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Benchmark Value-added Chains and Regional Clusters in R&D-intensive Industries

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Abstract

Although the phase of euphoria seems to be over, policy makers 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. Although there has been some progress in locating clusters, in most cases only limited knowledge on the geographical extent of regional clusters has been established. In the present article, we present a hybrid approach to cluster identification. Dominant buyer–supplier relationships are derived by qualitative input–output analysis from national input–output tables, and potential regional clusters are identified by spatial scanning. This procedure is employed to identify clusters of German research and development-intensive industries. A sensitivity analysis reveals good robustness properties of the hybrid approach with respect to variations in the quantitative cluster composition.

Keywords

national cluster templates, regional clusters, qualitative input–output analysis, spatial scanning

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Introduction

Strong regional clusters are increasingly viewed by both policy makers 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, 1998a, 2000). In Porter's diamond model, the presence of related and supportive industries in local production structures is underscored as principal determinant of regional competiveness. Because 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 and Wrobel 2011). In particular, cluster-based instruments are an integral part of European Union (EU) regional policy (see, e.g., Christensen et al. 2011; Popa and Vlăşceanu 2013). In most EU countries, cluster-oriented policy plays an important role at both national and regional levels (Oxford Research 2008). In Germany, for example, diverse national and regional programs have been set up to promote cluster development (Török 2012).

Although the cluster approach is based on agglomeration theory, a variety of definitions of "cluster" exist (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. Some approaches aim to identify regional clusters from a multidimensional perspective (cf. Brachert, Titze, and Kubis 2011; Delgado, Porter, and Stern 2014). However, 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 (Martin and Sunley 2003). Nevertheless, targeted cluster-based policies hinge crucially on the knowledge of where clusters are located and the sectors in which they are formed. Without the ability to effectively identify focused clusters, regional development agents and policy makers cannot receive feedback on the success or failure of their applied strategies and instruments.

However, the variety of cluster definitions is not the only reason for the existence of different approaches to identifying clusters. A given cluster concept may be differently operationalized (cf. vom Hofe and Chen 2006; vom Hofe and Bhatta 2007; Feser, Renski, and Koo 2009). The literature distinguishes two strands in the approach to the spatial scale of industrial clusters. The first strand follows seminal works of Sweeney and Feser (1998), Feser and Sweeney (2000), Marcon and Puech (2003), and Duranton and Overman (2005). To avoid problems with arbitrary predefined 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. Feser and Sweeney (2002) use the *D* function in a cross-metropolitan comparison of business clustering. Kosfeld, Eckey, and Lauridsen (2011) use the *K* function approach to measure spatial industry concentration in Germany on different spatial scales. Scholl and Brenner (2012) advance the distance-based techniques in identifying regional clusters. Because these methods usually require geocoded data, the data requirements are high.

The second strand in the literature applies spatial statistics tools to areal data. If geographical units are considered spatially independent in the presence of spillovers, spatial clustering tends to be underestimated (Guillain and Le Gallo 2010). Feser et al. (2001) 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, and Renski (2005) extended spatial analysis to the United States as a whole. Both studies use the Getis-Ord Gi* statistic to measure and test for local spatial clustering (Ord and Getis 1995). Recently, Pires et al. (2013) used the local Moran's 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 colocation of firms belonging to the same branch, the existence of linkages among actors is regarded as a crucial characteristic of industrial clusters. Within this context, applied cluster studies often focus on enterprises along value-added chains in which knowledge exchange is primarily supposed (cf. Kuah 2002). Although 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 (I-O) tables before searching for the location of potential industry clusters (cf. Feser and Bergman 2000; Feser, Sweeney, and Renski 2005; vom Hofe and Bhatta 2007; Titze, Brachert, and Kubis 2011).

Potentially different compositions of national cluster templates and regional clusters pose a great challenge for establishing a methodology of cluster identification. The present article aims to improve strategies of regional cluster identification. Against the backdrop of a weak cluster definition, we emphasize systematic, reliable, and comprehensive identification without fixing the geographical extent of potential spillover effects in advance. The article is in line with appreciative and empirical cluster research that has grown in importance in recent decades (Cruz and Teixeira 2010).

