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SPECIAL ISSUE PAPER

Regional knowledge production in nanomaterials: a spatial filtering approach

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Abstract Nanomaterials are seen as a key technology for the twenty-first century, and much is expected of them in terms of innovation and economic growth. They could open the way to many radically new applications, which would form the basis of innovative products. As nanomaterials are still in their infancy, universities, public research institutes and private businesses seem to play a vital role in the innovation process. Existing literature points to the importance of knowledge spillovers between these actors and suggests that the opportunities for these depend on proximity, with increasing distance being detrimental to the extent that spillovers can be realised. Due to the technological complexity, however, proximity could also be less important as relevant nanomaterials research is globally dispersed. Hence in this paper, we analyse the effects of co-location of R&D activities on nanomaterial patenting. Based on European Patent Office data at the German district level (NUTS-3), we estimate two negative binomial models in a knowledge production function framework and include a spatial filtering approach to adjust for spatial autocorrelation. Our results indicate

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that there is a significant positive effect of both public and private R&D on the production of nanomaterial patents. Moreover, we find a positive interaction between them which hints at the importance of their co-location for realising the full potential of an emerging technology like nanomaterials.

JEL Classification C21 · L60 · O32 · R11 · R12

1 Introduction

Nanomaterials have been identified as one of the key technologies for the twenty-first century. The application of nanomaterials is expected to result in new functionalities and properties for improving products or developing new products and applications (Meyer 2006). Nanomaterials are therefore believed to contribute substantially to innovativeness, economic growth and employment (Bozeman et al. 2007). A nanometre is defined as one millionth of a millimetre (10^{-9}m); nanomaterials refer to functional structures sized less than 100 nm (Youtie et al. 2008). Such structures give the material specific properties, allowing them to be used in new ways, to bring about new effects in larger structures of which they are part, e.g. the 'lotus effect' of surfaces. In this respect, the term 'nanomaterials' narrows the broader term 'nanotechnology' down to the intersection with material sciences, an area where almost all of today's applications of nanotechnology have been achieved (Jopp 2006). Nanomaterials can be applied in various industries and technology sectors, which qualifies them as a cross-sectional technology. In fact, nanotechnology in general has been described as exhibiting certain characteristics of a 'General Purpose Technology' (GPT) like the information and communication technology (Youtie et al. 2008).

Given the perspective of many radically new applications, which could form the basis of innovative products, it will be of particular interest for science, technology and innovation (STI) policy to explore and evaluate the opportunities to promote research and development (R&D) activities to generate new knowledge in the field of nanomaterials. As it has become a part of conventional wisdom that most developed market economies are now based on knowledge, new economic theories have included knowledge more directly in production functions (Griliches 1979). The reasoning behind this analysis is based on the idea that investments in knowledge, which may be embodied in people and technology, increase the productivity of capital and labour, resulting in new products and processes. The endogenous growth model developed extensively by Romer (1990, 1994) states that knowledge production increases with research input. Moreover, knowledge is likely to spill over, which refers to the fact that organisations like universities, research centres and firms benefit from each others' R&D activities on the same topic (Arrow 1962). Several studies, however, have shown that the opportunities for knowledge spillovers depend on proximity, with increasing distance being detrimental to the extent that spillovers can be realised (e.g., Jaffe 1989; Feldman 1994; Audretsch and Feldman 1996). The reason for this is the 'stickyness' of knowledge (Von Hippel 1994), which means that knowledge is highly contextual and requires interaction and frequent contact to spill over (Feldman and Audretsch 1999).

In other words, it is the co-location of R&D activities that may play an important role. As nanomaterials are still in their infancy and commercialised products at an early phase of their life-cycles, spillovers (and cooperation) between universities, public research institutes and private businesses seem important towards the creation of the required knowledge for actually benefiting from nanomaterial applications. However, research on nanomaterials is at the same time a complex task which requires particular technology expertise. In fact, it could very well be that nanomaterials research is globally dispersed and not necessarily concentrated at a few locations. Following an endogenous growth rationale, the generic STI policy implication to promote R&D where it is spatially concentrated, in order to benefit from increasing returns and knowledge spillovers (Laranja et al. 2008), might thus prove not to be helpful when it comes to an emerging technology field like nanomaterials. In fact, national or regional STI policy initiatives have already led to the establishment of 'science parks' and 'nanoclusters' that receive substantial public support (for an exemplary case see Yang et al. 2009). Nevertheless, the question remains whether we can really substantiate positive effects from co-location and spatial concentration of R&D activities outside of dedicated nanomaterial science parks or whether nanomaterials are rather a 'global business'. An answer to this question will provide important implications for the shaping of STI policies for emerging technology fields.

Hence, in this paper, we wish to analyse knowledge creation in nanomaterials using the knowledge production function (KPF) framework. The objective is to identify the determinants of knowledge production by linking the observable, intermediary R&D output—patents—to observable inputs at the regional level. We consider three types of inputs: private and public investments in R&D (both in terms of personnel), as well as the technological specialisation of a region. As we set off to analyse regional knowledge production activities, one aspect ought to be taken into consideration, that is, the correlation 'in space' among regions. Spatial autocorrelation (SAC) (Cliff and Ord 1981) can be defined as the correlation amongst the values of a georeferenced variable that is attributable to the proximity of the objects to which the values are attached. SAC may be due, among other reasons, to self-correlation, omitted/unobserved variables, redundant information, or spatial spillover effects. It is most evident, for example, in the case of Germany, in the still-existing East/West economic divide. Accounting for SAC is necessary in order to correctly assess the economic relations being studied since it makes standard statistics such as correlation coefficients potentially inappropriate. To account for SAC, we introduce a spatial filter—within a negative binomial estimation—in a KPF framework, in order to account for residual SAC (that is, correlation not being explained by the model), and with a view to finding out whether innovative activities in the field of nanomaterials systematically depend on regional characteristics.

The remainder of the paper is organised as follows: Sect. 2 will focus on the role of co-location and knowledge spillovers in fostering the development of emerging technologies like nanomaterials. Section 3 presents our KPF model and discusses the issues of non-linearity and spatial dependence when estimating the KPF. Section 4 shows the results of the empirical application to German nanomaterial patents. Section 5 closes with concluding remarks and avenues for further research.

2 Co-location and knowledge spillovers in nanomaterials

It has been widely acknowledged that innovation, technological change and eventually economic growth are based on knowledge, a key concept of endogenous growth theory (Romer 1990, 1994; Aghion and Howitt 1992). While new knowledge can be used by established firms, particularly entrepreneurial firms serve as a conduit for transforming knowledge that otherwise might have remained uncommercialized into new products (Audretsch and Keilbach 2008). The production of new knowledge depends on investments into R&D activities. Making technological knowledge an endogenous factor, endogenous growth theory allows for increasing returns to investment in R&D (Romer 1994). Knowledge created by proprietary R&D activities, however, is likely to spill over. Arrow (1962) argued that spillovers occur during the production and use of new knowledge as a result of indivisibilities in both inputs and outputs, uncertainty, low appropriability, and excludability. A substantial body of literature has therefore focused on the importance of spillovers or externalities of knowledge in generating economic growth (e.g., Romer 1990; Krugman 1991; Jaffe 1989; Acs et al. 1992, 1994; Feldman 1994; Audretsch and Feldman 1996). In this respect, many studies have pointed to the role of localised spillovers from relevant knowledge sources that result from proximity which facilitates communication and learning (e.g., Jaffe 1989; Feldman 1994; Audretsch and Feldman 1996).

