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Benchmark Value Added Chains and Regional Clusters in German R&D Intensive Industries

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Abstract. Although the phase of euphoria seems to be over, policymakers and regional agencies have maintained their interest in cluster policy. Modern cluster theory provides reasons for positive external effects that may accrue from interaction in a group of proximate enterprises operating in common and related fields. While there is some progress in locating clusters, in most cases only limited knowledge on the geographical extent of regional clusters is established. The present paper presents a hybrid approach to cluster identification. While dominant buyer-supplier relations are derived by qualitative input-output analysis (QIOA) from national I-O tables, potential regional clusters are identified by spatial scanning. This procedure is employed to identify clusters of German R&D intensive industries. In a sensitivity analysis, good robustness properties of the hybrid approach are revealed with respect to variations in the quantitative cluster composition.

Keywords: National cluster templates, regional clusters, qualitative input-output analysis (QIOA), spatial scanning

JEL: R12, R15

1. Introduction

Strong regional clusters are increasingly seen by policymakers and regional development agencies as a response to economic globalization. The notion of competitive advantages for countries and regions with enterprises organized in clusters has been popularized mainly by Porter (1990, 1998, 2000). In Porter's diamond model, the presence of related and supportive industries in local production structures is highlighted as one of the principal determinants of regional competiveness. As efficient clusters are associated with high growth in productivity and innovation potential, the cluster approach has become more attractive to various fields of economic policy (Kiese/Wrobel 2011). In particular, cluster-based instruments are an integral part of EU regional policy (see e.g. Christensen et al. 2011; Popa/Vlăşceanu 2013). In most EU countries cluster-oriented policy plays an important role at national and regional level (Oxford Research 2008). This holds true also for Germany where diverse national and regional programmes have been set up to promote cluster development (Török 2012).

Although the cluster approach is based on agglomeration theory, a variety of definitions for the term cluster exists (Martin and Sunley 2003). Diverse forces of agglomeration engendering economies of localization and urbanization are differently accentuated in alternative cluster concepts. Moreover, regional actors forming local networks are believed to vary in different types of clusters. The vagueness of the cluster concept makes the identification of industry clusters difficult. This holds true especially for geographical extent and the spatial scale at which such structures take place. Nevertheless, targeted cluster-based policies hinge crucially on the knowledge of where clusters are located and the sectors in which they are formed. Without identifying focused clusters, regional development agents and policy makers do not receive any feedback on the success or failure of applied strategies and instruments.

However, the variety of cluster definitions is not the only reason for the existence of different approaches to the identification of clusters. A given cluster concept may be differently operationalized (cf. vom Hofe/Chen 2006; vom Hofe/Bhatta 2007; Feser/Renski/Koo 2009). The literature distinguishes between two strands in the approach to the spatial scale of industrial clusters. The first follows seminal works by Marcon/Puech (2003) and Duranton/Overman (2005). In order to avoid problems with arbitrary pre-defined geographical entities these studies treat space as continuous. Industrial cluster structures are investigated for varying window sizes using the Kernel density or cumulative probability functions. The K function approach is utilized by Kosfeld/Eckey/Lauridsen (2011) in measuring spatial industry concentration in Germany on different spatial scales. Scholl/Brenner (2012) advance the distance-based techniques in identifying regional clusters. As these methods usually require geo-coded data, the data requirements are high.

The second strand in the literature applies spatial statistics tools to areal data. If geographical units are considered to be spatially independent in the presence of spillovers, spatial clustering tends to be underestimated (Guillain/Le Gallo, 2010). Feser/Koo/Renski/Sweeney (2001) and Feser/Sweeney (2002) were the first to explicitly account for spatial interaction between regions in an applied cluster study in the US state of Kentucky. In a follow-up study, Feser/Sweeney/Renski (2005) extended spatial analysis to the United States as a whole. Both studies make use of the Getis-Ord G_i^* statistic to measure and test for local spatial clustering (Ord/Getis 1995). Recently, Pires et al. (2013) have used the local Moran test for localizing industrial clusters in Brazil. A major drawback to both local methods is the necessity of fixing the environments of the regions in accounting for spatial dependence.

Beyond co-location of firms belonging to the same branch, the existence of linkages between actors is regarded as a crucial characteristic of industrial clusters. Within this context, applied cluster studies often focus on enterprises along value-added chains where knowledge exchange is primarily supposed (cf. Kuah 2002). While Porter (2003) aims to establish the composition of such chains directly at the regional level by locational correlation analysis, most other studies derive benchmark chains from national input-output tables before searching for the location of potential industry clusters (cf. Feser/Bergman 2000; Feser/Sweeny/Renski 2005; vom Hofe/Bhatta 2007; Titze/Brachert/Kubis 2011). A directly regional approach to cluster identification has already been proposed by Ó hUallacháin (1984) who advocated the use of regional input-output tables for this purpose. The problem with purely local approaches lies in the fact that information on gaps in a region's value-added chains that may hinder regional development is lacking. For most countries, such information can only be derived from national benchmarks owing to a lack of input-output tables on a regional and sectoral disaggregated level that are required for a more exact identification of industrial clusters.

Potentially different compositions of national cluster templates and regional clusters pose a great challenge for a methodology of cluster identification. The present paper aims at improving strategies of regional cluster identification. Against the backdrop of a weak cluster definition, we place great emphasis on systematic, reliable and comprehensive identification without fixing the geographical extent of potential spillover effects in advance. The papers ties in with appreciative and empirical cluster research that has grown in importance over the last decades (Cruz/Teixeira 2010).

First, at the national level, the dominant related sectors of R&D intensive industries are identified by qualitative input-output analysis (QIOA). However, the fact that in many cases not all enterprises in these sectors belong to the respective value-added chains must be allowed for. In defining an automotive cluster, for instance, only a part of the enterprises in the plastics and related sectors can be included, as a considerable number of firms are not involved in the production of motor vehicles.

Thus, QIOA has to be supplemented by quantitative input-output analysis in order to avoid distortion effects that may arise from defining overly heterogeneous clusters. Here, downstream and upstream sectors are considered depending on their involvement in the production activities of the key industry.

Secondly, at the local level, it has to be established whether and how spatial externalities and spillovers should be allowed for in locating regional clusters. Most applied cluster studies ignore the presence of spatial interaction between interrelated geographical units. In order to allow for varying reaches of the geographical extent of regional interaction, the flexible approach of spatial scanning is adopted here (Kulldorff 1997). On the basis of Kulldorff's scan test, the variable extent of potential regional clusters is accurately captured.

The paper is organised as follows. Section 2 reflects theoretical elements of the cluster concept. A hybrid approach to identification of industrial clusters is explained in section 3. In section 4, these methods are employed in identifying potential regional clusters of R&D intensive industries in Germany. Sector 5 deals with a robustness check of identified cluster structures. Finally, in section 6 the findings are discussed with a view to further empirical cluster research.

2. Elements of cluster theory

The number of articles on industrial clusters has risen in the last decades, as has the number of journals dealing with this subject. The theory of clusters embraces a variety of approaches. There have been some promising attempts in the literature based on bibliometric analyses, which aim to organize the different strands, concepts and topics of research on industrial clusters. In so doing, the founders, the evolution and the disseminators can be reliably identified in a comprehensive manner (Cruz/Teixeira 2010; Lazaretti/Sedita/Caloffi 2014).

Most of these approaches originate from agglomeration theory. This theory explains the concentration of enterprises and workers in one or several locations by internal and external economies of scale. Positive externalities in the form of economies of localization arising from geographical concentrations of specialized industries have already been described by Alfred Marshall (1920) in an analysis of industrial organization. The geographical concentration of an industry may result in certain advantages, for instance, from the availability of specialized skills and the proximity to suppliers. The inclusion of knowledge spillovers changes the point of view from a static to a dynamic perspective. In the case of industry-specific knowledge spillovers, agglomeration economies are termed Marshall-Arrow-Romer (MAR) externalities (Glaeser et al. 1992).

Hoover (1948) pointed to additional effects from an agglomeration of firms from different industries. Such urbanization externalities may, for instance, be ascribed to the possibility of serving large local markets. General benefits in agglomerations may also occur from the availability of a sound infrastructure and research institutions. Beyond that, knowledge spillovers between firms from different branches play a crucial role. Innovative solutions applied in a particular branch may be usefully adopted by other sectors that are faced with similar problems. Dynamic advantages for regional actors arising from diversity are termed Jacobs externalities (Jacobs 1969; Glaeser et al. 1992).