First, at the national level, the dominant related sectors of research and development (R&D)-intensive industries are identified by qualitative input–output analysis (QIOA). However, we recognize that in many instances not all enterprises in these sectors belong to the respective value-added chains. In defining an automotive cluster, for example, only some of the enterprises in the plastics and related sectors can be included, because several firms are not involved in the production of motor vehicles. Thus, QIOA must be supplemented by qualitative input–output analysis to avoid distortion effects that may arise from defining overly heterogeneous clusters. Here, we consider downstream and upstream sectors depending on their involvement in the production activities of the key industry.

Second, at the local level, it is necessary to establish 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. To allow for varying reaches of the geographical extent of regional interaction, we adopt the flexible approach of spatial scanning (Kulldorff 1997). Kulldorff's scan test can accurately capture the variable extent of potential regional clusters.

This article is organized as follows. In the next section, we discuss the theoretical elements of the cluster concept. Then, we explain a hybrid approach to identification of industrial clusters, after which we employ the methods to identify potential regional clusters of R&D-intensive industries in Germany. We then conduct a robustness check of identified cluster structures. We conclude with a discussion of the findings.

Elements of Cluster Theory

The number of articles on industrial clusters has risen in recent decades, as has the number of journals publishing work on this subject. The theory of clusters embraces a variety of approaches. There have been some promising efforts in the literature based on bibliometric analyses that attempt 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 and Teixeira 2010; Lazzaretti, Sedita, and Caloffi 2013).

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 were originally described by Alfred Marshall ([1890] 1920) in an analysis of industrial organization. The geographical concentration of an industry may result in certain advantages due to, for example, 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) highlights additional effects of an agglomeration of firms from different industries. Such urbanization externalities, for example, may 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 among 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 the "diamond model," Porter (1990) introduces a mixed view of innovation and growth (see also Porter 1998a, 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 rather 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 1998a, 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 explains 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) also provides 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 and 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 (1998b, 199) 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 ("coopetition"). Competition is expected to prevail among horizontally linked enterprises. Vertical links between establishments as well as strategic alliances with universities and research institutions are usually characterized by cooperation based on trust.

Despite some vagueness in the concept of clusters, recent studies seem to generally agree on four core elements (cf. Feser and Bergman 2000; Feser, Sweeney, and Renski 2005; Feser, Renski, and Koo 2009; Titze, Brachert, and Kubis 2011). First, a cluster consists of a group of firms operating in a core industry and its related sectors. Second, the establishments belonging to a cluster are interconnected (i.e., they form part of a network). Third, the enterprises are proximate to one another (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 a cluster to exist, enterprises need not necessarily be conscious of being part of a network of producers (Ketels, Lindqvist, and Sölvell 2006).

At the same time, there is no consensus on how the geographical boundaries of industrial clusters should be determined (Martin and Sunley 2003). This is a crucial issue, however, because policy measures and economic consequences of industrial clusters are closely related to cluster size as a function of the reach of spatial interactions. Martin and Sunley (2003) point out that top-down approaches using data (e.g., on employment or establishments) on pregiven administrative units must not necessarily find the geographical boundaries of industrial clusters. In particular, with very large spatial units, local clusters can be overbounded and obscured. However, small area data are not a panacea per se because such data may exaggerate the number and significance of clusters in the case of high specialization. Beyond that, localization economies may manifest at varying spatial scales (cf. Kosfeld, Eckey, and Lauridsen 2011), and most cluster analyses ignore this finding.

Another point related to the size of the administrative unit under analysis is the presence of spatial interaction between interrelated geographical units. At the local level, it needs to be established whether and how spatial externalities and spillovers should be allowed for in locating regional clusters. Most applied cluster studies do not address these broader spatial forces in their empirical framework, though impact on the colocation of firms might be expected. Thus, we use an administrative unit that is small enough to display economic differentiation and control for spatial interaction between regions. To allow for varying reaches of the geographical extent of regional interaction, we adopt the flexible approach of spatial scanning (Kulldorff 1997).