In fact, given the availability of modern information and communication technologies, the alleged importance of proximity for spillovers seems to be surprising. However, while the costs of transmitting information have more or less become invariant to distance, knowledge—particularly ‘sticky knowledge’ (Von Hippel 1994)—exhibits considerably different characteristics. As it is highly contextual knowledge, it can presumably be best transmitted via personal interaction and frequent contact. In this sense, proximity matters, as it moderates the opportunities for knowledge to spill over and to be applied to different uses (Feldman and Audretsch 1999). Organisations, i.e. firms, universities and other institutional actors, which are working on similar topics, will hence presumably benefit most from each other’s research when they are located closely together (Almeida and Kogut 1997). These organisations will therefore be more innovative than others located elsewhere although the extent of this spatial effect would depend on the respective industry and technology (Varga 2000). Indeed, a critical assumption underlying these arguments is that knowledge spillovers are more important in highly R&D intensive industries (Arrow 1962), i.e. science-based sectors (Pavitt 1984). This obviously holds true for nanomaterials, as their industrial application requires advanced technological capabilities and hence R&D investments.

As a result, technological knowledge on nanomaterials cannot be assumed to be instantaneously disseminated through spillovers, but needs to be acquired, which eventually depends on the R&D capabilities of the recipient (Laranja et al. 2008). The capacity to acquire and to exploit external knowledge has probably best been summarised in the literature on absorptive capacity (Cohen and Levinthal, 1989, 1990). Absorptive capacity is generally developed as a by-product of R&D activities. Consequently, government policies that are designed to foster R&D investment may have a positive impact on sustainable economic growth. This policy perspective hence emphasises the supply of scientific and technological knowledge through the promotion of R&D

(Laranja et al. 2008). However, due to the increasing returns to R&D, regional disparities will increase. This development becomes more pronounced in larger agglomerations, because they facilitate knowledge spillovers (Audretsch and Feldman 1996). Varga (2000) shows that it may be necessary to mobilise a critical mass of R&D activity in order to make intra-regional knowledge spillovers effective. As a consequence, lagging regions will also lack the required absorptive capacity to make use of technologies developed elsewhere (Laranja et al. 2008). Both increasing returns to R&D and targeted R&D support policies are likely to result in even stronger spatial concentration of R&D and inter-regional disparities.

This reasoning raises an important question: does co-location and agglomeration of universities, research centres and firms really matter when it comes to the creation of technological capabilities in an emerging technology like nanomaterials? Nanomaterials have been argued to show certain characteristics of a 'General Purpose Technology (GPT)' like the information and communication technology (Youtie et al. 2008). They are believed to contribute substantially to innovativeness, economic growth and employment (Bozeman et al. 2007). Nevertheless, nanomaterials come along with a high technological complexity, making it difficult for firms to access the economic potential of this technology. In fact, most applications of nanomaterials are still in their infancy. Many of them require the skills and expertise of technologically advanced universities and research institutes which have the ability to perform basic research activities. In this sense, we can argue that knowledge production in nanomaterials is different from other, more established but still highly R&D-intensive technological fields. In these fields, new knowledge which is subsequently protected by patents mainly stems from applied research in industry. In contrast to this, basic research, as it is necessary to advance the field of nanomaterials, is mostly performed at universities or government-funded research institutes which can actually 'afford' less application-oriented research.

In this respect, it could well be that specific technological capabilities are needed that may not be available in a region, even though the region itself might be a technology-oriented and R&D-intensive region. In fact, the perspective of endogenous growth theory assumes a rather linear relationship between the concentration of R&D activities and resulting benefits at the same location. It is much less clear to which extent knowledge generated in a region provides positive externalities to recipients in other regions (Martin and Sunley 1999), although this topic has recently generated a wide interest (see, for example, Paci and Usai 1999; Van Oort 2002; Audretsch 2003). Still, it might be questionable if spillover effects from neighbouring regions matter in our case study. As qualified nanomaterial research can be globally dispersed, and with the availability of advanced information and communication technologies, collaborations between industry and science could to a much smaller degree be dependent on geographical proximity. In other words, the positive effects from co-location on knowledge production would decay substantially for the field of nanomaterials.

Nevertheless, the nature of nanomaterials exhibiting characteristics of a General Purpose Technology suggests that benefits from co-location and agglomeration do exist. Nanomaterials are a cross-sectional technology, i.e. they are tangent to many different fields of technology (Youtie et al. 2008). In this respect, a 'critical mass' of general R&D activity would be instrumental for effective knowledge spillovers in nanomaterials. As noted before, R&D activity can be differentiated according to its source, i.e. industry or public R&D. We hypothesise that both sources will be conducive to knowledge production in nanomaterials.

H1a: The higher the industry R&D in a region, the higher the knowledge production in nanomaterials will be.
H1b: The higher the public R&D in a region, the higher the knowledge production in nanomaterials will be.

Moreover, our arguments suggest that industry and public R&D activities are complementary to each other. While universities typically focus more on basic research, firms place a higher emphasis on applications (Hall et al. 2003). Knowledge spillovers should hence become particularly effective. To capture the on-top effect of co-located industry and public R&D activities on knowledge production, we thus hypothesise a positive interaction effect.

H2: There is a positive interaction effect between industry and public R&D in a region on knowledge production in nanomaterials.

The expected results will sharpen our understanding of the association between concentrated and co-located R&D activities for nanomaterials as an emerging technology field. They may serve as a starting point for STI policy aiming at an improvement of the regional conditions for knowledge production in nanomaterials. The following section will thus outline our model to test our theoretical reasoning.

3 The model

3.1 Knowledge production function

Our research question is tackled using a knowledge production function (KPF) framework, as nanomaterial research can be assumed to be carried out in science-based sectors (Pavitt 1984). In a simple specification, the KPF model comprises private and public investments in R&D as generators of new knowledge. Moreover, the effect of these investments depends on the past stock of knowledge to which scientists may refer during the R&D process. The stock of knowledge in turn creates a specific profile of technological specialisation and expertise which can be assumed to be conducive to a certain technology competence of a region, for example, as a 'centre of excellence' (Romer 1990; Jones 1995; Furman et al. 2002).