While Romer (1986) deems a firm's incentive to innovate as best realized in monopolistic markets, Jacobs (1969) places the emphasis on competition. With his 'diamond model', Porter (1990) introduces a mixed view of innovation and growth (see also Porter 1998, 2000). With regard to his concept of a cluster as a group of firms in an industry along with its related sectors, agglomeration advantages can be regarded more as MAR than as Jacobs externalities. However, in contrast to MAR models, the structure of Porter's 'diamond model' is not monopolistic but competitive. Thus, Porter's externalities arise from geographically specialized industries with highly competitive enterprises. The 'diamond model' claims that firms' competitive advantages are affected by local business environments that are determined by four factors (Porter 1998, 2000): input factor and demand conditions, firm strategy, structure, and rivalry, as well as related and supporting industries. Each region has its own particular set of factor conditions that explain its orientation and outcome. Innovation and productivity growth are believed to depend crucially on the quality of these mutually interdependent factors. A certain influence of government on factor conditions, e.g. on qualification and the regulatory environment, gives a rationale for cluster-based policies.

Although the concept of clusters is strongly grounded in agglomeration theory, it does involve elements of location, innovation and network theory (Vom Hofe/Chen 2006).

Modern cluster theory shifts the focal point of view from cost benefits to competitive advantages and productivity growth. In his influential contribution to cluster-based development policy, Porter (2000) defines a cluster as a “geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities”. Within the network of firms, competition and cooperation take place at the same time (“cooptition”). Competition is expected to prevail among horizontally linked enterprises. Vertical links between establishments as well as strategic alliances with universities and research institutions will usually be characterized by cooperation on the basis of trust.

Although Martin/Sunley (2003) have pointed to some vagueness in the concept of clusters, particularly in more recent studies there seems to be a certain degree of agreement on four core elements (cf. Feser/Bergman 2000; Feser/Sweeney/Renski 2005; Feser/Rensky/Koo 2009; Titze/Brachert/Kubis 2011). Firstly, a cluster consists of a group of firms operating in a core industry and its related sectors. Secondly, the establishments belonging to a cluster are interconnected, i.e. they form part of a network. Thirdly, the enterprises are proximate to each other, i.e. a cluster is a geographic concentration of firms. Fourth, a critical mass of actors is presumed for agglomeration economies to be effective. However, for the existence of a cluster, enterprises need not necessarily be conscious of being part of a network of producers (Ketels/Lindqvist/Sölvell 2006).

3. Hybrid approach to cluster identification

Regional input-output tables are not furnished by official statistics in Germany (Kronenberg 2010). Therefore regional flows of goods between industries can only be calculated from the national input-output table. The identification of industry clusters is achieved in a multistage process. First, national cluster templates in the form of value-added chains of R&D core industries are designed. This approach highlights the prominent role of input-output flows in interactions between enterprises. Substantial inter-industry links are established with the aid of qualitative input-output analysis (QIOA). Next, regional production activity within value-added chains is appraised on the basis of district employment data with the aid of national Leontief coefficients. Finally, the localization of potential industry clusters is examined using spatial scanning.

3.1 Qualitative input-output analysis (QIOA) and national cluster templates

Generally, qualitative input-output analysis (QIOA) consists of techniques used to transform flows of goods between sectors into binary relationships. Specifically, QIOA aims to distinguish important from unimportant flows of goods between sectors. Parts of sectors that are related by dominant intermediate good flows form a common value-added chain. With the aid of QIOA, the relevant components of value-added chains can be identified. Methods of qualitative input-output analysis differ with respect to considerations of the kind of sector links and the appraisal of important links (c.f. Bon 1989; Schnabl 2000; Schnabl/Kohei 2003).

The filter approach of input-output-analysis identifies important flows of goods by determining an optimal filter rate. Schnabl (1994, 2000) has devised minimal flow analysis (MFA) as a layer-based method for analyzing structures of production. In contrast to traditional QIOA, the MFA method takes into account direct and indirect sector links in the form of layers of different orders. Using this method, the binarization of the national input-output table is achieved on the basis of an iteratively determined optimal filter rate (for a recent application see Titze/Brachert/Kubis 2011).

The starting point is the Leontief model

(1) $\mathbf{x} = \mathbf{A} \cdot \mathbf{x} + \mathbf{y}$

where **x** is the vector of production values, **A** is the matrix of input coefficients and **y** the vector of final demand. In the representation

(2) $\mathbf{x} = \mathbf{M} \cdot \mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1} \cdot \mathbf{y}$

the matrix **M** is known as the Leontief inverse which is given by the power series

(3) $\mathbf{M} = (\mathbf{I} - \mathbf{A})^{-1} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + ...$

Using the decomposition (3), layers $\mathbf{T}_1$, $\mathbf{T}_2$, $\mathbf{T}_3$, … in the form of intermediary flow matrices of different orders can be derived. With the diagonal matrix $<\mathbf{x}>$ of the vector of production values **x**, $<\mathbf{x}>=\text{diag}(\mathbf{x})$, the total transaction matrix **T** reads

(4) $\mathbf{T} = \mathbf{A} \cdot <\mathbf{x}>$.[1]

This matrix is made up of the layers

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[1] In order to build strongly on the technical structure, the actual demand vector **y** may be replaced by the summing-up vector **ı** or its scalar multiple (Schnabl 1994, 2000).

$$\mathbf{T}_1 = \mathbf{A}\cdot < \mathbf{y} >$$

(5) $$\mathbf{T}_2 = \mathbf{A}\cdot < \mathbf{A}\cdot\mathbf{y} >$$

$$\mathbf{T}_3 = \mathbf{A}\cdot < \mathbf{A}^2\cdot\mathbf{y} > \text{ … etc.}$$

The exponentiation of the matrix **A** continues until no element t_k^{ij} of the matrix $\mathbf{T}_k$, k=0,1,2,3,…., exceeds a given filter value F.

The layers $\mathbf{T}_1$, $\mathbf{T}_2$, $\mathbf{T}_3$, … are mapped onto binary matrices $\mathbf{W}_1$, $\mathbf{W}_2$, $\mathbf{W}_3$, … which elements w_k^{ij} are defined by

(6) $$w_{ij}^k = \begin{cases} 1, \text{if } t_{ij}^k > F \\ 0, \text{otherwise} \end{cases}.$$

As values of one of the elements w_k^{ij} indicate dominant links between sectors i and j in the k*th* step, the binary matrices $\mathbf{W}_k$, k=1,2,3,…, can be referred to as adjacency matrices of orders k.[2]

By Boolean multiplication (operator "*"), more complex adjacency matrices $\mathbf{W}^{(k)}$, k=1,2,3, …, representing the connection between layer-wise adjacency matrices $\mathbf{W}_k$ are obtained,

(7) $$\mathbf{W}^{(k)} = \mathbf{W}_{k-1} * \mathbf{W}^{(k-1)},$$

with $\mathbf{W}^{(0)} = \mathbf{I}$. The elements of the binary matrices $\mathbf{W}^{(k)}$ tend to approach zero with rising k indicating the increasing irrelevance of intermediate flows of goods at higher orders of adjacency. In this way, the qualitative matrices $\mathbf{W}^{(k)}$ reproduce the information on sector linkages borne by the Leontief inverse that is required to determine the dependence matrix **D**:

(8) $$\mathbf{D} = \#(\mathbf{W}^{(1)} + \mathbf{W}^{(2)} + \mathbf{W}^{(3)} + ...)$$

The dependence matrix **D** is computed by Boolean addition (operator "#"). Its elements d_{ij} indicate whether sector j is directly or indirectly supplied by sector i at a minimum level F.

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[2] Whereas in traditional QIOA $\mathbf{W}_k = \mathbf{W}_0$ for all k, in MFA the adjacency matrices $\mathbf{W}_k$ generally differ from step to step k.

An index on the type of sector linkages is obtained from the connectivity matrix **H**:

(9) $\mathbf{H} = \mathbf{D'} + 2 \cdot \mathbf{D}$.

Exclusively dominant flows between a sector and its suppliers captured by the **D**-matrix are termed unidirectional linkages. They are ranked higher than weak linkages, indicating that a sector is connected with other branches via deliveries in the wrong direction (**D'**-matrix). Substantial flows of goods in both directions constitute bilateral linkages. Specifically, an element h_{ij} of the connectivity matrix **H** reflects the characteristics of linkages between sector i and j in the following way:

$$
(10) \quad h_{ij} = \begin{cases} 0\text{: no link between sectors i and j,} \\ 1\text{: a weak link between sectors i and j,} \\ 2\text{: unidirectional link between sectors i and j,} \\ 3\text{: bilateral links between sectors i and j.} \end{cases}
$$

Uni- and bilateral links are of particular importance when detecting national cluster templates using QIOA.

