R. Patuelli, A. Vaona, C. Grimpe

Poolability and aggregation problems of regional innovation data : an application to nanomaterial patenting

Quaderno N. 08-10

Poolability and Aggregation Problems of Regional Innovation Data: An Application to Nanomaterial Patenting

Roberto Patuelli,[a,1] Andrea Vaona[b] and Christoph Grimpe[c]

[a] Institute for Economic Research (IRE), University of Lugano, Switzerland
The Rimini Centre for Economic Analysis, Rimini, Italy

[b] Institute for Economic Research (IRE), University of Lugano, Switzerland
Kiel Institute for the World Economy, Kiel, Germany

[c] ZEW Centre for European Economic Research, Mannheim, Germany
Catholic University of Leuven, Belgium
University of Zurich, Switzerland

Abstract

Research and development (R&D) in the field of nanomaterials is expected to be a major driver of innovation and economic growth. In this respect, many countries, as national systems of innovation, have established support programs offering subsidies for industry- and government-funded R&D. 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, implicitly assumes poolability of regional data. We apply our reasoning to Germany, which has well-known – and wide – regional disparities, for example between the former East and West. Based on analyses at the level of NUTS-3 regions, 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. Our findings have implications for further research in the field, that is, a careful evaluation of poolability and aggregation is required before estimating knowledge production functions at the regional level. Policy considerations are offered as well.

Keywords: nanotechnology, patents, poolability, Germany, spatial autocorrelation

JEL-Classification: L60, O32, R11, R12

---

[1] Corresponding author. Address: Institute for Economic Research (IRE), University of Lugano, via Maderno 24, CP 4361, CH-6904 Lugano, Switzerland. E-mail: roberto.patuelli@lu.unisi.ch. Phone: +41-(0)58-666-4166. Fax: +39-02-700419665.

1   Introduction

The importance of nanotechnology is ever more acknowledged by scholars in innovation studies. Nanotechnology is assumed to have a wide array of potential applications, e.g. in biotechnology, optics, chemistry or material sciences, which is why it has been considered as a 'General Purpose Technology (GPT)' like ICT (Youtie et al. 2008). Their application is expected to result in incremental and radical innovations (Meyer 2006). Nanotechnology is therefore believed to contribute substantially to economic growth and employment (Bozeman et al. 2007). Most of the 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). Such structures 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.

Given the perspective of many radically new applications, which could form the basis of innovative products, 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 (Lundvall 1992; Nelson 1993; Edquist 1997) but the concept has been extended to the regional level as well (Cooke et al. 1997; Howells 1999; Cooke et al. 2000). The fundamental idea behind the concept of regional systems of innovation is the notion that industries tend to concentrate in certain spaces. 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 (Howells 2005; Buesa et al. 2006). Many regions have recognized the importance of promoting research activities in nanotechnology, which has led to the establishment of 'science parks' and 'nanoclusters' that are 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. For example, Germany is often studied by making a distinction between the former West and East Germany areas (Brixy and Grotz 2004; Fritsch 2004; Günther 2004). In this paper, we aim to 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. This will allow scholars in the field and policy makers to single out local specificities and to appropriately taylor innovation policies.

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. Bode analyses regional innovative activities and R&D spillovers, as well as agglomeration externalities, in Germany.

In particular, while tests carried out on the North/South of Germany or on agglomerated/peripheral regions do not seem to suggest poolability problems, additional tests on high/low innovativeness and labor productivity (Bode 2004a, b) 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 to provide a more explicit treatment – and subsequent evaluation – of poolability problems in innovation analyses.

We also tackle one further problem. We check whether 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). So there could be a mismatch in the data between innovation inputs and output. By testing regions at different aggregation levels, we aim to eliminate this mismatch.

The remainder of the paper is structured as follows. Section 2 introduces the concept of knowledge production functions. Section 3 describes our dataset and our econometric estimation and testing method. Section 4 shows our results first for the whole of Germany and afterwards for subsets of our data for East and West Germany. Finally, Section 5 sets out our results concerning aggregation issues. Section 6 concludes with limitations of our study and avenues for further research.

2 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 (KPF) (Griliches 1979). The basic idea behind a KPF 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 field of technology. Endogenous growth theory postulates that knowledge production increases with research input, and in particular with input in terms of human capital (Romer 1990; Aghion and Howitt 1992). In this paper, 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 leads to a specific profile of technological specialization 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; Porter and Stern 2000).

Patents have been frequently employed as measures of output in a KPF framework (for example, Griliches 1990; Patel and Pavitt 1997) as they can be characterized as intermediary outcomes in the innovation process (for a discussion of their role as measures of innovation

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 KPF 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.