As in many empirical studies involving a KPF (e.g., Griliches 1990; Patel and Pavitt 1994), our measure of output is patents (see, for example, Acs et al. (2002), for a discussion of their role as measures of innovation). Without doubt, the use of patents as an indicator of technological innovation has some disadvantages (Griliches 1990). First of all, not all inventions are patented as firms may choose other protection strategies like secrecy. Moreover, although a granted patent guarantees a certain level of originality and newness, research has shown that the value of patents is highly skewed, leading to a 'long tail' in the distribution (Harhoff et al. 2003), that is, only some patents are highly valuable. After all, a patent may not be mixed up with an innovation that was successfully commercialised as patents are rather intermediary R&D outputs. Regarding the relationship between input and output, it has to be considered that time lags exist between R&D expenditure and patenting. Accordingly, our KPF is generically given by the following expression:

$$\ln y_{i,t} = \alpha \ln x_{i,t-1} + \beta \ln z_{i,t-1} + \chi \ln a_{i,t-1} + \varepsilon, \tag{1}$$

where $y_{i,t}$ is the output of the knowledge production function in region i and time t, $x_{i,t-1}$ is the research input; $z_{i,t-1}$ is the stock of knowledge of the region; $a_{i,t-1}$ includes other variables affecting innovation output; ε is the error term assumed to be identically and independently distributed with a zero mean and constant variance; α, β and χ are the sets of parameters to be estimated.

In addition to the above elements, the final model estimated in this paper includes—as an additional variable (or set of variables)—a so-called 'spatial filter' (see Sect. 3.3). The resulting model is then given by:

$$\ln y_{i,t} = \alpha \ln x_{i,t-1} + \beta \ln z_{i,t-1} + \chi \ln a_{i,t-1} + sf_i + \varepsilon, \tag{2}$$

where sf_i is the ith element—corresponding to region i—of the selected spatial filter.

While Sect. 3.3 illustrates in a more detailed way how the spatial filter decomposition is computed, we first discuss, in the following section, the estimation issues tied to the nature of the data.

3.2 Estimation of count data regressions

The model specified above aims to explain the dependent—the output of the KFP—in terms of a number of explanatory variables. In our model, output is measured as the number of patent applications in the field of nanomaterials submitted over a certain period in a given region. It is immediately clear that we are dealing with count data, that is, a variable that cannot assume values smaller than 0, and that will have to be treated as an integer.

Given the nature of the data (non-negative and skewed), hypothesising a Gaussian-based underlying distribution as it is done for example in ordinary least squares (OLS) estimations is misleading. Poisson regressions are commonly used for estimating models with count data as a dependent variable. In this case, a generalised linear model (GLM) can be adopted, using the logarithm—rather than the identity function—as a link function. As a consequence, our model could be presented as:

$$y_{i,t} = \exp\left(\alpha \ln x_{i,t-1} + \beta \ln z_{i,t-1} + \chi \ln a_{i,t-1} + \varepsilon\right), \tag{3}$$

the exponential function being the inverse of the logarithm. However, a Poisson regression implies an equivalence between the conditional variance and the conditional mean. This is often not true in economics where an overabundance of zeros, as well as under- or over-dispersion, are frequent phenomena.

While we will discuss the former problem later in the paper, the latter is often taken into account by employing a negative binomial distribution. A discrete variable may follow this distribution as a result of a two-stage model including an unobserved gamma-distributed variable E with mean 1 and variance $1/\theta$, while the discrete variable at study is Poisson distributed conditionally to E with mean μ and variance equal to $\mu + \mu^2/\theta$ (Venables and Ripley 2002). The dispersion parameter θ (a value of 1 gives as a special case the Poisson model) is iteratively fitted, and can be estimated according to different methods (by maximum likelihood or by means of θ's moment estimator). An initial (first-iteration) estimate of θ can be obtained, for example, from a Poisson regression. A preliminary overdispersion test (Cameron and Trivedi 1990), based on a Poisson estimation of our model, rejected strongly the null hypothesis of $\theta = 1$, showing that an overdispersion adjustment is necessary. As a consequence, the negative binomial estimation framework was chosen for our analysis. The next section discusses how spatial autocorrelation can be accounted for in such an estimation framework.

3.3 Spatial autocorrelation and spatial filtering

As briefly hinted at in Sect. 1, a critical aspect when analysing data at the regional level is considering the role that 'space' plays in the knowledge production process. On the one hand, an established literature and the popular theories of the new economic geography (NEG) aim to explain and model spatial effects from an economic viewpoint through the definition, for instance, of spatial spillover effects. On the other hand, spatial econometric techniques attempt to take into account the spatial effects that are left unexplained, which emerge as spatial autocorrelation (SAC) in the regression residuals. Our contribution aims to provide a further tool for avoiding the problem of residual SAC in a KPF model.

While the economic aspects of the regional innovation systems studied here are included in the proposed KPF model (Eq. 1), additional econometric adjustments, in order to model the possible residual SAC, are desirable, if SAC emerges in the regression residuals.

The most commonly used indicator of SAC is Moran's I (MI). The statistic is computed as follows:

$$I = \frac{N \sum_i \sum_j w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_i \sum_j w_{i,j}\right) \sum_i (x_i - \bar{x})^2}, \tag{4}$$

where N is the number of cases; x_i is the value of the variable X in region i; and $w_{i,j}$ is the (i, j) cell value of the geographic weights matrix $\mathbf{W}$ (defined below). Positive values of the MI imply that positive SAC; that is, similar values of the variable examined tend to be found for regions that are geographically close. On the other hand, negative MI values imply negative SAC, meaning a tendency to discordance between the values of close regions.

The above measure of SAC requires the use of a geographic weights matrix usually referred to as $\mathbf{W}$. This is an exogenously-defined $(N \times N)$ matrix which defines the relations of proximity between the regions—or within any other type of georeferenced data. Binary geographic weights matrices are often used for this aim. A value of 1 for the generic cell (i, j) implies that the two regions i and j are neighbours while the opposite applies for the value 0. Several standardisation schemes exist for the use of the $\mathbf{W}$ matrix, of which the most frequently employed is row-standardisation (for additional coding schemes, see Tiefelsdorf et al. (1999); Getis and Aldstadt (2004)).

The spatial econometric literature has proposed, in particular over the last two decades, a number of techniques, aimed at controlling for autocorrelation of both the dependent and the explanatory variables, as well as of the residuals (see, for example, the Cliff–Ord-type model, Anselin 1988 or Griffith 1988). While these techniques are widely used in many fields of analysis they are based among other restrictions on an assumption of normality (with the exception of spatial logit/tobit models). However, as seen in Sect. 3.2, count data are not properly analysed unless the characteristics of their distribution (discrete, non-negative, highly skewed) are explicitly considered in the econometric model.

As a solution to the above problem, we propose the use of eigenvector-based spatial filtering techniques (Griffith 2000, 2003) in order to account for spatial structures due to unobserved/omitted variables. The advantage of employing a spatial filtering approach is that it does not require a normality assumption nor other estimation restrictions and that it can therefore be applied to regressions with any underlying distribution (for example, to logistic and Poisson regression). Moreover, while other spatial filtering techniques such as, for example, the one in Getis (1995), work directly on the data by computing spatial and non-spatial components the technique used here leaves the original data unchanged while 'adding' explanatory power by means of the spatial filter.