The minimal flows by which the value-added chains are formed depend crucially on the chosen filter value. In MFA, the filter value is not fixed in advance but determined endogenously. The industrial structure implied by the optimal filter rate should be characterized by a balance between conflicting qualitative conditions of comprehensiveness and reduction.

This objective suggests evaluating the information contents of alternative classifications. In this case, the entropy index E of Shannon/Weaver (1949),

(11) $E_\ell = \sum_s p_{\ell s} \cdot \mathrm{ld}(1/p_{\ell s})$,

can be computed for each structure ℓ. Here p is the probability of the occurrence of one of the states s in (10). The information measure E is maximized in cases of equal occurrence of all states. Starting with a filter value F_0 of 0 with the maximum number of bilateral relations, F_ℓ is incremented by equal steps until the last bilateral relation breaks off for a filter value of F_L. According to this approach, the optimal filter rate is the ratio that maximizes the entropy E at a discrete step in the interval between F_0 and F_L.[3]

[3] Schnabl (1994) recommends that the maximum step number L be 50.

However, the entropy function often fails to show a clear peak and runs very flat around the maximum. This is why it is necessary to fine-tune by assessing the residual cumulated connectivity matrix $\mathbf{H}_{res}$,

(12) $\mathbf{H}_{res} = \mathbf{H}_{cum} - 2 \cdot L$,

with $\mathbf{H}_{cum}$ as the cumulative connectivity matrix:

(13) $\mathbf{H}_{cum} = \sum_{\ell=1}^{L} \mathbf{H}_{\ell}$.

Subject to (12) the "residual" matrix is obtained from $\mathbf{H}_{\ell,cum}$ by subtracting the possible number of unilateral links. The values in the matrix H_{cum} range from 0 (no relation at all) to $3 \cdot L - 1$.[4] According to (12) the elements of the matrix H_{res} ensue by subtracting a basic amount from the matrix H_{cum}. Because this algorithm focuses on dominant bilateral relations, the basic amount is defined as $2 \cdot L$. All negative values of the matrix H are set at 0. An element of the matrix H_{res} indicates the number of filter steps comprising a strong bilateral connection. Schnabl (1994, 2000) now suggests calculating the average value of an element of the matrix H_{res}, which forms a control measure for the calculation of the optimal filter rate.[5] The final optimal filter rate F* is chosen as the filter rate that is assigned to the mean of the step values corresponding to the entropy and H_{res} criteria.

3.2 Regional value-added chains and cluster employment

With the aid of QIOA, national cluster templates can be derived for industries of interest. Production of a cluster template is composed by value-added generated in the core industry and related sectors. Taking into account direct and indirect linkages, the production value x_{C_i} of the national cluster template C_i can be calculated by using the coefficient m_{ij} of the Leontief inverse $\mathbf{M}$:

(14) $x_{C_i} = x_i + \sum_{j \in C_i} (m_{ij} + m_{ji}) \cdot x_j$.

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[4] If the maximum number of filter steps is set at 50 the matrix H_{cum} reaches values from 0 to 149. The value of 149 indicates that a bilateral relation breaks off at the last filter step 50 (50·3–1).

[5] Sum of the elements of the matrix H_{res} divided by the number of non-zero elements.

According to (14), cluster production x_{C_i} is obtained by enlarging the production value of the core industry, x_i, by the link-weighted sum of production values of its related industries. Generally, linkages accruing from both purchasing and supply chains can be involved.

As regional input-output tables are not available for all areas in most nations, knowledge of the magnitude of production of regional value-added chains is often missing. In general, the strength of links between connected industries will vary across space. However, as the Leontief coefficients m_{ij} render the average degree of connectedness between the sectors, they can be used to estimate production values of regional value-added chains $C_{i,r}$:

(15) $\hat{x}_{C_i,r} = x_{i,r} + \sum_{j \in C_i} (m_{ij} + m_{ji}) \cdot x_{j,r}$

The potential regional production values $\hat{x}_{C_i,r}$ are grounded in national industry linkages to approximate unknown real production values $x_{C_i,r}$ of regional value-added chains. On the one hand, the $\hat{x}_{C_i,r}$ values function as sufficient estimators in measuring the size of value-added chains in order to identify potential regional clusters. On the other hand, they may help regional agents to identify missing parts of local value-added chains that prevent the exploitation of spatial spillovers among industries.

At a highly disaggregated regional level, industry-specific production values are ordinarily not available. By contrast, employment data are provided in most countries by government agencies or other public bodies. Therefore, potential regional clusters are identified using the number of employed persons, B, as an indicator of sector-specific economic activity in the specific areas of the country. Abstracting from possible differences in labour productivity, potential cluster employment, $\hat{B}_{C_i,r}$, can be calculated on the basis of (15):

(16) $\hat{B}_{C_i,r} = B_{i,r} + \sum_{j \in C_i} (m_{ij} + m_{ji}) \cdot B_{j,r}$,

This assumption implies that the output shares of the study industries equal the respective employment shares.

3.3 Spatial scanning and regional clusters

Using employment figures $\hat{B}_{C_i,r}$ of the regional value-added chains, the study area is scanned for hot spots of industrial relations. Kulldorff's spatial scan test (Kulldorff/Nagarwal 1995; Kulldorff 1997) that determines the most likely cluster as well as secondary clusters by a likelihood ratio approach is utilized in this process. The test statistic is obtained by scanning the environments of each centroid of a region (e.g. district, county, travel-to-work area) for employment in a core industry and its related sectors. In contrast to local Getis-Ord and local Moran tests, no fixed reach of the area around a region's centre has to be set. Instead, the search for employment incidences is carried out for varying window sizes up to a maximum distance. The existence of industry clusters with different spatial scales (cf. Kosfeld/Eckey/Lauridsen 2012) makes the spatial scan test particularly appealing.[6] By successively increasing the window size around the regions, it is possible to test whether the observed counts significantly exceed the expected number of employment events under randomness.

Let $\hat{B}_{C_i,Z}$ be the number of employment cases and B_Z the total number of industrial workers in a circular zone Z. In addition, the total number of cases and population in the study area are denoted by $\hat{B}_{C_i}$ and B respectively. Under the assumption that the events are generated by a Poisson process, the likelihood ratio is given by

$$\text{(13)} \quad LR_Z \propto \left(\frac{\hat{B}_{C_i,Z}}{\hat{\lambda} \cdot B_Z} \right)^{M_Z} \cdot \left(\frac{\hat{B}_{C_i} - \hat{B}_{C_i,Z}}{\hat{B}_{C_i} - \hat{\lambda} \cdot B_Z} \right)^{M-M_Z} \cdot I\left(B_{C_i,Z} > \hat{\lambda} \cdot B_Z\right).$$

with $\hat{\lambda} = \hat{B}_{C_i} / B$ as the estimated incidence rate under the null hypothesis of no spatial clustering. The indicator function I takes the value 1 if the observed counts, $\hat{B}_{C_i,Z}$, exceed the expected number of events, $\hat{\lambda} \cdot B_Z$, inside zone Z. In this case the relative risk RR_Z of an event occurring within the circle,

[6] Often, an upper limit for the size of the scanning window is specified in the form of the maximum percentage of the population at risk (Kulldorff 2003). In empirical regional research, a maximum distance for spatial interaction is usually set.

(14) $$RR_Z = \frac{\hat{B}_{C_i,Z}}{\hat{\lambda} \cdot B_Z}$$

is larger than one. Thus, the specification of I initiates a scan for high-value clusters (hot spots) instead of a test for either high- or low-value clusters.

For fixed M and N the likelihood ratio LR_z is an increasing function of the number of cases in zone Z. The most likely cluster is achieved by maximizing LR_z over all possible zones and centroids of the areal units. With area data, the number of windows to be scanned for each location is usually considerably lower than the number of regions as all events are assigned to the regional centroids. Each secondary cluster is obtained conditional to the clusters detected in the previous stages. In this way, the problem of dependency in multiple testing procedures that was present in predecessors such as Openshaw’s Geographical Analysis Machine (GAM) (Openshaw et al. 1987) or Turnbull's Cluster Evaluation Permutation Procedure (CEPP) (Turnbull et al. 1990) is avoided (Kulldorff/Nagarwalla 1995).

Testing for significance of the maximized likelihood ratio LR_z is done by Monte Carlo simulation. The scan statistic is the likelihood ratio that is maximized over all zones with different sets of events of all regional centroids in the study region up to a given threshold. The distribution of the test statistic is obtained by multinomial randomization under the null hypothesis. With R as the rank of the maximized likelihood ratio of the real data set in a large number of random replications S, the p value of the test is R/(S+1). Potential regional industry clusters are characterized by values lower than the nominal significance level α for coherent territories.