3 Description of the Empirical Application

3.1 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 anything but trivial. Several different search strategies have been developed by bibliometricians and patent analysts to single out the field of nanomaterials (Hullman and Meyer 2003; Schummer 2004; Zitt and Bassecoulard 2006). We make use of the results of a search strategy that evolved from a collaborative project with a major European chemicals company. This company 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). In total, there are 439 NUTS-3 regions in Germany.

When employing patent data, a distinction has to be made between patent applicant and patent inventor. The applicant is the holder of the patent right while the document itself also shows the name(s) of the inventor(s). Patents prepared within the employee's labor contract are assigned to the firm which needs to pay compensation to the inventor reflecting the patent's economic value. Differences between the applicant and the inventor are relevant when it comes to the spatial assignment of a patent as the applicant and the inventor are typically not located at the same place. In this respect, the inventors of a patent are typically geographically dispersed around the applicant's location. Taking the location of the applicant 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 as a reference for the assignment of nanomaterial patents. Moreover, as there could be several inventors on a patent document, we apply a fractional counting approach to assign every inventor mentioned and his or her region 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 the 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. We compute the shares of these R&D employees over the total number of employees to exclude a potential size effect. To take the technological specialization of a region into account, we analyse the patent applications (also referenced on the inventor's location) in other technology fields like mechanics, electronics, chemicals and pharmaceuticals. Patent applications in other 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 in logs). While the sector shares should give an insight on the economic orientation of a region, the GDP per capita should map the general economic power. Moreover, we add three dummy variables indicating the centrality, urbanization and agglomeration patterns of a region. 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.[3]

Figure 1 provides a graphical visualization of the number of nanomaterial patents in each German district. On the one hand, it seems to be obvious that there is not a smooth geographical distribution of patents in Germany. On the other hand, 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 of the patents appear to be located in the major German cities and in specialized regions.[4] Inversely, the East German *kreise* are characterized – with few exceptions, such as Dresden, Halle and Berlin – by low patenting activities.

---

[3]   This choice shelters us from a possible endogeneity bias, as innovation takes time to spread and to have an impact on local economies.

[4]   An area of particular interest should be the one of Mannheim/Ludwigshafen in South-West Germany, where BASF, the largest chemicals company in Europe and a multiple nanomaterial patentee, is located. Another area of interest is the Ruhr area in the West of Germany.

Figure 1: Geographic distribution of applications for nanomaterial patents by inventor
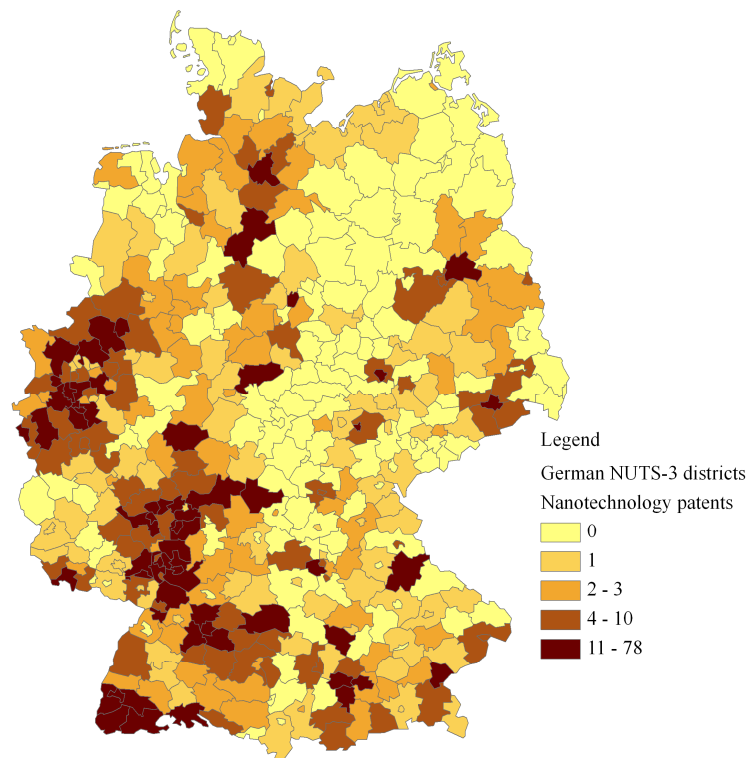
In the following, we will argue that (i) spatial econometric adjustments are necessary but that (ii) poolability of the 439 regions is questionable.

3.2   Estimation Method

On the basis of the model presented in Section 2, and because of the characteristics of the data at hand, we follow Grimpe and Patuelli (2008), 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 adjust for spatial autocorrelation. The main characteristics and advantages of our estimation strategy are summarized below.

Our model explains the output of the KFP, 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), which is Poisson-distributed conditionally to E with mean μ and variance $\mu + \mu2/\theta$ (see, for example, Venables and Ripley 2002). The dispersion parameter θ is fitted iteratively by different methods (by maximum likelihood or by means of a moment estimator).