Mathematically, the spatial filtering techniques employed here are related to the computational formula of the MI. The starting point for the computation of a spatial filter is the definition of a spatial weights matrix (for example, a binary contiguity matrix). The methodology uses eigenvector decomposition techniques, in order to extract orthogonal and uncorrelated numerical components from a given $(N \times N)$ geographic weights matrix (Tiefelsdorf and Boots 1995). In this regard, the proposed approach is reminiscent of principal components analysis (PCA): in fact, both methodologies generate orthogonal and uncorrelated new 'variables' that can be employed in a regression analysis framework. However, on the one hand the PCA components may be given a straightforward economic interpretation since the computed eigenvectors are used to construct linear combinations of the variables concerned. On the other hand, a spatial filter is a linear combination of (a subset of the) eigenvectors extracted from an exogenous spatial weights matrix. Consequently, they do not have a straightforward economic meaning, and represent the latent SAC (or redundant information due to spatial interdependencies) that can be related to the georeferenced variable being studied, *according to the given geographic weights matrix*. In other words, the single eigenvectors may represent specific spatial patterns tied to administrative or socio-economic factors.

Formally, the above-mentioned eigenvectors are computed from a modified geographic weights matrix:

$$\left(\mathbf{I}-\mathbf{1}\mathbf{1}^{\mathrm{T}}/N\right)\mathbf{W}\left(\mathbf{I}-\mathbf{1}\mathbf{1}^{\mathrm{T}}/N\right), \tag{5}$$

where $\mathbf{W}$ is the given geographic weights matrix; $\mathbf{I}$ is an $(N \times N)$ identity matrix; and $\mathbf{1}$ is an $(N \times 1)$ vector containing only 1's. Because of the transformation carried out (see Griffith 2003), the sequence in which the eigenvectors of the modified matrix in Eq. (5) are extracted so as to maximise the sequential residual MI values. Consequently, the first extracted eigenvector, E1, is the one which shows the greatest MI value among all subsequent eigenvectors. Accordingly, the second extracted eigenvector, E2, is the one which shows the greatest MI value while being uncorrelated to E1. The process continues with the final extraction of N eigenvectors. The resulting set of vectors is the complete set of all possible (mutually) orthogonal and uncorrelated map patterns (Getis and Griffith 2002). Notably, when visualised on a map, the first two extracted eigenvectors often identify major (smooth) geographical patterns along the cardinal points, that is, North–South and East–West (for example, the German East/West former divide). The subsequent eigenvectors tend to display map patterns at a gradually smaller scale (from global to regional to local patterns).

The above eigenvectors may be employed as additional regressors in an otherwise non-spatial regression framework. The advantage implied by the orthogonality of the eigenvectors is that no issues arise with respect to partial correlations and multicollinearity. Additionally, (a subset of) the eigenvectors may function as proxies for missing explanatory variables. As such, we expect the spatial filter to also accommodate an excess share of zeros (with respect to the expected share in a Poisson distribution) in the dependent. From a spatial dependence point of view the eigenvectors account for the residual SAC in the data, therefore 'cleaning' the regression residuals. Actually, each eigenvector used as a regressor is considered to be part of the final 'spatial filter' for the dependent variable.

However, it is clear that employing all N eigenvectors in a regression framework is not desirable for reasons of model parsimony. Further, in a cross-sectional framework, the number of explanatory variables would be equal to or greater than the number of observations. A smaller set of so-called 'candidate' eigenvectors should then be selected from the full set of eigenvectors. This can be done on the basis of their MI values; that is, by selecting the most relevant spatial patterns. An MI threshold value can be used in this regard (see, for example, Sect. 4.2). Once a set of M $(< N)$ candidate eigenvectors has been defined a further selection may be carried out in order to relate the exogenous spatial patterns identified by the eigenvectors to the data at hand. Since the eigenvectors are orthogonal and uncorrelated this second selection of eigenvectors can be carried out in a stepwise regression framework. The resulting subset of selected eigenvectors is what we will call the 'spatial filter' for the variable analysed. On the other hand, the final residuals of the stepwise regression are the spatially filtered component of the variable examined.

In summary, our spatial filtering approach to the estimation of a KPF for innovation in nanomaterials aims to provide a number of benefits: (i) it clears SAC in the regression residuals, (ii) while allowing, differently from other methods, to employ a Poisson-based estimation strategy (including the negative binomial overdispersion adjustment); (iii) finally, we may expect the spatial filter to account for possible excess zeros problems as well. On the basis of the methodology presented above, the next section describes the empirical application carried out for our analysis of nanomaterial patents.

4 The empirical application to German nanomaterial patents

4.1 Data

As our knowledge production function framework suggests, we regress the number of nanomaterial patents on private and public investments in R&D, on the stock of technology as well as on control variables and the spatial filter. Regarding the control variables, we focus on the size, the structure of the economy, and geographic/urban characteristics of a region, that is typology, urbanisation level, and agglomeration. Most challenges in data collection arise from the correct identification of nanomaterial patents. Given the diversity in opinion about how to define nanotechnology, a variety of search strategies has been developed by bibliometricians and patent analysts to capture the field (for a detailed discussion see Zitt and Bassecoulard 2006; Schummer 2004; Hullmann and Meyer 2003). As a reliable identifying tag for nanotechnology patents has not yet become available at patent offices,[1] this study has adopted a search strategy that evolved from a collaboration with a major European chemicals company which is one of the largest patent applicants in nanomaterials. We focus our analysis on patent applications at the European Patent Office (EPO) as these patents can, in contrast to patent applications at national patent offices, be regarded as higher quality patents because the application costs are higher, so discouraging poor quality patent applications.[2] Moreover, these applications can be assumed to be closer to commercialisation which reflects the reasoning that nanomaterials should lead to economic benefits (Haas et al. 2003).

The search strategy focused broadly on the field of nanomaterials. Searches were carried out in the databases ‘Derwent World Patent Index’, EPFULL, PCTFULL and PATDPAFULL. The ‘Derwent World Patent Index (DWPI)’ is a database which comprises the abstracts for patent documents from 41 countries, where the full abstract text was screened. The DWPI is the most comprehensive database of enhanced patent documents available. Patent documents are analysed, abstracted and indexed manually by experts which facilitates the search. With regard to the other three databases, which contain full patent documents, the search concentrated on the title, on the abstract, as well as on the claims. A substantial number of keywords in the field of nanomaterials

[1] Patents are classified through an international coding system (IPC). Although there is a special IPC class for nanotechnology patents (B82B) only a small fraction of relevant patents is actually assigned to this class (Haas et al. 2003). Nevertheless, the EPO has begun introducing a new identifier as an additional patent class (Y01N) which aims to provide information on developments in emerging technology fields. Consistency checks show, however, that many nanomaterial patents have not yet been marked with this tag, particularly less recent patent documents.