In many cases, a variety of potential clusters is detected by spatial scanning for regional systems with a large number of regional units. In such applications not all possible clusters may be of substantive interest. Using employment data, clustering in coherent territories reflects the focus of production activities in a specific field in the regions concerned. Statistically significant industry clusters originally detected by the spatial scanning method may lack a critical mass for externalities (Menzel and Fornahl 2010). Porter (1998, 2000) stresses the role of a critical mass of a geographical concentration of interconnected companies taking a key position in an economic sector. Thus, the importance of a value-added chain in a region is determined by both dimensions, that is, focus and size (Feser et al. 2005). The size criterion is taken into account by adopting a threshold for the minimum cluster size.[7] Cluster districts with scarce employment in the core industry (< 100 employees) are not viewed as constituents of a regional cluster.

4. Empirical analysis

4.1 Data

In order to analyze the composition of value-added chains in R&D intensive industries, the German input-output table 2006 is used (Federal Statistical Office of Germany, 2010). The table consists of 71 sectors at the two- and, in part, three-digit level according to the classification of products by activity (CPA). Because the aim is to identify regional production linkages, imports are excluded from the analysis. The year 2006 is chosen for comparative purposes as more meaningful results of traditional cluster mapping are available for this year than for subsequent periods.

In order to identify potential regional clusters in R&D intensive industries, employment data at NUTS-3 level are provided by the German Federal Employment Office. The NUTS-3 level covers 439 urban and rural districts that vary considerably in size and economic power. The territorial sizes of the districts are obtained from the regional data bank of the Federal Statistical Office Germany. The employment statistic of the German Federal Employment Office provides the deepest subdivision of Germany for which sectoral employment data are available. The number of employees subject to social security contributions is available for the given 71 sectors of the Statistical classification of economic activities in the European Community (NACE Vers. 1.1). Both classifications, CPA and NACE, are linked as they share the same conceptual framework.

In all industrial sectors firms spend a part of their revenue on research and development (R&D). Most of the almost 52 billion € German R&D expenditure in 2006 comes from large companies. Only an estimated share of 9 per cent comes from small and medium enterprises (SME) (Grenzmann et al., 2009). Four two-digit industries account for roughly two thirds of private R&D expenditure. The automotive

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[7] The threshold of 1000 employees used here is in accordance with traditional cluster mapping of the European Cluster Observatory (European Communities, 2008).

industry is clearly dominant, with a share of about one third. This is followed by the electrical industry with 20 per cent, the chemical industry with 17 per cent and the machinery industry with 9 per cent. Because the individual contributions to amounts spent on research and development by these sectors are considerably larger than those of all other branches, they are called R&D intensive industries.

With one exception, employment data of R&D intensive industries at the district level are available for two-digit NACE codes. In the automotive and machinery industry, employment data refer to the divisions “Manufacture of motor vehicles, trailers and semi-trailers” (code 34) and “Manufacture of machinery and equipment” (code 29). A differentiation can be made within the chemical industry, where the “Manufacture of pharmaceuticals, medical chemicals and botanical products” (code 24.4) can be separated from “Manufacture of other chemicals and chemical products” (code 24 \ 24.4). The electrical industry is divided into “Manufacture of office machinery and computers” (code 30), “Manufacture of electrical motors, generators and transformers” (code 31), “Manufacture of radio, television and communication equipment and apparatus” (code 32) and “Manufacture of medical, precision and optical instruments, watches and clocks” (code 33). As the IT sector as a whole is often the focus of intention in innovation economics, the “hardware sector” (code 30) is combined with the “software sector” (“Computer and related activities”, code 72) for identification of regional IT clusters.

4.2 Cluster templates of German R&D intensive industries

Cluster templates in the form of value-added chains of R&D intensive industries are formed by using all inter-industry linkages included in the German input-output table 2006 (Federal Statistical Office of Germany, 2010). The significant flows are determined by qualitative input-output analysis (QIOA). As flows of goods between industries are analyzed regardless of their place of departure and destination, cluster templates are aspatial constructs. Yet they mirror the predominant links of an industry with its suppliers and buyers.

Significant flows of goods between industries are defined by the optimal filter rate that is determined by minimal flow analysis (MFA). Table 1 provides information on the choice of optimal filter rate from qualitative input-output-analysis.[8] Whereas the entropy index E takes the maximum value of 200.0 in the fifth step, the average value of the $\mathbf{H}_{res}$ matrix without zero elements refers to step 11. In step 8, as the middle of both step values, the optimal filter rate F* of 0.01271 is determined. Using this filter rate, 362 significant bilateral links and 1147 weak and unidirectional links, respectively, between the 71 sectors are categorized as important.

Table 1: Choice of the optimal filter rate

Step	Filter	Order k[b]	Entropy[c]	Values h_{ij} of the connectivity matrix $\mathbf{H}$			
				0	1	2	3
1	0.00010	11	86.8	420	187	187	4176
2	0.00182	7	152.1	512	650	650	3158
3	0.00363	6	181.8	672	964	964	2370
4	0.00545	5	197.2	972	1175	1175	1648
5	0.00727	5	200.0	1242	1232	1232	1264
6	0.00908	5	195.3	1654	1269	1269	778
7	0.01090	5	189.9	1812	1296	1296	566
8	0.01271	5	176.5	2314	1147	1147	362
9	0.01453	4	169.9	2504	1085	1085	296
10	0.01635	4	161.2	2720	1014	1014	222
11[a]	0.01816	4	149.5	2996	907	907	160
12	0.01998	4	146.3	3068	878	878	146
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
49	0.08718	2	19.1	4850	59	59	2
50	0.08900	2	NA	4854	58	58	0

[a] This filter step has been chosen according to the control measure for the determination of optimal filter rates. The matrix H_{res} contains 60 elements showing values above 0. The sum of elements in this matrix reaches a value of 645 and this leads to an average value of 645/60 = 10.75 that is rounded up to 11. - [b] Maximum order of included adjacency matrices according to equation (7). - [c] Values are multiplied by 100 for better readability.

Source: Authors' own calculations.

The qualitative composition of value-added chains of R&D intensive industries is defined by the endogenously determined optimal filter value of 0.01271. Using this filter rate, the first adjacency matrix $\mathbf{W}_1$ is obtained according to (6). From this, we discern important direct linkages in the German input-output system. In determining the optimal filter rate, additional indirect linkages are considered. For this, higher-order adjacency matrices $\mathbf{W}_k$ up to order 5 prove to be relevant.

[8] The analysis is carried out for the so-called standard structure. In this case the total demand vector in (5) will be replaced by a synthetic vector that is given in the simplest case by the summing-up vector $\mathbf{\iota}$. In doing so, the core matrix reveals its technological structure and is not "biased" through total demand (see Schnabl 1994, 2000).

Table 2 shows that the number of related sectors in the cluster templates varies substantially across industries. Whereas the pharmaceutical industry is only supplied by the chemical industry, input-output relationships in the machinery and chemical industries are highly complex. The automotive industry and the divisions of the electrical industry inclusive of the IT sector are each significantly linked with several sectors.

Table 2: Cluster templates for German R&D intensive industries

Cluster templates	Related industries
Automotive cluster (34)	25.2, 28, 31.
Chemical cluster (24 \ 24.4)	17, 19, 20, 21.2, 22.2-22.3, 24.4, 25.1, 25.2, 26.1, 26.2-26.8, 27.4, 27.5, 36
Pharmaceutical cluster (24.4)	24 \ 24.4
Machinery and equipment cluster (29)	25.1, 25.2, 26.1, 26.2-26.8. 27.1-27.3, 27.5, 28, 31, 35, 36
IT cluster (30 and 72)	28, 64, 73
Electrical machinery and apparatus clusters (31)	28, 29, 33, 34, 35
Radio, television, communication equipment and apparatus clusters (32)	28
Medical, precision and optical instruments clusters (33)	25.2, 28, 31

Note: The description of the related sectors is listed in Table A1 of the appendix.

Source: Authors' own calculations.