Hybrid Approach to Cluster Identification

Regional I-O 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 I-O 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 I-O flows in interactions among enterprises. Substantial interindustry links are established with the aid of QIOA. Second, 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.

QIOA and National Cluster Templates

In a general sense, QIOA consists of techniques used to transform flows of goods between sectors into binary relationships. More 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 QIOA differ with respect to considerations of the kind of sector links and the appraisal of important links (cf. Bon 1989; Schnabl 2000; Schnabl and Kohei 2003).

The filter approach of I-O 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 I-O table is achieved from an iteratively determined optimal filter rate (Titze, Brachert, and Kubis 2011).

The starting point of MFA analysis is the well-known Leontief model. In a first step, the method makes use of the decomposition of the Leontief inverse. In doing so, different layers $\mathbf{T}_1$, $\mathbf{T}_2$, $\mathbf{T}_3$, ... representing different stages of the production process can be derived. For each of these layers, we test whether a certain intermediate input flow exceeds a specific filter rate F. If so, the respective flow is set to "1" and "0" otherwise:

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

Applying matrix operations, we receive information on whether two sectors are connected by dominant intermediate input flows, regardless of the number of involved production steps ("length of a path"). The layerwise binary matrices $\mathbf{W}_1$, $\mathbf{W}_2$, $\mathbf{W}_3$, ... are then used to calculate a so-called dependency matrix $\mathbf{D}$. Its elements take values of 1 and 0 indicating whether sector j is directly or indirectly supplied by sector i at a minimum level F ($d_{ij} = 1$) or not ($d_{ij} = 0$).

An index on the type of sector linkages is obtained from the connectivity matrix $\mathbf{H}$:

$$\mathbf{H} = \mathbf{D}' + 2 \cdot \mathbf{D}. \tag{2}$$

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

$$\begin{array}{ll} 0: & \text{no link between sectors } i \text{ and } j, \\ 1: & \text{a weak link between sectors } i \text{ and } j, \\ 2: & \text{unidirectional link between sectors } i \text{ and } j, \\ 3: & \text{bilateral links between sectors } i \text{ and } j. \end{array} \tag{3}$$

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 rather 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 content of alternative classifications. In this case, Shannon and Weaver's (1949) entropy index E,

$$E_\ell = \sum\nolimits_{\mathrm{S}} p_{\ell \mathrm{S}} \cdot \mathrm{l}d(1/p_{\ell \mathrm{S}}), \tag{4}$$

can be computed for each structure ℓ. Here p is the probability of the occurrence of one of the states s in equation (2). 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.[1]

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

$$\mathbf{H}_{\mathrm{res}} = \mathbf{H}_{\mathrm{cum}} - 2 \times L, \tag{5}$$

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

$$\mathbf{H}_{\mathrm{cum}} = \sum\nolimits_{\ell=1}^{L} \mathbf{H}_\ell. \tag{6}$$

Subject to equation (5), the "residual" matrix is obtained from $\mathbf{H}_{\ell,\mathrm{cum}}$ by subtracting the possible number of unilateral links. The values in the matrix $\mathbf{H}_{\mathrm{cum}}$ range from 0 (no relation at all) to $3 \cdot L - 1$.[2] According to equation (5), the elements of the matrix $\mathbf{H}_{\mathrm{res}}$ ensue by subtracting a basic amount from the matrix $\mathbf{H}_{\mathrm{cum}}$. Because this algorithm focuses on dominant bilateral relationships, the basic amount is defined as $2 \cdot \mathrm{L}$. All negative values of the matrix $\mathbf{H}$ are set at 0. An element of the matrix $\mathbf{H}_{\mathrm{res}}$ 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 $\mathbf{H}_{\mathrm{res}}$, which forms a control measure for the calculation of the optimal filter rate.[3] 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 $\mathbf{H}_{\mathrm{res}}$ criteria.

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 measured 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 $\mathbf{M}$:

$$x_{C_i} = x_i + \sum\nolimits_{j \in C_i} (m_{ij} + m_{ji}) \times x_j. \tag{7}$$

According to equation (7), 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. In general, linkages accruing from both purchasing and supply chains can be involved.