[2] We date the nanomaterial patents according to their application date as opposed to the granting date which conforms to common practice (e.g. Griliches 1981). The application date has the advantage of being closer to the actual completion of the invention.

were used.[3] Moreover, the search comprised patents with a size indication of less than 100 nm (Youtie et al. 2008). The reason for searching multiple sources of information was to get an overview of nanomaterial patenting as complete as possible.

Talking about patents necessarily involves a discussion about the differentiation between patent applicant and patent inventor. While the applicant is the holder of the patent right, the document itself also shows the name(s) of the inventor(s). Typically, a firm would be the applicant of a patent invented by the firm's R&D employees. In the German patent system, patents prepared within the employee's labour contract belong to the firm which in turn has to compensate the inventor according to the economic value of the patent. The differentiation between the applicant and the inventor is relevant in a spatial sense: While the applicant is typically located at one place, the inventors may be geographically dispersed at and around the applicant's location. Most larger firms, however, maintain several R&D units while all patents are applied for from the firm's headquarter. This situation also applies to the large German science organisations like the Fraunhofer Society or the Max Planck Society. Both organisations are headquartered in Munich while the individual member institutes are scattered around Germany. Focusing on the patent applicant would hence lead towards a biased estimation of the innovative capacity of a particular region. We therefore revert to the inventor's location as a reference for the assignment of nanomaterial patents. Moreover, as patents may have been invented by several inventors located in different regions, we apply a fractional counting approach to assign every region mentioned the respective share of the nanomaterial patent.

Focusing on our explanatory variables, we measure the R&D inputs by means of the number of employees in private and public R&D. The headcount is entered in relative terms into our estimation: private (public) R&D is defined as industry (public) R&D employees as a share of the total workforce.[4] Moreover, in order to measure the importance of their joint location in a region, we include an interaction term of private and public R&D in our second model specification (see Table 2). These measures rely on a critical assumption, which is that nanomaterial research may be carried out in any field of science. In other words, we use general and not nanomaterial-specific R&D employment. The reason for this is twofold. First, we have discussed the cross-sectional nature of nanomaterials. In any field of science and with the broad availability of technical equipment (e.g. powerful microscopes to make nano-structures visible), research has to an increasing extent been focused on the nanoscale in a search for new functionalities. Obviously, there seems to be no longer a border between 'traditional' and nano-scale research (Jopp 2006). Second, and this reason is much more practical in nature, neither firms nor universities or public research centres

[3] The search script leans against the one elaborated by the Fraunhofer ISI institute (Haas et al. 2003). It cannot be understood by persons not skilled in the programming of such scripts. The ten keywords which were able to identify most nanomaterial patents are: "nanopartic? nanotube, nanoscale, nanofiltration, nanocomposite, nanostructure? nanoporous, nanofiber, nanowire, nanotechnology", where "?" denotes an unlimited truncation.

[4] The number of people working in R&D is highly correlated with the actual R&D investments. We use this measure in order to reflect our theoretical arguments on the importance of interaction between people at co-located R&D sites for knowledge spillovers.

differentiate their R&D between nano-scale and other types. Data are therefore not available.

The technology stock of a region is identified by analysing patent applications (again referenced on the inventor's location) in the fields of mechanics, electronics, chemicals and pharmaceuticals. Patent applications in other technological fields are left out of the estimation as a reference group. Again, shares are calculated on the total number of patents produced in a region. The technology stock hence represents the technological specialisation of a region. As nanomaterials have been characterised as exhibiting a cross-cutting nature, our specialisation patterns can also be assumed to reflect the stock of technological knowledge available for the scientists. Moreover, we include as control variables the economic structure and size of the regions to eliminate sheer size effects. For this purpose, we include the shares of employees employed in the manufacturing and services sector, the GDP per capita both in logs and as a squared term in logs, as well as the population in logs. Finally, we add three dummy variables, which are intended to control for the urban characteristics of the regions. The first dummy variable identifies the 'central cities', a formal classification of the 'core' areas of the main German cities, which can be regarded as central business districts (CBDs). We expect a negative sign for this variable, because particularly firms tend not to be located in the center of the main cities but rather in their peripheral areas. The second dummy variable identifies highly urbanised regions in order to distinguish them from lower density regions. Finally, the third dummy variable tells which regions belong to areas with urban agglomerations, proxying for clusters of economic activity. Following our reasoning for the central city dummy, we expect positive signs for the urbanisation and agglomeration dummies meaning that firms and universities tend to be located in urbanised and agglomerated areas – rather than in rural areas—in order to exploit externalities. The three dummies were computed by authors on the basis of a composite index developed by Böltgen and Irmen (1997).[5] With the exception of the technology stock, which has been identified using data from the EPO, the remaining explanatory variables are taken from the German federal statistical office (Destatis) and from the European statistical office (Eurostat). As in other studies in the field (e.g. Audretsch and Keilbach 2008), our unit of analysis are the German districts (*kreise*), i.e. the NUTS-3 level.[6] 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. By using the sum of patents over several years for the dependent variable, we account for both the short-term and long-term effects of R&D inputs on patent output. In fact, Hall et al. (1986) find a rather strong contemporaneous relationship between R&D and patenting which should in this context reduce endogeneity problems.[7]

At the spatial level, we may inspect the geographical distribution of the dependent variable, as well as the level of spatial autocorrelation (SAC) inherent to the

[5] Correlation between the three dummy variables is rather low, below 0.4.

[6] As an alternative, higher aggregations like urban planning regions were used which, however, lead to a substantial loss of information. Details are available from the authors upon request.

[7] Endogeneity appears to be a sensitive issue in any KPF-type study. Although localised R&D may lead to patents, it has to be taken into account that successful inventors are also inclined to invest more in R&D.