6

The above estimation framework is augmented with the use of spatial filtering methods in the case of spatial autocorrelation (SAC). SAC (Cliff and 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 $I = \left[N \sum_i \sum_j w_{i,j} (x_i - \bar{x})(x_j - \bar{x}) \right] / \left[(\sum_i \sum_j w_{i,j}) \sum_i (x_i - \bar{x})^2 \right]$, where: N is the number of georeferenced units; x_i is the value of the variable X for unit i; and w_{ij} is the value of cell (i, j) of the spatial weights matrix $\mathbf{W}$ (defined below). Positive values of the MI imply positive SAC, and vice versa. The computation of the MI requires the use of a spatial weights matrix $\mathbf{W}$, which defines the relations of proximity between the 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.[5]

It has been shown that, when regression residuals are spatially correlated, the regression coefficients may be biased and/or have inefficient standard errors (Anselin and Griffith 1988). Several econometric techniques have been developed over the last two decades to control for SAC (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 MI. It extracts orthogonal and uncorrelated numerical components (eigenvectors) from a given (N x N) spatial weights matrix (Tiefelsdorf and Boots 1995), therefore drawing comparisons to principal components analysis (PCA).[6] The extracted eigenvectors represent the latent SAC – 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: $\mathbf{W}$ is the given geographic weights matrix; $\mathbf{I}$ is an (N x N) identity matrix; and $\mathbf{1}$ is an (N x 1) vector containing only ones. The resulting sequence in which the eigenvectors are extracted maximizes the sequential residual MI values. Consequently, the first extracted eigenvector, e_1, is the one which shows the greatest MI value among all eigenvectors of the modified matrix. The second extracted eigenvector, e_2, is the one which shows the greatest MI 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 and Griffith 2002).

---

[5] 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. (2006).

[6] However, while PCA components may be given a straightforward economic interpretation (they are used to construct linear combinations of the variables concerned), a spatial filter is a linear combination of eigenvectors extracted from an *exogenous* spatial weights matrix.

After selection on the basis of an MI threshold value,[7] stepwise regression and manual backward elimination (see Grimpe and Patuelli 2008), a subset of the above eigenvectors – all statistically significant at least at the 95 per cent level – is employed as additional regressors in the estimation of our otherwise non-spatial model. No issues arise with respect to partial correlations and multicollinearity, because of the orthogonality and independence of the eigenvectors. From a spatial dependence point of view, these eigenvectors – their linear combination being hereforth referred to as our 'spatial filter' – account for the residual SAC resulting from the regression analysis.

3.3 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 parts of the dataset.

Suppose to have a dataset whose observations could be grouped, for sake of simplicity, in two different ways. 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, $E(y_{ig} \,|\, x_{ig})$, where $i = 1, \ldots, I$ and $g = 1, \ldots, G$ are two indices identifying each observation according to the groups they belong to. Suppose we specify a linear model of $E(y_{ig} \,|\, x_{ig})$ 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

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

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

---

[7] 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**.

where $j = 1, \ldots, I$, $h = 1, \ldots, G$ 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 $\beta_g = \beta$.

There exist other tests as well. Ziemer and Wetzstein (1983) built a poolability test on the basis of the forecast risk performance of the pooled and unpooled estimators. Han and Park (1989) extended the test for structural change proposed by Brown et al. (1975) to a panel data setting, while Baltagi et al. (1996) proposed a nonparametric test for poolability.

Finally, there exist also three mean squared error (MSE) criteria helping to choose on 'pragmatic grounds' between the pooled and unpooled estimators (Wallace 1972; McElroy 1977).

The tests and criteria above, however, rely on the assumptions of linearity of the model for $E(y_{ig} \,|\, x_{ig})$, 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 imposed on the unrestricted model to obtain the restricted one.

There is a rich empirical literature on poolability testing. For example, Vaona and Patuelli (2008) and Vaona (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 former West and East German divide, is presented in the next section.

4 Poolability of German Innovation Data

4.1 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 model results for 439 NUTS-3 regions

	Baseline model (SF) Coefficients
Human capital inputs	
Share of industry-funded R&D employees	14.247 (4.830)***
Share of government-funded R&D employees	12.597 (3.631)***
Regional specialization	
Share of mechanics patents	−1.455 (0.901)
Share of electronics patents	1.582 (0.893)*
Share of chemicals patents	2.996 (0.938)***
Share of pharmaceuticals patents	0.585 (1.119)
Controls	
Share of employees in manufacturing	0.001 (0.007)
Share of employees in services	0.069 (0.018)***
GDP per capita (in logs)	291.389 (140.252)**
GDP per capita (in logs)^2	−28.457 (13.687)**
GDP per capita (in logs)^3	0.925 (0.445)**
Population (in logs)	0.165 (0.005)***
Central city dummy	−0.282 (0.137)**
Urbanization dummy	0.551 (0.144)***
Agglomeration dummy	0.332 (0.119)***
Spatial filter	1.000 (0.061)***
Intercept	−996.286 (478.406)**
θ	3.063
Observations	439
Null deviance (dof)	1722.21 (438)
Residual deviance (dof)	418.44 (389)
AIC	1754.359
Pseudo R^2	0.605
MI	−0.062