4.3 Regional value-added chains of German R&D intensive industries

At the national level, value-added of cluster templates could be calculated by taking into account the strengths of the linkages between the core industries and their related sectors. In order to identify potential R&D clusters across space, value-added chains have to be represented by employment. Furthermore, the amalgamation of the core industries with their connected sectors presupposes an assessment of the degree of their relatedness. While input and output coefficients only measure the strength of direct buyer-supplier interactions, both direct and indirect production linkages are captured by the coefficients of the Leontief inverse **M** ("inverse coefficients"). Both ratios are available from national input-output analysis

(Statistisches Bundesamt, 2010). It should be kept in mind that the inverse coefficients from the national I-O analysis reflect average and not actual flow intensities across space. Here the more comprehensive concept of interrelationships is employed in forming value-added chains. In a robustness check, variations of sectoral linkages are also examined.

4.3 Identifying potential regional clusters of R&D intensive industries

Industrial activity is very unevenly distributed in Germany. Spatial concentrations of industrial companies are observed at different geographical scales in nearly all sectors (Kosfeld/Eckey/Lauridson 2011; Brenner 2006). The clustering of value-added chains of R&D industries is also confirmed global autocorrelation analysis. Highly significant Moran's I values are measured in a distance band from 20 to 100 kilometres for all regional R&D value-added chains. Beyond this radius, the Moran coefficient remains at least weakly significant for all industries up to the maximum size used of 220 kilometres.

Thus, searching for spatial clustering of R&D industries and their related sectors is well-founded in research. A limitation of the reach is generally necessary in order to avoid measuring dispersion instead of concentration. Here the chosen maximum window size conforms to the $d_{max}/4$ rule (Kosfeld et al., 2011).[9].The localization of clusters is accomplished with the aid of the method of spatial scanning.

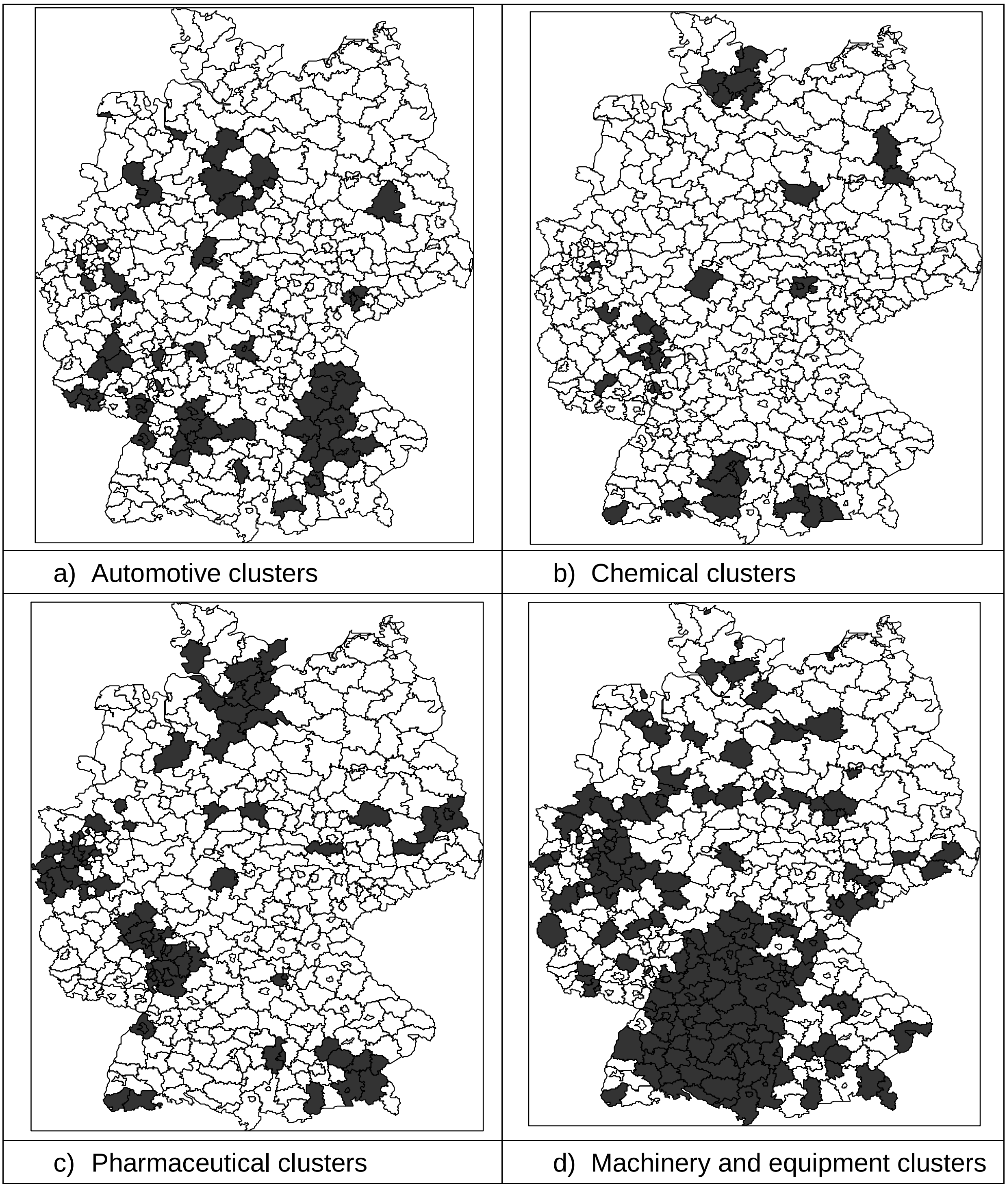
Figure 1a) shows that the manufacture of motor vehicles, together with their parts and accessories, is mainly concentrated in the western regions of Germany. Apart from Schleswig-Holstein and Hamburg, automotive clusters are detected in all West German federal states. Only three smaller clusters are identified in East Germany in the areas of Eisenach, Zwickau/Chemnitz and Teltow-Fläming.

The largest automotive clusters are located in the federal states of Lower Saxony, Baden-Wuerttemberg and Bavaria. According to the cluster mapping of the European Cluster Observatory (www.clusterobservatory.eu), the most important regional clusters identified in the areas around Hanover and Braunschweig (Lower Saxony), Stuttgart and Karlsruhe (Baden-Wuerttemberg) as well as Upper and Lower Bavaria

[9] As an alternative to using a fraction of the maximum distance d_{max} between the centres of the regions, the maximum cluster size can be determined by the medium or average distance (cf. Duranton and Overman, 2005)

belong to the 16 largest automotive clusters in Europe (Blöcker et al., 2009). However, despite the considerable correspondence in identifying the main regional focuses of automobile production, the method of cluster mapping fails in delineating the exact boundaries of clusters. Partly through the use of a finer geographical scale, the spatial scan approach succeeds in a more exact delineation of these regional clusters.

Figure 1: Regional R&D clusters I: Non-electrical industries



a) Automotive clusters

b) Chemical clusters

c) Pharmaceutical clusters

d) Machinery and equipment clusters

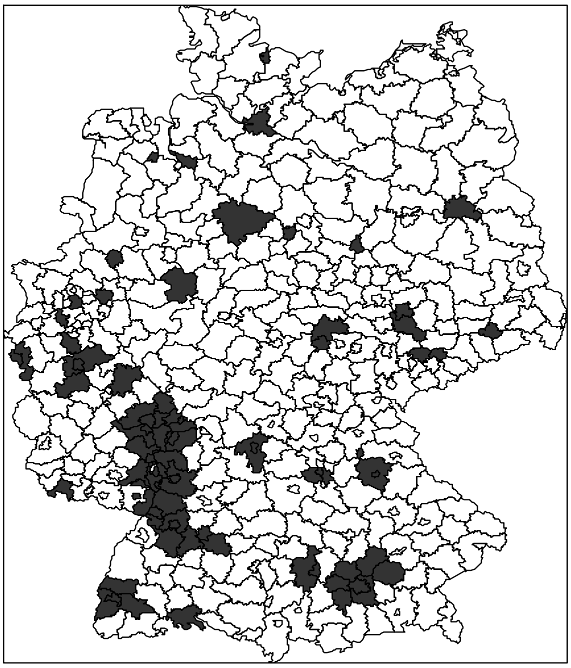
Although the Saarland cluster is rated only as a two star cluster, it also belongs to the above-mentioned group (European Commission 2011). Employment concentration in automobile production proves to be significant within a slightly reduced area of this small German federal state. Additional, mostly isolated, employment clusters in the manufacture of motor vehicles and related sectors are found in the Rhine-Ruhr area, Rhineland-Palatinate, Northern and Southern Hesse, western Lower Saxony and Upper Palatinate. Most of these areas are rated as two star clusters by the mapping method of the European Cluster Observatory.