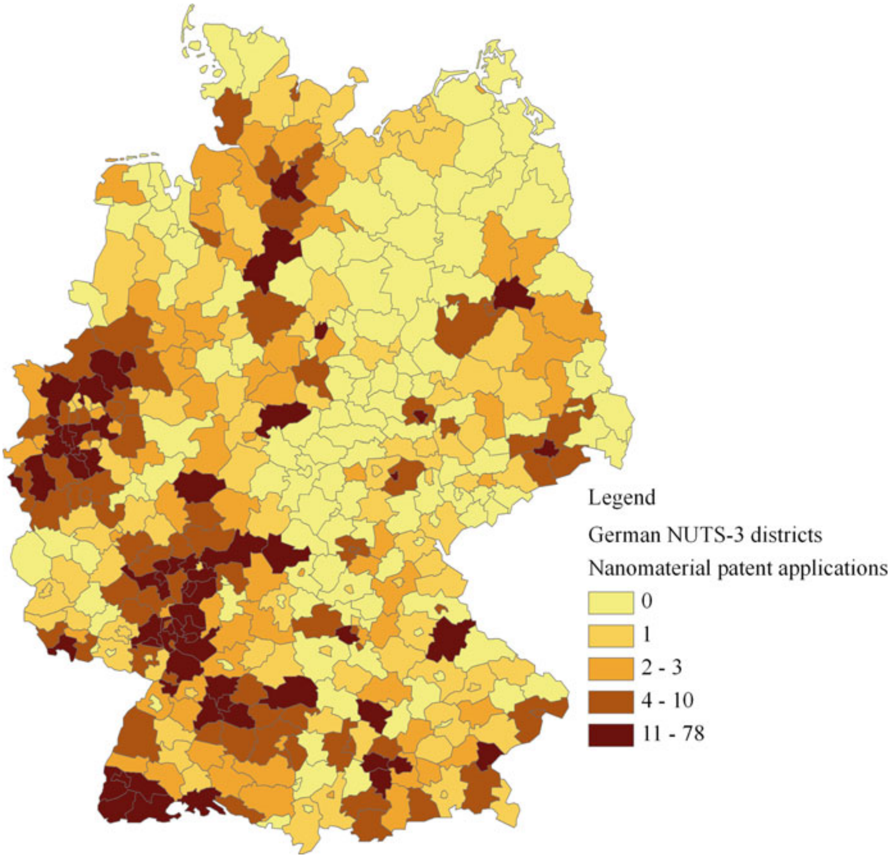

Fig. 1 Geographic distribution of nanomaterial patent applications by inventor

data. Figure 1 provides a graphical visualisation of the number of nanomaterial patents in each German district. From the visual inspection of the map, it is clear that the geographical distribution of the patent applications cannot be considered random. A prevalence of high values for the Western regions of Germany can be highlighted. Most patents appear to be located—reasonably—in the major German cities and in specialised districts. Inversely, the East German *kreise* are identifiable—with few exceptions, such as Dresden, Halle and Berlin—with low patenting activities. Looking at SAC, the resulting value of the Moran's I for the dependent is equal to 0.28, which denotes positive and significant SAC. The main argument why we observe SAC should be the existence of knowledge spillovers between the regions (see, for example, Anselin et al. 1997; Parent and LeSage 2008). Besides, SAC could occur if nanomaterial patents are developed in firms or universities and research institutes in a particular region while the inventors live either in that region or closely in neighbouring regions and commute to their work. Both aspects should lead to a rather high correlation between the individual regions.

Table 1 Descriptive statistics

Variable	Obs.	Mean	SD	Min	Max
Dependent variable					
Nanomaterial inventor patents	439	4.866	9.490	0.000	78.000
Knowledge inputs					
Share of industry R&D employees (%)	439	0.008	0.011	0.000	0.080
Share of public R&D employees (%)	439	0.004	0.009	0.000	0.096
Regional specialisation					
Share of mechanics patents (%)	439	0.436	0.163	0.039	1.000
Share of electronics patents (%)	439	0.245	0.144	0.000	0.792
Share of chemicals patents (%)	439	0.149	0.137	0.000	0.708
Share of pharmaceuticals patents (%)	439	0.064	0.067	0.000	0.420
Controls					
Share of employees in manufacturing (%)	439	27.558	11.338	3.881	65.530
Share of employees in services (%)	439	8.073	3.705	2.277	21.475
GDP p.c. (in thousands of Euros)	439	23.167	9.515	11.255	77.940
Population (thousands)	439	127.363	153.474	23.509	2, 439.539

This level of spatial dependence will have to be adequately captured (explained) by our controls and explanatory variables, ideally resulting in spatially uncorrelated regression residuals. If this objective cannot be achieved by a non-spatial regression, then spatial econometric adjustments are necessary. The next section presents and briefly discusses the findings obtained for the spatial regressions.

4.2 Results

In total, 2161 nanomaterial patents were identified. Focussing on the patent applicant, most patents turn out to be applied for by companies (81.3%) while universities and research institutes account for 11.1% of the total. The remainder refers to patent applications by individuals or government agencies. Table 1 shows the descriptive statistics of our model variables. It turns out that on average almost five nanomaterial patents have been applied for in German regions from 2000 to 2004, with a minimum of 0 and a maximum of 78 patent applications in a region.

Figure 2 shows a histogram of the nanomaterial patents for the 439 German districts. There are only a few regions that exhibit a very high number of patents while the vast majority of regions possesses no patents at all (136 regions) or only a few. The figure suggests that the distribution of patents is highly skewed, and that we may face a problem of excess zeros (that is, the case in which the share of zeros in the dependent exceeds the share of zeros expected according to the Poisson distribution).[8]

[8] Had a spatial filter not been employed, the excess zeros problem could have been dealt with by means of zero-inflated negative binomial or hurdle models (Mullahy 1986; Lambert 1992), which, however, require separate modeling of the binary choice part (equal to zero or positive), or by means of a Tobit model, which, on the other hand, assumes a Gaussian linear model for the positive part.

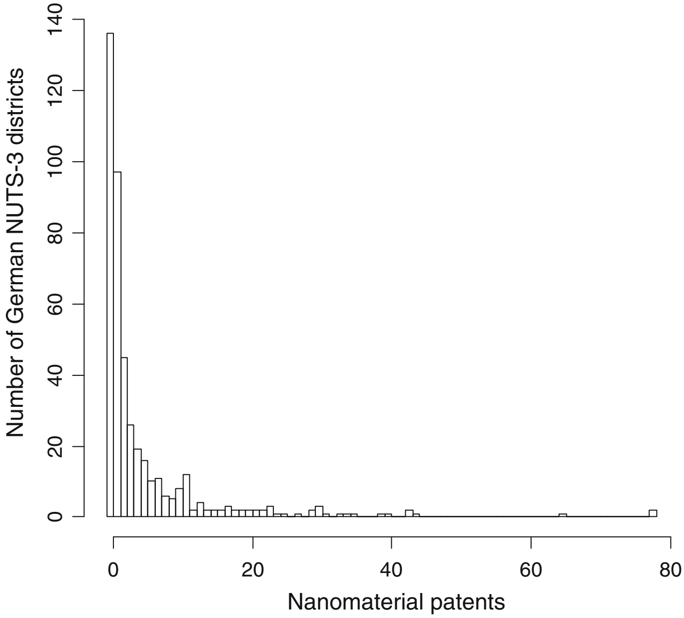

Fig. 2 Histogram of nanomaterial inventor patents

Regarding the explanatory variables it turns out that there are considerably more industry R&D employees than public scientists. Moreover, most regions are specialised on mechanics, followed by electronics and chemicals. In terms of employment, the regions are on average more focused on manufacturing than services. The average GPD per capita equals roughly € 23,000 with substantial regional disparities. These disparities also emerge in terms of population with an average of around 127,000 individuals per region. Our three dummy variables identify 72 central cities, 287 highly urbanised regions, and 147 regions (mostly in West Germany) in agglomerated areas, respectively.