***, ** and * denote significance at the 99, 95 and 90 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 high importance of government-funded R&D personnel confirms that nanomaterials are in a rather early stage of technology 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 for knowledge creation in nanomaterials. Moreover, nanomaterials patenting also tends to be facilitated by a rather modern economic structure of a region as pointed out by the positive coefficient of the services sector in comparison to the manufacturing sector. Our results further show that the level of economic development of a region and its number of inhabitants matter considerably. Finally, we find 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.

4.2   Poolability of West and East German Districts

4.2.1   Poolability Hypothesis and Test

The empirical findings presented in Section 4.1 for our baseline model 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. While this may be seen as a highly desirable assumption, one might raise concerns over its soundness. 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 and 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.

On the basis of the discussion above, we propose to test for the poolability of our data with respect to the former West/East subdivision. Formally, we test the hypothesis:

$$H_0 : \beta_W = \beta_E = \beta, \tag{8}$$

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).

Consequently, we compare the restricted model estimated (under H_0) in Section 4.1 and the unrestricted model, which is obtained by interacting all explanatory variables with two

dummies, identifying West and East German districts, respectively.[8] The likelihood ratio test for the two models (see Equation (7)), under 16 restrictions, returns a value of 80.65, 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.

4.2.2 Unpooled Results for East and West Germany

This section presents the results obtained by estimating, on the basis of the poolability result above, our knowledge production function (Equation (1)) separately for West and East German districts. Accordingly, following the estimation strategy outlined in Section 3.2, 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 a spatial filter, when required by autocorrelated regression residuals.

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. The main difference with respect to the baseline estimation is that the share of employees in private R&D becomes insignificant.

With regard to the estimates obtained for the 113 East German districts, it is easy to note that our results change dramatically. Differently from the West German case, we now find a significant effect of the share of employees in industry-funded R&D. Almost no other significant effect can be identified, aside from a (weak) negative effect of specialization in mechanics, which is in fact hardly a suitable vehicle for nanomaterials or nanotechnologies altogether, 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. For West Germany, we can identify a significant effect of government-funded R&D employees and, consistent with the baseline results, significant effects 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. As a consequence, it seems that in general public research institutions drive the West German nanomaterials research, while in East Germany nanomaterial patenting is predominantly driven by the 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. The importance of industry in East Germany therefore hints at the existence of specific nanomaterial-related inventive capabilities. From a policy perspective, it seems sensible to particularly foster public research in East German locations where there is already a rather strong industrial basis for nanomaterials, also to favor cooperation, specialization and accumulation of knowledge.

---

[8]   It should be noted that, 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.

Table 2: Unpooled model results for West and East German NUTS-3 regions

	West/East Germany unpooled models	
	West Germany	East Germany
Human capital inputs		
Share of industry-funded R&D employees	4.102 (3.969)	75.468 (24.442)***
Share of government-funded R&D employees	8.699 (3.485)**	1.531 (15.103)
Regional specialization		
Share of mechanics patents	0.344 (0.947)	–4.531 (2.733)*
Share of electronics patents	3.314 (0.870)***	0.245 (2.279)
Share of chemicals patents	5.282 (0.978)***	0.029 (2.517)
Share of pharmaceuticals patents	3.167 (1.076)***	1.499 (2.609)
Controls		
Share of employees in manufacturing	0.005 (0.006)	0.006 (0.036)
Share of employees in services	0.088 (0.021)***	0.115 (0.066)*
GDP per capita (in logs)	80.733 (136.984)	4896.883 (3302.363)
GDP per capita (in logs)^2	–8.819 (13.297)	–488.587 (334.560)
GDP per capita (in logs)^3	0.316 (0.429)	16.236 (11.293)
Population (in logs)	0.184 (0.072)**	0.114 (0.158)
Central city dummy	–0.305 (0.146)**	0.036 (0.691)
Urbanization dummy	0.412 (0.167)**	0.491 (0.381)
Agglomeration dummy	0.322 (0.136)**	1.507 (0.319)***
Spatial filter	1.000 (0.090)***	–
Intercept	–245.827 (469.404)	–16348.471 (10861.27)
θ	3.109	1.427
Observations	326	113
Null deviance (dof)	1176.86 (325)	306.985 (112)
Residual deviance (dof)	346.03 (293)	88.665 (97)
AIC	1485.992	302.115
Pseudo R^2	0.634	0.745
MI	–0.019	0.020

***, ** and * denote significance at the 99, 95 and 90 per cent levels. Robust standard errors in parentheses.

5 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 (2008), 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 headquarter of the firm – and the residence address of the related inventor(s) are given. Consequently, if the inventors tend to live in districts nearby the ones in which the research facilities are located, a distortion in the data could emerge, generating, for example, artificial spatial autocorrelation (SAC).