A highly significant spatial clustering of production activity with regard to chemicals and chemical products occurs in the tri-border region of Rhineland-Palatinate, Baden-Wuerttemberg and Hesse. Focal production sites in this area are the districts of Mannheim, Darmstadt and Mainz-Bingen. This contiguous territory is extended to the north by the chemical cluster in Middle and Northern Hesse. In Baden-Wuerttemberg, two isolated clusters are further evident at the borders with France and Switzerland respectively. Coherent chemical clusters are found around Ulm/Biberach and Weilheim-Schongau/Starnberg. Scattered centres of chemical production are located in the Rhine-Ruhr area. While these clusters are also revealed using the methodology of the European Cluster Observatory, the hot spots in Middle and Northern Hesse have remained undetected by traditional cluster mapping. This also applies to the chemical clusters in Schleswig-Holstein and East Germany.

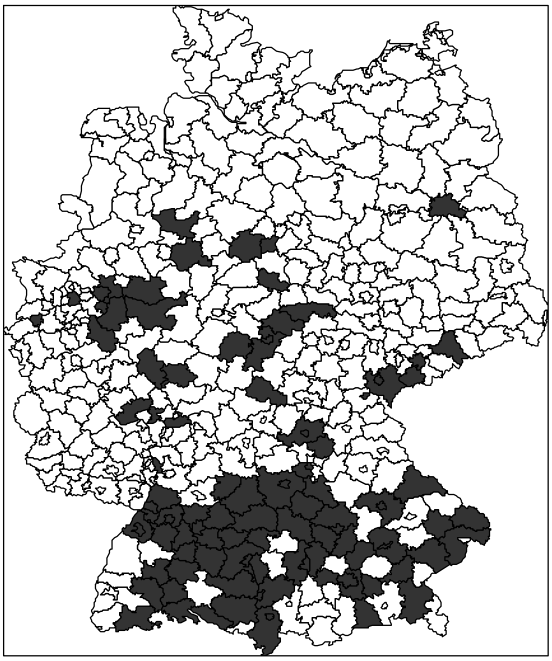
A comparison of Figures 1 b) and 1c) reveals some overlap in regional clustering in the value-added chains of the chemical and pharmaceutical industry. This is particularly the case for the Rhine-Main cluster with the city of Ludwigshafen as the core of the pharmaceutical industry. Compared to the manufacture of chemical products, the manufacture of pharmaceuticals is much more pronounced in the Rhine-Ruhr cluster. Moreover, the northern pharmaceutical cluster covers Hamburg as well as some neighbouring districts of Lower Saxony. Except for their boundaries, these centres of pharmaceutical production as well as those in southern Baden-Wuerttemberg and Upper Bavaria are also detected by cluster mapping. The spatial scan method points additionally to significant regional clustering in the southern part of East Germany.

No direct comparison with the star cluster mapping is available for the manufacture of machinery and equipment. However, a comparison with production technology clearly exhibits a cluster in Baden-Wuerttemberg that almost spans the state. With the exception of the potential northern cluster, the centres of mechanical engineering in Figure 1d) are well in line with the star clusters. Yet the spatial scan method points to non clustering areas in the Free State of Bavaria which have not emerged from the traditional mapping technique.

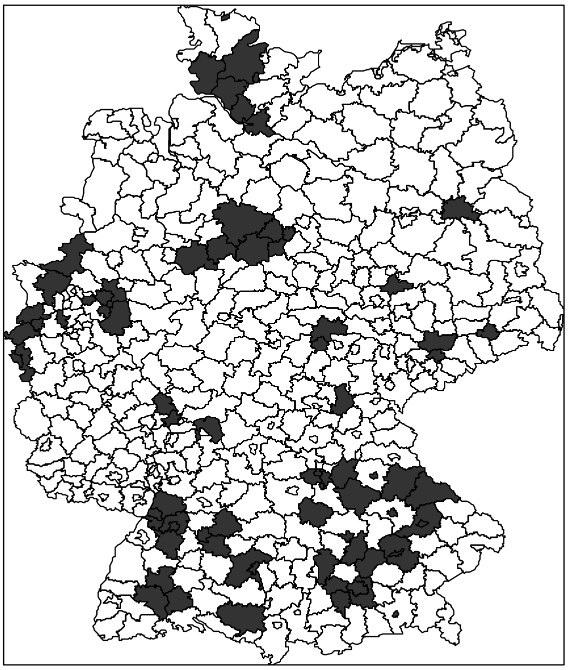
Figure 2: Regional R&D clusters II: Electrical industries



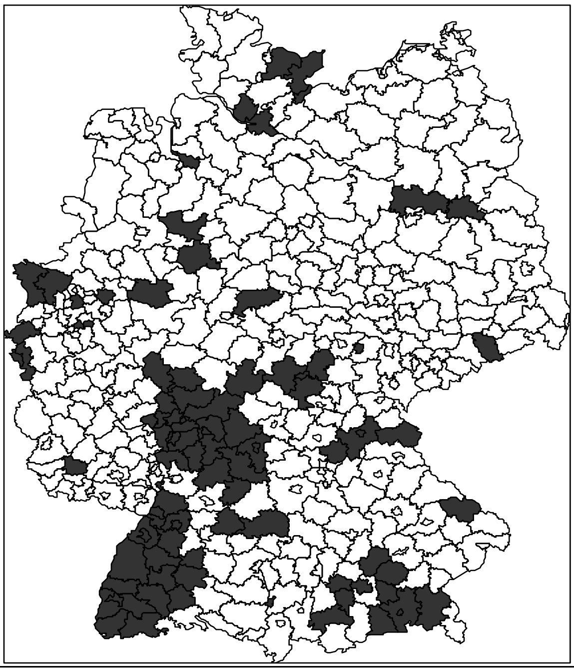
a) IT clusters



b) Electrical machinery and apparatus clusters



c) Radio, television, communication equipment and apparatus clusters



d) Medical, precision and optical instrument clusters

Hot spots of IT activity are illustrated in Figure 1e). The three star clusters of the European Cluster Observatory around Karlsruhe, in Upper Bavaria and Lower Franconia are identified as well by spatial scanning. This also applies to the one star cluster regions of Stuttgart, Darmstadt, Düsseldorf, Cologne, Dresden, Detmold and Upper Palatinate.[10] However, the cluster boundaries of the star rating method appear to be very fuzzy. Moreover, significant clustering of IT activity emerges additionally in the regions of Berlin, Hamburg, Hanover, Bremen and the Saxony Triangle.

Figures 1f-1h reveal that the centres of production activity of the sectors “electrical machinery and apparatus”, “radio, television, communcation equipment” and “apparatus and medical, precision and optical instruments” are located most notably in South Germany and North-Rhine Westfalia. In contrast to both other sectors, the South German communication equipment and apparatus clusters tend to be relatively incoherent. A striking variation is the lack of a northern cluster of manufacture of electrical machinery and apparatus.

5. Robustness of cluster structures

In identifying potential regional clusters using the method of spatial scanning, both regional and national employment data have been used. While regionally disaggregated data are available for the core industries of regional values chains, the proportions of related industries must be estimated from national figures. The method of inverse coefficients transfers the national average of employees in related industries directly or indirectly involved in production activities in the core industry to regional value-added chains. Yet the inverse coefficients will not normally be constant but will differ from region to region. Local clusters, for instance, may give reason for an engagement of an above average proportion of workers from related industries in production of the core industry on account of potential technological externalities. On the other hand, employees who are only indirectly involved in core production activities may not necessarily participate in cluster activities. This implied vagueness gives rise to an analysis of the stability of the identified cluster structures in R&D intensive industries.

[10] In the IT sector no region is rated a two star cluster by the mapping method of the European Cluster Observatory (European Commission, 2011).

The robustness of cluster structures with respect to the utilization of inverse or I-O coefficients is illustrated in Table 3. In none of the cases are different numbers of clusters observed. The two methods produce exactly the same regional clusters for the valued-added chains in the automotive and IT industry. A change in size in a single cluster is observed in manufacture of machinery and equipment, manufacture of radio, TV and communication equipment and apparatus and manufacture of medical, precision and optical instruments. In the pharmaceutical industry, a switch between both types of coefficients is involved with an expansion and reduction of one cluster respectively. Although the geographical extent of two clusters will expand for the value-added chain of manufacture of electrical machinery and apparatus with both methods, the changes are minor with respect to spatial employment concentration. In particular, owing to the overlap with manufacture of pharmaceuticals, the size of altogether four regional clusters varies in manufacture of chemicals and chemical products.