Because regional I-O tables are not available for all areas in most countries, 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, because 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 $C_{i,r}$:

$$\hat{x}_{C_{i,r}} = x_{i,r} + \sum\nolimits_{j \in C_i} (m_{ij} + m_{ji}) \times x_{j,r}. \tag{8}$$

The potential regional production values $\hat{x}_{C_{i,r}}$ are grounded in national industry linkages to approximate unknown real production values $\hat{x}_{C_{i,r}}$ 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 to identify potential regional clusters. On the other hand, they may help regional agents 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. In 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 labor productivity, we can calculate potential cluster employment, $\hat{B}_{C_{i,r}}$, in accordance with equation (8):

$$\hat{B}_{C_{i,r}} = B_{i,r} + \sum\nolimits_{j \in C_i} (m_{ij} + m_{ji}) \times B_{j,r}. \tag{9}$$

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

Spatial Scanning and Regional Clusters

Because value added by industry is usually not available at a highly disaggregated regional level, employment figures of the regional value-added chains must be used to identify potential regional clusters. To this end, different approaches can be pursued. Aspatial methods preferably rely on cluster indices capturing dimensions such as specialization, size, and focus to detect clustering across space (cf. Sternberg and Litzenberger 2004; European Commission 2011).[4] In treating regions as closed economies, these methods disregard all forms of spatial interaction. Furthermore, they are typically characterized by a purely descriptive orientation.

With the aid of local spatial methods, the restriction of isolated regions in the search for regional clusters can be overcome. By accounting for local spatial association, the search procedures explicitly capture cluster activity across regional boundaries. Both the Getis-Ord Gi* and the local Moran's test have been used to detect hot spots of industrial activity (Feser, Sweeney, and Renski 2005; Pires et al. 2013). While Feser, Sweeney, and Renski (2005) implement the Gi* test for a first-order neighborhood, Pires et al. (2013) define adjacency by the concept of *k*-nearest neighbors. Instead of fixing the neighborhood in advance, adjacency can alternatively be defined by a predetermined distance. The effect of global spatial autocorrelation on the distribution of local statistics makes the search for hot spots difficult (cf. Anselin 1995; Ord and Getis 1995; Getis 2010).

Kosfeld, Eckey, and Lauridsen (2011) establish the existence of industry clusters in Germany on different spatial scales. However, the Getis-Ord Gi or Gi* and local Moran's statistics are defined for a predetermined distance or neighborhood. In statistical software such as GeoDa and R, permutation tests for both methods are designed for a fixed surrounding. Though not developed for searches within varying regional surroundings, local Moran's or Getis-Ord Gi* tests could, in principle, be carried out for a series of spatial weights matrices. However, such a procedure would come along with a considerable loss of power because of the enormous surge of the number of multiple comparisons. For a large number of comparisons, the individual Bonferroni or Sidac-type significance levels in multiple testing will be close to zero, making the dependent tests extremely conservative (Abdi 2007). Thus, such a procedure will have little power to detect different patterns of economic activity across space.

In view of this limitation, Aldstadt (2010) highlights a set of search procedures that are specially designed to determine the cluster size automatically. A prominent member of this class of methods is Kulldorff's spatial scan test. The spatial scan method is devised for detecting clusters of varying sizes by correctly addressing the multiple testing problem (Aldstadt 2010). Most significant clusters reject the null hypothesis of spatial randomness on their own strength, where the probability of falsely detecting a cluster is bounded by the significance level α (Neill 2006, 15). Thus, the procedure is particularly appealing when industry clusters exist with different spatial scales.

Kulldorff's spatial scan method works with both areal and point data (Kulldorff and Nagarwalla 1995; Kulldorff 1997). The spatial scan for potential clusters in a study area is based on a likelihood ratio approach. Specifically, likelihood ratio statistics are computed for usually irregularly shaped zones that are defined by circular windows around the centroids of each region up to a maximal size.[5] For each spatial unit, the likelihood ratio is maximized. The zones with the highest score values associated with each spatial unit are the most significant potential cluster areas. Because no closed-form distribution of the test statistics is known, the randomization testing approach is used for assessing statistical significance of most likely clusters. In contrast to automated cluster detection methods such as Openshaw's Geographical

Analysis Machine (Openshaw et al. 1987) or Besag and Newell's (1991) method, the spatial scan method adjusts for the multiple testing inherent in the search procedure (Kulldorff and Nagarwalla 1995; Kulldorff 1997).