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 (CBD)), 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).[9]

For our analysis, we select two functional region definitions: (i) the 271 German labor market regions ('*Arbeitsmarktregionen*' of the '*Gemeinschaftsaufgabe Verbesserung der regionalen Wirtschaftsstruktur*', which we will refer to as 'Aggregation 1'); and (ii) the 52 functional regions defined in Kropp and Schwengler (2008) through hierarchical clustering ('Aggregation 2'). Hence, we analyse increasingly aggregated data. Before estimating our KPF model for the new aggregation levels, we verify if our dummy indicators for central cities, urbanization and agglomeration levels are still suitable for our investigation (in other words, we check in how many cases a new functional region includes NUTS-3 districts with mixed 0 and 1 values). From an inspection of the data, we decide to exclude the dummy variable for central cities from both analyses (53/271 mixed cases for Aggregation 1, and 30/52 cases for Aggregation 2), and the remaining two dummy variables from the second analysis only (36/52 cases for the urbanization, and 17/52 for agglomeration).

We will take as our starting assumption that there is no substantial problem with the aggregation level used in our baseline model (see Table 1). If this hypothesis has to be rejected, we can expect our empirical findings at higher aggregation levels to be more meaningful (or to show higher significance levels). Table 3 shows the results obtained.

The results presented in Table 3 above show that the new geographical aggregations do not lead to improved estimates of the parameters of interest, that is, our human capital indicators for private and public R&D, which were both statistically significant in the baseline model. In the case of Aggregation 1, only industry R&D is significant, while, for Aggregation 2, public R&D alone is significant. The effects of population (size of the regions) and of specialization in chemicals remain strongly significant. Overall, we note a moderate variation of significance levels and coefficient estimates. From a comparison with the results of Table 1, it is evident that aggregating the initial NUTS-3 regions only led to increased explanatory power (higher R^2 values), but did not provide better information on the KPF estimated and the related regression parameters. It is noteworthy that, when estimating the KPF for Aggregation 2, no significant residual SAC is left, and consequently a spatial filtering adjustment is not necessary (larger regions appear to capture better industrial agglomerations).

---

[9]   '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)

Table 3: Model results for higher aggregated regional data

	Models for aggregated regions	
	Aggregation 1	Aggregation 2
Human capital inputs		
Share of industry-funded R&D employees	11.530 (4.454)**	–21.438 (11.766)*
Share of government-funded R&D employees	10.043 (7.800)	74.662 (20.644)***
Regional specialization		
Share of mechanics patents	–1.999 (1.017)*	–0.177 (2.579)
Share of electronics patents	0.627 (0.978)	1.894 (2.121)
Share of chemicals patents	3.559 (1.005)***	5.475 (2.594)**
Share of pharmaceuticals patents	–0.822 (1.223)	2.686 (4.318)
Controls		
Share of employees in manufacturing	–0.002 (0.008)	0.096 (0.021)***
Share of employees in services	0.007 (0.027)	0.102 (0.051)**
GDP per capita (in logs)	876.894 (532.663)*	8158.383 (2449.299)***
GDP per capita (in logs)^2	–83.535 (52.549)	–814.050 (244.585)***
GDP per capita (in logs)^3	2.648 (1.727)	27.070 (8.138)***
Population (in logs)	1.017 (0.082)***	1.104 (0.097)***
Urbanization dummy	0.247 (0.147)*	
Agglomeration dummy	0.214 (0.143)	
Spatial filter	1.000 (0.082)***	
Intercept	–3074.892 (1798.813)*	–27266.37 (8172.740)***
θ	6.068	5.233
Observations	271	52
Null deviance (dof)	2168.48 (270)	613.22 (51)
Residual deviance (dof)	256.29 (239)	50.23 (39)
AIC	1102.4	349.61
Pseudo R^2	0.869	0.974
MI	–0.033	–0.042

***, ** and * denote significance at the 99, 95 and 90 per cent levels. Robust standard errors

Our results suggest that the aggregation level of the baseline model is appropriate for our analysis, and that our results appear to deteriorate as we move towards higher aggregation levels, presumably due to the loss of information and variation in the data. This finding may be linked to the fact that functional regions, differently from NUTS-3 districts, are *not* real administrative entities, and therefore cannot put in place policies aiming to foster innovation.