Table 3: Alterations of regional clusters between inverse coefficient and input coefficients method

Cluster	Method	Number of additional clusters	Number of expanded clusters	Number of additional cluster districts
Automotive clusters	Inverse coefficients	0	0	0
	I-O coefficients	0	0	0
Chemical clusters	Inverse coefficients	0	2	4
	I-O coefficients	0	2	6
Pharmaceutical clusters	Inverse coefficients	0	1	5
	I-O coefficients	0	1	1
Machinery and equipment clusters	Inverse coefficients	0	1	5
	I-O coefficients	0	0	0
IT clusters	Inverse coefficients	0	0	0
	I-O coefficients	0	0	0
Electrical machinery and apparatus clusters	Inverse coefficients	0	2	4
	I-O coefficients	0	2	2
Radio, television, communication equipment and apparatus clusters	Inverse coefficients	0	1	1
	I-O coefficients	0	0	0
Medical, precision and optical instruments clusters	Inverse coefficients	0	0	0
	I-O coefficients	0	1	3

The fuzziness of regional clusters is introduced not only by potential differences in the importance of direct and indirect linkages between industries. It also accrues from varying spatial concentrations of suppliers and customers around the core industries. In particular, in anticipating much more pronounced spatial spillovers, companies of related industries may be more strongly localized in regional clusters. Such behaviour is simulated by doubling the inverse coefficients in defining regional added chains. Alterations in cluster detection involved in this approach are summarized in Table 4.

Table 4: Alterations of regional clusters between inverse coefficients and double inverse coefficients method

Cluster	Method	Number of additional clusters	Number of expanded clusters	Number of additional cluster districts
Automotive clusters	Inverse coefficients	0	1	1
	Double inverse coefficients	0	1	1
Chemical clusters	Inverse coefficients	1	4	11
	Double inverse coefficients	0	1	3
Pharmaceutical clusters	Inverse coefficients	1	4	34
	Double inverse coefficients	0	1	3
Machinery and equipment clusters	Inverse coefficients	0	2	5
	Double inverse coefficients	0	3	8
IT clusters	Inverse coefficients	0	2	3
	Double inverse coefficients	0	1	1
Electrical machinery and apparatus clusters	Inverse coefficients	0	3	6
	Double inverse coefficients	0	3	3
Radio, television, communication equipment and apparatus clusters	Inverse coefficients	0	1	1
	Double inverse coefficients	0	1	1
Medical, precision and optical instruments clusters	Inverse coefficients	0	0	0
	Double inverse coefficients	0	2	2

For most R&D intensive industries, no substantive changes arise. However, the formation of regional value-added chains by the doubling of the inverse coefficients leaves one undetected cluster in each of three core industries. In addition, the isolated cluster of Dresden is left undetected in manufacturing of chemicals and chemical products, while the single cluster of Berlin is not identified in manufacturing of radio, television and communication equipment and apparatus. In the case of the value-added chain of the pharmaceutical industry, the twin cluster of Lörrach and Waldshut in southern Germany is not identified when the inverse coefficients are doubled. But none of the three undetected potential clusters belong to the main production sites of the respective core industries.

In general, the boundaries of the originally identified clusters change slightly more with the double inverse coefficients method compared to the method of input coefficients. In the chemical and pharmaceutical industry, however, somewhat more noticeable differences occur. While the number of potential clusters is virtually unaffected in manufacturing of chemicals and chemical products, differences in their size increase considerably. The contraction of existing clusters with double inverse coefficients becomes even more pronounced in manufacture of pharmaceuticals. This effect is due mainly to the strong relatedness between both industries that by its very nature makes a clear separation of their value-added chains difficult. Beside this special case, the identified regional clusters show a high degree of robustness with respect to a variation in the quantitative cluster composition.

6. Conclusion

EU and national regional development and innovation policy draw in large part on advantages ascribed to regional clusters. Although the concept of a cluster rests upon agglomeration theory, its definitional fuzziness poses a challenge for policy makers and regional planning agencies. The characteristic of an open concept finds its expression in empirical cluster research. Researchers make use of a variety of techniques in establishing dominant links between industries in order to form cluster templates. Likewise, different approaches have been considered in locating industrial clusters.

In this paper the focus of attention is the identification of potential clusters of German R&D intensive industries. For this purpose, a two-step procedure is employed. In the first step, national cluster templates of R&D intensive core industries are formed with the aid of qualitative input-output analysis (QIOA). Dominant input-output linkages between the core industries and related sectors are deduced from on a filter rate that is endogenously developed with minimal flow analysis (MFA). In the second step, potential regional clusters of R&D intensive industries are localized in space. In this step, regional value-added chains of the core industries are formed by making allowances for direct and indirect linkages with their dominant related sectors. Potential regional clusters are identified using the technique of spatial scanning that is highly flexible with respect to the scale of clustering.

In identifying industrial clusters by analyzing the flow of goods between suppliers and customers, it is presumed that interaction between companies takes place primarily along their value-added chains. In addition, the formation of benchmark clusters on the basis of the national input-out table provides regional planning agencies with information on parts missing from regional value-added chains. This adds to an understanding of the importance of complementary or related industries in the development of a cluster. Such information is lacking when the composition of value-added chains is deduced directly from locational correlation analysis of sectoral employment.

Most previous studies have localized economic clusters purely descriptively, using single or complex indicators. Recently, local spatial methods such as the Gets-Ord G_i^* or Moran's I_i test have also been applied. Although the testing procedures allow explicitly for spatial dependencies across districts, they are inflexible with respect to varying spatial scales of coherent industrial groupings. Cluster theory does not provide conclusive information on the geographical extent of a cluster. By contrast, there is much empirical evidence of varying scales of industrial clusters. Using Kulldorff's spatial scanning method, the search for regional clusters is accomplished by varying the size of the window around each district up a maximum value. Potential regional clusters meet criteria of both focus and size.

Strong regional clusters are increasingly seen as a response to economic globalization by policy makers and regional development agencies. The notion that countries and regions with enterprises organized in clusters have a competitive advantage is closely related to the influential work of Porter. Because of the presumed connection between clustering and high productivity growth and innovation potential, the cluster approach has become more appealing in different fields of economic policy. However, up to now there has been little empirical evidence for the impact of clustering on the economic performance of enterprises and the development of regions. In many cases, an obstacle in the way of a valid evaluation of clustering effects results from a certain fuzziness in establishing the borders of regional clusters. Leaving aside the industrial overlap in one special case, the hybrid methodology employed in cluster identification that is introduced in this paper meets a high degree of robustness. Thus, this approach is expected to provide a sound basis for evaluating the impact of industrial clusters on sectoral performance and regional development.

References

Blöcker, A., Jürgens, U., Meißner, H.-R. (2009), Innovationsnetzwerke und Clusterpolitik in europäischen Automobilregionen, LIT, Münster.

Bon, R. (1989), Qualitative Input-Output Analysis, in: Miller, R.E., Polenske, K.R., Rose, A.Z. (eds), Frontiers in Input-Output Analysis, Oxford University Press, Oxford, UK, 222–231.

Brachert, M., Titze, M., Kubis, A. (2011), Identifying Clusters from a Multidimensional Perspective: Methodical Aspects with an Application to Germany, Papers in Regional Science 90, 419–440.

Brenner, T. (2006), Identification of local industrial clusters in Germany, Regional Studies 40, 991–1004.

Christensen, T.A., Meier zu Köcker, G., Lämmer-Gamp, T., Thomsen, M.S., Oleson, K. (2011), Cluster and network policy programmes in Europe, NGP Cluster Excellence Conference, May 2011, Copenhagen, Denmark.

Cruz, S.C.S., Teixeira, A.A.C. (2010): The Evolution of the Cluster Literature: Shedding Light on the Regional Studies–Regional Science Debate, Regional Studies 44, 1263–1288.

Duranton, G., Overman H.G. (2005), Testing for localization using micro-geographic data, Review of Economic Studies 72, 1077–1106.

European Commission (2011), Star Clusters in Germany, Europa INNOVA, European Cluster Observatory, Center for Strategy and Competitiveness (CSC), Stockholm School of Economics, Stockholm. Accessed on 8/22/2012 from http://www.clusterobservatory.eu/common/galleries/downloads/Star_clusters_Germany2.pdf.

European Communities (2008), The Concepts of Clusters and Cluster Policies and their Role for Competitiveness and Innovation: Main Statistical Results and Lessons Learned, Commission Staff Working Document SEC (2008) 2637, Luxembourg.

Federal Statistical Office of Germany (2010), Volkswirtschaftliche Gesamtrechnungen – Input-Output-Rechnung 2006, Fachserie 18, Reihe 2, Wiesbaden.

