001).

[6] For poolability testing purposes, both models (restricted and unrestricted) are computed without a spatial filter, in order to ensure the use of the same set of explanatory variables.

[7] 'The results of any statistical analysis will be conditional on the scale, orientation and origin of the grid as well as the scale of the study area. Properties of the surface at scales smaller than the sampling grid will not be detectable since they will have been filtered out while processes operating at scales larger than the study area will display sufficient variation within the study area.' (Haining 1990, p. 47)