6   Conclusions

In this paper we have focused on two issues. In the first place we checked whether different regions can be pooled within the same sample when estimating a KPF for nanomaterial patents in a country with a large regional divide as Germany. In the second place, we tackled the issue whether estimating a KPF at different levels of regional aggregation have an impact on econometric results. This analysis has been performed in order to account for the fact that

there is typically a geographic mismatch between the location of the inventor and the actual location of the research facility where the inventive work was carried out. Our result provide important implications for the empirical study of regional innovation systems.

Regarding poolability we have found that East Germany has a statistically different KPF than West Germany. We found that in East Germany innovation in nanomaterials is positively correlated with the share of industry-funded R&D employees but no role is played by government-funded R&D employees and by the stock of accumulated knowledge as represented by the share of mechanics, electronics, chemicals and pharmaceutical patents. On the contrary in Western Germany the opposite happens. This is rather worrying as it would seem that in a field like nanomaterials, where public research dominates, East Germany seems to rely only on the private sector without having an adequate level of knowledge to successfully activate this engine of growth.

Finally, the level of aggregation at which we analyse our sample matters, as estimates performed at higher aggregation levels eventually lead to worsening results. Moreover, our findings suggest that the NUTS-3 aggregation level chosen in our baseline model is most appropriate.

Acknowledegments

References

Acs Z.J., L. Anselin and A. Varga (2002) Patents and Innovation Counts as Measures of Regional Production of New Knowledge. *Research Policy* 31 (7), 1069-85

Aghion P. and P. Howitt (1992) A Model of Growth through Creative Destruction. *Econometrica* 60 (2), 323-51

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

Anselin L. and D.A. Griffith (1988) Do Spatial Effects Really Matter in Regression Analysis? *Papers in Regional Science* 65 (1), 11-34

Baltagi B.H. (2001) *Econometric Analysis of Panel Data* (2nd ed.). Chichester New York: Wiley

Baltagi B.H. and J.M. Griffin (1983) Gasoline Demand in the OECD: An Application of Pooling and Testing Procedures. *European Economic Review* 22 (2), 117-37

Baltagi B.H., J. Hidalgo and Q. Li (1996) A non-Parametric Test for Poolability Using Panel Data. *Journal of Econometrics* 75 (2), 345-67

van den Berg J., B. Candelon and J.-P. Urbain (2008) A Cautious Note on the Use of Panel Models to Predict Financial Crises. *Economics Letters* 101 (1), 80-3

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 and 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'. Paper presented at the 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 (1), 43-64

Bozeman B., P. Laredo and V. Mangematin (2007) Understanding the Emergence and Deployment of "Nano" S&T. *Research Policy* 36 (6), 807-12

Brixy U. and 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 and D. Knyphausen-Aufsess (eds), *Advances in Interdisciplinary European Entrepreneurship Research* (pp. 141-52). Muenster: Lit

Brown R.L., J. Durbin and J.M. Evans (1975) Techniques for Testing the Constancy of Regression Relationships over Time. *Journal of the Royal Statistical Society* 37 (2), 149-92

Buesa M., J. Heijs, M. Martínez Pellitero and T. Baumert (2006) Regional Systems of Innovation and the Knowledge Production Function: The Spanish Case. *Technovation* 26 (4), 463-72

Cliff A.D. and J.K. Ord (1981) *Spatial Processes: Models & Applications*. London: Pion

Cooke P., M. Gomez Uranga and G. Etxebarria (1997) Regional Innovation Systems: Institutional and Organisational Dimensions. *Research Policy* 26 (4-5), 475-91

Cooke P., P. Boekholt and F. Toedtling (2000) *The Governance of Innovation in Europe: Regional Perspectives on Global Competitiveness*. London New York: Pinter

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 (5), 525-42

Getis A. and D.A. Griffith (2002) Comparative Spatial Filtering in Regression Analysis. *Geographical Analysis* 34 (2), 130-40

Getis A. and J. Aldstadt (2004) Constructing the Spatial Weights Matrix Using a Local Statistic. *Geographical Analysis* 36 (2), 90-104

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 (2), 160-79

Griliches Z. (1979) Issues in Assessing the Contribution of Research and Development to Productivity Growth. *Bell Journal of Economics* 10 (1), 92-116

Griliches Z. (1990) Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature* 28 (4), 1661-707

Grimpe C. and R. Patuelli (2008) *Knowledge Production in Nanomaterials: An Application of Spatial Filtering to Regional Systems of Innovation* (Quaderni della Facolta' di Scienze Economiche No. 08-06). Lugano: University of Lugano

Günther J. (2004) Innovation Cooperation: Experiences from East and West Germany. *Science and Public Policy* 31 (2), 151-8