As hinted at in Sect. 4.1, a non-spatial model could be considered appropriate—in addition to its explanatory power from an economic theory viewpoint—if it were able to properly account for spatial dependence. Therefore, we may look at the value of the MI statistic computed on the residuals, which, for the simple non-spatial negative binomial estimations is equal to 0.19 and 0.20, for Model 1 and Model 2 (Table 2), respectively. This MI value clearly shows positive and significant SAC that is not accounted for by our non-spatial models.

In order to adjust for SAC, we propose the use of spatial filtering-enhanced models, as described as Sect. 3.3. We start by defining a spatial weights matrix **W** of dimension 439×439, that is, a square matrix with as many rows and columns as the German *kreise*. Following a rook contiguity rule,[9] for each pair (i, j) of districts, the corre-

[9] Alternative spatial weights matrices–and the related spatial filters—have been tested, based on: (i) k-nearest neighbours; and (ii) distance. The rook contiguity matrix has proven to be the most appropriate choice for the problem at hand.

Table 2 Results of the negative binomial models

	Model 1		Model 2	
	Coefficient	SE	Coefficient	SE
Knowledge inputs				
Share of industry R&D employees	10.895	4.509**	6.029	5.808
Share of public R&D employees	9.719	3.462***	6.627	4.217
Interaction (industry*public R&D)			761.333	358.454**
Regional specialisation				
Share of mechanics patents	−0.894	0.897	−0.546	0.914
Share of electronics patents	2.024	0.890**	2.341	0.928**
Share of chemicals patents	3.402	0.932***	3.767	0.966***
Share of pharmaceuticals patents	1.396	1.154	2.209	1.128*
Controls				
Share of employees in manufacturing	0.003	0.006	0.007	0.007
Share of employees in services	0.072	0.018***	0.064	0.018***
GDP p.c. (in logs)	−0.769	5.170	−0.444	4.860
GDP p.c. (in logs)^2	0.045	0.254	0.025	0.238
Population (in logs)	0.196	0.056***	0.196	0.058***
Central city dummy	−0.351	0.135***	−0.329	0.142**
Urbanisation dummy	0.484	0.142***	0.456	0.148***
Agglomeration dummy	0.355	0.116***	0.403	0.112***
Spatial filter (joint significance)	1.000	0.056***	1.000	0.058***
Intercept	−0.492	26.144	−2.028	24.647
Θ	3.383	–	3.118	–
Null deviance (dof)	1812.00	(438)	1783.01	(438)
Residual deviance (dof)	422.09	(386)	424.79	(390)
AIC	1747.80	–	1755.80	–
Pseudo-R^2	0.719	–	0.645	–
Pseudo-adjusted-R^2	0.681	–	0.601	–
MI (p-value)	−0.071	(0.022)	−0.045	(0.154)

***,**,*Statistical significance at the 1, 5, 10% level, respectively. Robust standard errors are given

sponding cell (i, j) in $\mathbf{W}$ assumes value 1 if the two districts share a border, while it takes on value 0 if they do not share a border. The matrix is then rescaled, so as to sum 1 over all values (C-coding, see Chun et al. 2005; Tiefelsdorf and Griffith 2007). After transforming $\mathbf{W}$ as in Eq. (5), we then extract the related 439 orthogonal and uncorrelated eigenvectors, as well as the corresponding eigenvalues. Because of the matrix transformation applied, all the eigenvectors have the property of maximising SAC, while being orthogonal to the previously extracted eigenvectors. Consequently, the first eigenvectors show smooth surface partitions, resembling North-South and East-West patterns. A visualisation of the geographical distribution of the first two eigenvectors extracted for the spatial weight matrix $\mathbf{W}$ utilised in our study is given in Fig. 4 in Appendix.

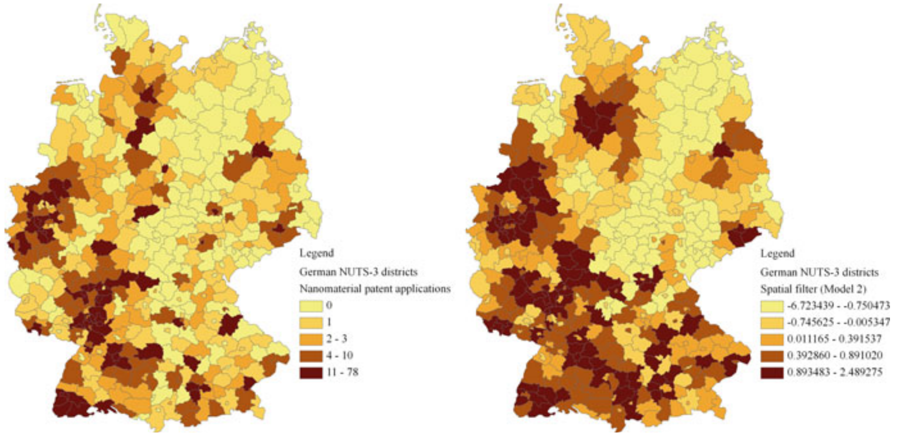

Fig. 3 Comparison between the geographical distributions of nanomaterial patent applications (*left*) and of the spatial filter computed for Model 2 (*right*)

We select a subset of eigenvectors—which we will refer to as 'candidate eigenvectors'—according to the following threshold: $\mathrm{MI}(e_i)/\max_i[\mathrm{MI}(e_i)] > 0.25$, where $\mathrm{MI}(e_i)$ is the MI computed on a generic eigenvector i. This threshold level roughly corresponds to a 95% of variance explained in a regression of a generic $\mathbf{Y}$ on $\mathbf{WY}$. The result of the selection process is a subset of 98 candidate eigenvectors to be used for estimation purposes. The candidate eigenvectors are added, as explanatory variables, to the non-spatial models (Eq. 1), and evaluated in a stepwise regression framework. A stepwise negative binomial is used, for consistency with the estimation of the non-spatial model. The economic variables are set up as a minimum model, which cannot be discarded, while the single eigenvectors are added or thrown out on the basis of their contribution to the model fitness, as measured by the Akaike information criterion (AIC) (Akaike 1974). Because AIC-based stepwise tends to overfit, a final backward selection is made manually, as additional eigenvectors are dropped on the basis of χ^2 tests and according to a 95% significance level.

The final result of the selection process is a set of 38 and 33 eigenvectors, for Model 1 and Model 2, respectively, all statistically significant (95% at least). The spatial filtering specification appears to serve its purpose, since the MI values (reported in Table 2) for the spatial model's residuals are much lower (−0.071 and −0.045) and even insignificant in the case of Model 2. The spatial filters computed have taken up the unexplained spatial dependence and spatial heterogeneity, as it is exemplified in Fig. 3, for the case of Model 2, by a visual comparison with the geographical distribution of nanomaterials patents (the dependent variable). In addition, filling in for missing explanatory variables, the spatial filters appear to accommodate the high number of zeros in the dependent variable (136), which is not adequately taken care of by non-spatial negative binomial models as shown, for Model 2, in Table 3.