Feser, E., Bergman, E. (2000), National Industry Cluster Templates: A Framework for Applied Regional Cluster Analysis, Regional Studies 34, 1–20.

Feser, E., Koo, K., Renski, H., Sweeney, S. (2001), Incorporating Spatial Analysis in Applied Industry Cluster Studies, Discussion Paper, University of North Carolina, Chapel Hill, NC.

Feser, E., Sweeney, S. (2002), Theory, Methods and a Cross-metropolitan Comparison of Business Clustering, in: McCann, P. (ed.), Industrial Location Economics, Cheltenham, UK, 222–257.

Feser, E., Sweeney, S., Renski, H. (2005), A Descriptive Analysis of Discrete U.S. Industrial Complexes, Journal of Regional Science 45, 395–419.

Feser, E., Renski, H., Koo, J. (2009), Regional Cluster Analysis with Interindustry Benchmarks, in: Goetz, S., Deller, S.C., Harris, T.R. (eds.), Targeting Regional Economic Development, Routledge, New York, ch. 12, 213–240.

Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., Shleifer, A. (1992), Growth in Cities, Journal of Political Economy 100, 1126–1152.

Grenzmann, C., Kladobra, A., Kreuels, B. (2009), FuE-Datenreport 2009 – Tabellen und Daten, Essen.

Guillain, R., Le Gallo, J. (2010), Agglomeration and Dispersion of Economic Activities in Paris and Its Surroundings: An Exploratory Spatial Data Analysis, Environment and Planning B: Planning and Design 37, 961–981.

Hoover, E.M. (1948), The Location of Economic Activity, McGraw-Hill, New York, N.Y.

Jacobs, J. (1969), The Economy of Cities, Random House, New York, N.Y.

Kiese, M., Wrobel, M. (2011), A Public Choice Perspective on Regional Cluster and Network Promotion in Germany, European Planning Studies 19, 1691–1712.

Kosfeld, R., Eckey, H.-R., Lauridsen, J. (2011), Spatial Point Pattern Analysis and Industry Concentration, Annals of Regional Science 47, 311–328.

Kronenberg, T. (2010), Erstellung einer Input-Output-Tabelle für Mecklenburg-Vorpommern, AStA – Wirtschafts- und Sozialstatistisches Archiv 4, 223–248.

Kuah, A.T.H. (2002), Cluster Theory and Practice: Advantages for the Small Business Locating in a Vibrant Cluster, Journal of Research in Marketing and Entrepreneurship 3, 206–228.

Kulldorff, M. (1997), A Spatial Scan Statistic, Communications in Statistics: Theory and Method 26, 1481–1496.

Kulldorff, M., Nagarwalla, N. (1995), Spatial disease clusters: detection and inference, Statistics in Medicine 14, 799–810.

Kulldorff, M. (2010), SatScan^{TM} User’s Guide for version 9.0, Accessed on 8/22/2012 from http://satscan.org/.

Lazzaretti, L., Sedita, S. R., Caloffi, A. (2013): Founders and disseminators of cluster research. In: Journal of Economic Geography 14, 21–43.

Marcon, E., Puech, F. (2003), Evaluating the geographic concentration of industries using distance-based methods, Journal of Economic Geography 3, 409–428.

Marshall, A. (1920), Principles of Economics, 8th ed., McMillan, London, Original work published 1890.

Martin, R., Sunley, P. (2003), Deconstructing Clusters: Chaotic Concepts or Policy Panacea? Journal of Economic Geography 3, 5–35.

Menzel, M.-P., Fornahl, D. (2010), Cluster life cycles ─ dimensions and rationales of cluster evolution. Industrial and Corporate Change 19, 205–238.

Ó hUallacháin, B. (1984), The Identification of Industrial Complexes, Annals of the Association of American Geographers 73, 420–436.

Openshaw, S., Charlton, M., Wymer, C., Craft, A. W. (1987). A mark I geographical analysis machine for the automated analysis of point data sets. International Journal of Geographical Information Systems 1, 335–358.

Ord, J.K, Getis, A. (1995), Local Spatial Autocorrelation Statistics: Distributional Issues and an Application, Geographical Analysis 27, 286–305

Oxford Research (2008), Cluster Policy in Europe, Europe Innova Cluster Mapping Project, Kristiansand, Norway.

Pires, J.C., Cravo, T., Lodaro, S., Piza, C. (2013), Industrial Clusters and Economic Performance in Brazil, IDB Working Paper Series No. IDB-WP-475, Inter-American Development Bank.

Popa, I., Vlăşceanu, C. (2013), Cluster Policies in the European Union ─ Engines for Sustainable Economic Development and Competitiveness, Annals of the University of Oradea, Economic Science Series, 22, 1581–1587.

Porter, M.E. (1990), The Competitive Advantage of Nations, New York, N.Y.

Porter, M.E. (1998), Clusters and the New Economics of Competition, Harvard Business Review 76, 77-90.

Porter, M.E. (2000), Location, Competition, and Economic Development: Local Clusters in a Global Economy, Economic Development Quarterly 14, 15–34.

Porter, M.E. (2003), The Economic Performance of Regions, Regional Studies 37, 549–578.

Roelandt, T.J.A., Den Hertog, P. (1999), Cluster Analysis and Cluster-Based Policy Making in OECD Countries: An Introduction to the Theme, in: Organization for Economic Co-operation and Development (OECD) (ed.), Proceedings, Boosting Innovation: The Cluster Approach, pp.9–23.

Schnabl, H. (1994), The Evolution of Production Structures, Analyzed by a Multi-Layer Procedure, Economic Systems Research 6, 51–68.

Schnabl, H. (2000), Struktur-Evolution. Innovation, Technologieverflechtung und sektoraler Strukturwandel, Oldenbourg, Munich.

Schnabl, H., Kohei, Y. (2003), Structural development of Germany and Japan 1980 – 1995, Journal of Applied Input-Output Analysis 9, 93–115.

Shannon, C.E., Weaver, W. (1949), The Mathematical Theory of Communication, University of Illinois Press, Urbana, IL.

Scholl, T., Brenner, T. (2012), Detecting Spatial Clustering Using a Firm-Level Cluster-Index, Working Papers on Innovation and Space, Philipps University Marburg, Marburg, Germany.

Sternberg, R., Litzenberger, T. (2004), Regional Clusters in Germany – Their Geography and their Relevance for Entrepreneurial Activities, European Planning Studies 12, 767–791.

Titze, M., Brachert, M., Kubis, A. (2011), The Identification of Regional Industrial Clusters Using Qualitative Input-Output Analysis (QIOA), Regional Studies 45, 89–102.

Török, R. (2012), Innovation Landscapes ─ A study on innovation approaches in three selected EU member States, Research and Innovation, European Commission, Brussels.

Turnbull, B.W., Iwano, E.J., Burnett, W.S., Howe, H.L., Clark, L.C. (1990), Monitoring for clusters of disease: Applications to leukemia incidence in upstate New York, American Journal of Epidemiology 132, 136–143.

Vom Hofe, R., Chen, K. (2006), Whither or Not Industrial Clusters: Conclusions or Confusions?, The Industrial Geographer 3, 2–28.

Vom Hofe, R., Bhatta, S.D. (2007), Method for Identifying Local and Domestic Industrial Clusters Using Interregional Commodity Trade Data, The Industrial Geographer 4, 1–27.

Appendix

Table A1: R&D intensive industries and their related sectors

Code	Sector
17	Manufacture of textiles
19	Manufacture of leather and leather products
20	Manufacture of wood and wood products
21.1	Manufacture of pulp, paper and paperboard
21.2	Manufacture of articles of paper and paperboard
22.2 - 22.3	Printing and service activities related to printing; reproduction of recorded media
24 \ 24.4	Manufacture of chemicals and chemical products
24.4	Manufacture of pharmaceuticals, medical chemicals and botanical products
25.1	Manufacture of rubber products
25.2	Manufacture of plastic products
26.1	Manufacture of glass and glass products
26 \ 26.1	Manufacture of other non-metallic mineral products without glass and glass products
27.1 - 27.3	Manufacture of basic iron and steel and of ferro-alloys; Manufacture of tubes; Other first processing of iron and steel
27.4	Manufacture of basic precious and non-ferrous metals
27.5	Casting of metals
28	Manufacture of fabricated metal products, except machinery and equipment
29	Manufacture of machinery and equipment n.e.c.
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus n.e.c.
32	Manufacture of radio, televison and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
36	Manufacture of furniture; manufacturing n.e.c.
72	Computer and related service activities
73	Research and development services

Source: Classification of Economic Activities NACE Rev. 1.1 (Commission Regulation (EC) No 29/2002)