Hahn F.R. (2008) Testing for Profitability and Contestability in Banking: Evidence from Austria. *International Review of Applied Economics* 22 (5), 639-53

Haining R. (1990) *Spatial Data Analysis in the Social and Environmental Sciences*. Cambridge: Cambridge University Press

Han A.K. and D. Park (1989) Testing for Structural Change in Panel Data: Application to a Study of U.S. Foreign Trade in Manufacturing Goods. *Review of Economics and Statistics* 71 (1), 135-42

Harhoff D., F.M. Scherer and K. Vopel (2003) Citations, Family Size, Opposition and the Value of Patent Rights. *Research Policy* 32 (8), 1343-63

Howells J. (1999) Regional Systems of Innovation? In D. Archibugi, J. Howells and 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 (8), 1220-34

Hullman A. and M. Meyer (2003) Publications and Patents in Nanotechnology. An Overview of Previous Studies and the State of the Art. *Scientometrics* 58 (3), 507-27

Jones C. (1995) R&D Based Models of Economic Growth. *Journal of Political Economy* 103 (4), 739-84

Kropp P. and 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

McElroy M.B. (1977) Weaker MSE Criteria and Tests for Linear Restrictions in Regression Models with non-Spherical Disturbances. *Journal of Econometrics* 6 (3), 389-94

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 (10), 1646-62

Moran P. (1948) The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society B* 10, 243-51

Nelson R.R. (ed.) (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 (4), 435-66

OECD (2002) *Redefining Territories: The Functional Regions*. Paris: Organisation for Economic Co-operation and Development

Patel P. and K. Pavitt (1997) The Technological Competencies of the World' S Largest Firms: Complex and Path-Dependent, but Not Much Variety. *Research Policy* 26 (2), 141-56

Patuelli R., D.A. Griffith, M. Tiefelsdorf and P. Nijkamp (2006) *The Use of Spatial Filtering Techniques: The Spatial and Space-Time Structure of German Unemployment Data* (TI Discussion Paper 06-049/3). Amsterdam: VU University Amsterdam

Porter M. and S. Stern (2000) *Measuring the "Ideas" Production Function: Evidence from International Output* (NBER Working Paper No. 7891). Cambridge: NBER

Romer P.M. (1990) Endogenous Technological Change. *Journal of Political Economy* 98 (5), S71-S102

Schiavo S. and A. Vaona (2008) Poolability and the Finance-Growth Nexus: A Cautionary Note. *Economics Letters* 98 (2), 144-7

Schummer J. (2004) Multidisciplinarity, Interdisciplinarity, and Patterns of Research Collaboration in Nanoscience and Nanotechnology. *Scientometrics* 59 (3), 425-65

Tiefelsdorf M. and B. Boots (1995) The Exact Distribution of Moran's *I*. *Environment and Planning A* 27, 985-99

Tiefelsdorf M., D.A. Griffith and B.N. Boots (1999) A Variance Stabilizing Coding Scheme for Spatial Link Matrices. *Environment and Planning A* 31, 165-80

Vaona A. (2008) Regional Evidence on Financial Development, Finance Term Structure and Growth. *Empirical Economics* 34 (1), 185-201

Vaona A. and M. Pianta (2008) Firm Size and Innovation in European Manufacturing. *Small Business Economics* 30 (3), 283-99

Vaona A. and R. Patuelli (2008) New Empirical Evidence on Local Financial Development and Growth. *Letters in Spatial and Resource Sciences* 1 (2-3), 147-57

Venables W.N. and B.D. Ripley (2002) *Modern Applied Statistics with S* (4th ed.). New York: Springer

Wallace T.D. (1972) Weaker Criteria and Tests for Linear Restrictions in Regression. *Econometrica* 40 (4), 689-98

Watson P.L. and R.B. Westin (1975) Transferability of Disaggregate Mode Choice Models. *Regional Science and Urban Economics* 5 (2), 227-49

Youtie J., M. Iacopetta and S. Graham (2008) Assessing the Nature of Nanotechnology: Can We Uncover an Emerging General Purpose Technology? *The Journal of Technology Transfer* 33 (3), 315-29

Ziemer R.F. and M.E. Wetzstein (1983) A Stein-Rule Method for Pooling Data. *Economics Letters* 11 (1-2), 137-43

Zitt M. and E. Bassecoulard (2006) Delineating Complex Scientific Fields by a Hybrid Lexical-Citation Method: An Application to Nanosciences. *Information Processing and Management* 42 (6), 1513-31

QUADERNI DELLA FACOLTÀ

Quaderno n. 98-01
P. Balestra, *Efficient (and parsimonious) estimation of structural dynamic error component models*

Quaderno n. 99-01
M. Filippini, *Cost and scale efficiency in the nursing home sector : evidence from Switzerland*