With regard to the knowledge inputs our results in the first model specification (Model 1) indicate that both public and private R&D have a positive and significant effect on the creation of nanomaterial patents. Moreover, Model 2 shows a positive effect of the interaction term between public and private R&D. Hence, all our

Table 3 Observed and estimated frequencies (0–4), Model 2

Frequencies	0	1	2	3	4
Observed	136	97	45	26	19
Negative binomial	92	82	59	41	30
Spatial filtering negative binomial	126	78	52	35	25

hypotheses receive support. The findings first of all hint at the importance of both sources of R&D in an additive way. There is also an effect ‘on top’ which is picked up in our second model specification by the interaction term. The positive effect of the interaction term on knowledge production underpins our reasoning of the benefits of co-location of public and private R&D. Apparently, it is of great importance for a region whether opportunities for knowledge spillovers and collaboration (which we cannot observe though) arise.

Focusing on the regional specialisation there are highly significant and positive effects of a regional specialisation in electronics and chemicals across the two models. In fact, most nanomaterials are based on chemical structures or processes. But electronics seem to play an important role as well. Having established a stock of knowledge in these scientific fields hence creates an advantage for engaging in nanomaterial research. Interestingly, electronics and chemicals have been identified as core science-based sectors by Pavitt (1984) for which the KPF approach is appropriate. A specialisation in pharmaceuticals becomes weakly significant in Model 2 while mechanics patents seem not to be relevant at all.

With regard to the control variables, we can observe a positive and significant effect of a regional economic orientation towards the services industries. This hints at the importance of a rather modern economic orientation of a region. Furthermore, there is a positive and significant size effect indicated by the coefficient for population. These last findings make it clear that it is not only a sheer size effect that a region can succeed in nanomaterial research and knowledge production. Size matters but nanomaterial patenting seems to be dependent much more on knowledge inputs in terms of personnel and on an adequate technological specialisation. Finally, the urban characteristics of the regions, as well as localisation, matter. The central city and urbanisation dummies show negative and positive signs, respectively, suggesting that factories and research facilities tend to be located in highly urbanised districts but less often in the nucleus of medium/large cities. The agglomeration dummy also presents a positive coefficient, suggesting that economies of agglomeration play a role in the production of knowledge in nanomaterials. This finding is consistent with new economic geography and endogenous growth theories.

5 Conclusion, limitations and further research

In this paper, we have investigated the knowledge creation in nanomaterials as a specific economic activity using the knowledge production function (KPF) framework. Our objective was to analyse the determinants of knowledge production and the effects from co-located R&D activities by linking the observable R&D output—patents—to observable inputs. We considered three types of inputs: public and private R&D in terms of personnel as well as the technological specialisation of a region. Our results show that co-location matters considerably. Both public and private R&D are relevant for nanomaterial patenting in an additive but also an interactive way. This finding suggests that co-located R&D provides opportunities for knowledge spillovers and collaboration between the actors. Against the background of high technological complexity and a global dispersion of relevant nanomaterial research capabilities, regions with co-located R&D can thus still benefit from the economic potential of an emerging technology like nanomaterials.

However, our results also suggest that there is a ‘critical mass’ of R&D activities going on in a region required to actually be able of conducting fruitful research in nanomaterials. On the one hand, the reason for this lies in the cross-sectional nature of nanomaterials with potential applications in many fields of science. On the other hand, our results have substantiated a significant contribution of accumulated technology knowledge in electronics and chemicals in a region. As a consequence, two major implications for STI policy can be derived. First, the rather generic policy implication of endogenous growth theory seems to be viable in the context of nanomaterials: in order to benefit from increasing returns and knowledge spillovers, policy initiatives and public support should be focused on those regions that have previously shown to be technology-oriented and with high levels of R&D activity. The second and more interesting implication for policy makers is that these efforts should be limited to regions with a characteristic profile of technology specialisation in electronics and chemicals. Moreover, supporting a close collaboration between the actors to facilitate knowledge spillovers should spur the production of nanomaterials. In this respect, the already existing ‘nanoclusters’ or ‘nanoscience parks’ actually seem to be promising instruments for positioning the region as a hub for nanomaterial research.

Hence, our findings contribute to an understanding of how STI policies should be designed in the context of nanomaterials as an emerging technology with high expectations for future economic growth. Although the complexity of nanomaterial research can be assumed to be substantial, we are able to underline its regional dimension. Nevertheless, we need to acknowledge some limitations of our study. First, we are not able to distinguish between nano-specific and -unspecific R&D inputs. However, we have argued that the cross-sectional nature of nanomaterials does not lead to severe problems in this respect. Moreover, our measures for knowledge inputs, i.e. employment in public or private R&D units, are rather coarse and can only be regarded as a rough proxy. Also, we do not attempt to model the extent of knowledge spillovers within or between regions nor collaboration patterns. As outlined above, many studies in the field chose a similar approach which is mainly due to a lack of data availability.

Future research should, in particular, try to generate empirical evidence on the long-term determining factors of knowledge production in nanomaterials. These factors might indeed change with the maturity of the technology field. As first-mover advantages can be considered to be important in order to attract firms, research institutes as well as public funding, it would be particularly interesting to investigate the characteristics of a region that succeeds in realising such advantages when a promising new technology is still in its infancy. Another aspect is the relationship between public and private R&D which needs to be explored in more detail. In this context it would be particularly interesting to see how both types of R&D can collaborate so that knowledge actually spills over from academia to industry and viceversa resulting in increased research productivity. These insights would probably best stem from a case study approach.

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Appendix

See Fig. 4.

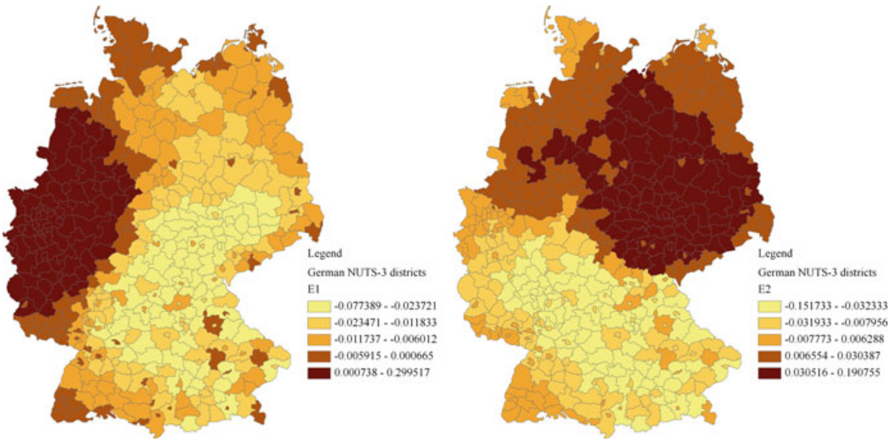

Fig. 4 First two eigenvectors (E1, E2) extracted from the transformed spatial weights matrix W

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