Quaderno n. 99-02
L. Bernardi, *I sistemi tributari di oggi : da dove vengono e dove vanno*

Quaderno n. 99-03
L.L. Pasinetti, *Economic theory and technical progress*

Quaderno n. 99-04
G. Barone-Adesi, K. Giannopoulos, L. Vosper, *VaR without correlations for portfolios of derivative securities*

Quaderno n. 99-05
G. Barone-Adesi, Y. Kim, *Incomplete information and the closed-end fund discount*

Quaderno n. 99-06
G. Barone-Adesi, W. Allegretto, E. Dinenis, G. Sorwar, *Valuation of derivatives based on CKLS interest rate models*

Quaderno n. 99-07
M. Filippini, R. Maggi, J. Mägerle, *Skalenerträge und optimale Betriebsgrösse bei den schweizerische Privatbahnen*

Quaderno n. 99-08
E. Ronchetti, F. Trojani, *Robust inference with GMM estimators*

Quaderno n. 99-09
G.P. Torricelli, *I cambiamenti strutturali dello sviluppo urbano e regionale in Svizzera e nel Ticino sulla base dei dati dei censimenti federali delle aziende 1985, 1991 e 1995*

Quaderno n. 03-08
  L. Crivelli, G. Domenighetti, M. Filippini, *Federalism versus social citizenship : investigating the preference for equity in health care*

Quaderno n. 03-09
  M. Farsi, *Changes in hospital quality after conversion in ownership status*

Quaderno n. 03-10
  G. Cozzi, O. Tarola, *Mergers, innovations, and inequality*

Quaderno n. 03-11
  M. Farsi, M. Filippini, M. Kuenzle, *Unobserved heterogeneity in stochastic cost frontier models : a comparative analysis*

Quaderno n. 04-01
  G. Cassese, *An extension of conditional expectation to finitely additive measures*

Quaderno n. 04-02
  S. Demichelis, O. Tarola, *The plant size problem and monopoly pricing*

Quaderno n. 04-03
  F. Rossera, *Struttura dei salari 2000 : valutazioni in base all'inchiesta dell'Ufficio federale di statistica in Ticino*

Quaderno n. 04-04
  M. Filippini, M. Zola, *Economies of scale and cost efficiency in the postal services : empirical evidence from Switzerland*

Quaderno n. 04-05
  F. Degeorge, F. Derrien, K.L. Womack, *Quid pro quo in IPOs : why book-building is dominating auctions*

Quaderno n. 04-06
  M. Farsi, M. Filippini, W. Greene, *Efficiency measurement in network industries : application to the Swiss railway companies*

Quaderno n. 04-07
  L. Crivelli, M. Filippini, I. Mosca, *Federalism and regional health care expenditures : an empirical analysis for the Swiss cantons*

Quaderno n. 04-08
  S. Alberton, O. Gonzalez, *Monitoring a trans-border labour market in view of liberalization : the case of Ticino*

Quaderno n. 04-09
  M. Filippini, G. Masiero, K. Moschetti, *Regional differences in outpatient antibiotic consumption in Switzerland*

Quaderno n. 04-10
  A.S. Bergantino, S. Bolis, *An adaptive conjoint analysis of freight service alternatives : evaluating the maritime option*

Quaderno n. 07-04
   M. Farsi, *The temporal variation of cost-efficiency in Switzerland's hospitals : an application of mixed models*

Quaderno n. 08-01
   M. Farsi, M. Filippini, D. Lunati, *Economies of scale and efficiency measurement in Switzerland's nursing homes*

Quaderno n. 08-02
   A. Vaona, *Inflation persistence, structural breaks and omitted variables : a critical view*

Quaderno n. 08-03
   A. Vaona, *The sensitivity of non parametric misspecification tests to disturbance autocorrelation*

Quaderno n. 08-04
   A. Vaona, *STATA tip : a quick trick to perform a Roy-Zellner test for poolability in STATA*

Quaderno n. 08-05
   A. Vaona, R. Patuelli, *New empirical evidence on local financial development and growth*

Quaderno n. 08-06
   C. Grimpe, R. Patuelli, *Knowledge production in nanomaterials : an application of spatial filtering to regional system of innovation*

Quaderno n. 08-07
   A. Vaona, G. Ascari, *Regional inflation persistence : evidence from Italy*

Quaderno n. 08-08
   M. Filippini, G. Masiero, K. Moschetti, *Dispensing practices and antibiotic use*

Quaderno n. 08-09
   T. Crossley, M. Jametti, *Pension benefit insurance and pension plan portfolio choice*

Quaderno n. 08-10
   R. Patuelli, A. Vaona, C. Grimpe, *Poolability and aggregation problems of regional innovation data : an application to nanomaterial patenting*