Here employment figures $\hat{B}_{C_{i,r}}$ of the regional value-added chains are used for identifying most likely regional clusters in R&D-intensive industries across the study area. Let $\hat{B}_{C_i,Z}$ be the number of employment cases and B_Z the total number of industrial workers in a zone Z. 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

$$\mathrm{LR}_Z \propto \left(\frac{\hat{B}_{C_i,Z}}{\hat{\lambda} \cdot B_Z}\right)^{M_Z} \cdot \left(\frac{\hat{B}_{C_i} - \hat{B}_{C_i,Z}}{\hat{B}_{C_i} - \hat{\lambda} \cdot B_Z}\right)^{M - M_Z} \cdot I\left(B_{C_i,Z} > \hat{\lambda} \cdot B_Z\right), \tag{10}$$

where $\hat{\lambda} = \hat{B}_{C_i}/B$ is 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,

$$\mathrm{RR}_Z = \frac{\hat{B}_{C_i,Z}}{\hat{\lambda} \cdot B_Z}, \tag{11}$$

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.

Testing for significance of the maximized likelihood ratio LR_Z is done by Monte Carlo randomization. The scan statistics are these likelihood ratios that are maximized over all zones with different sets of events around all regional centroids in the study region up to a maximal window size.[6] 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 in question. Statistically significant industry clusters originally detected by the spatial scanning method may lack a critical mass for externalities (Menzel and Fornahl 2010). Porter (1998a, 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, Sweeney, and Renski 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.

Empirical Analysis

Data

In order to analyze the composition of value-added chains in R&D-intensive industries, we use the German I-O table for 2006 (Federal Statistical Office of Germany 2010). The table consists of seventy-one 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. We choose the year 2006 for comparative purposes because more meaningful results of traditional cluster mapping are available for this year than for subsequent periods.

To identify potential regional clusters in R&D-intensive industries, employment data at the Nomenclature des unités territoriales statistiques (NUTS-3) level is 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 seventy-one sectors of the Statistical classification of economic activities in the European Community (NACE Version 1.1). Both classifications, CPA and NACE, are linked because they share the same conceptual framework.

In all industrial sectors, firms spend a part of their revenue on R&D. Most of the almost €52 billion German R&D expenditure in 2006 comes from large companies. Only an estimated share of 9 percent comes from small- and medium-sized enterprises (Grenzmann, Kladobra, and Kreuels 2009). Four two-digit industries account for roughly two-thirds of private R&D expenditure. The automotive industry is clearly dominant, with a share of approximately one-third. This is followed by the electrical industry with 20 percent, the chemical industry with 17 percent, and the machinery industry with 9 percent. Because the individual contributions to amounts spent on R&D 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 industries, 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, in which 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 information technology (IT) sector as a whole is often the focus in innovation economics, the "hardware sector" (code 30) is combined with the "software sector" ("Computer and related activities," code 72) for the identification of regional IT clusters.

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 interindustry linkages included in the 2006 German I-O table (Federal Statistical Office of Germany 2010). The significant flows are determined by QIOA. Because 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 MFA. Table 1 provides information on the choice of optimal filter rate from QIOA.[8] While the entropy index E takes the maximum value of 200.0 in the fifth step, the average value of the $\mathbf{H}_{\text{res}}$ 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 1,147 weak and unidirectional links, respectively, between the seventy-one sectors are categorized as important.

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 equation (1). From this, we discern important direct linkages in the German I-O system. In determining the optimal filter rate, we consider additional indirect linkages. For this, higher-order adjacency matrices $\mathbf{W}_k$ up to order 5 prove to be relevant.

Table 2 shows that the number of related sectors in the cluster templates varies substantially across industries. While the pharmaceutical industry is only supplied by the chemical industry, I-O 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 to several sectors.

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. 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

Table 1. Choice of the Optimal Filter Rate.

				Values h_{ij} of the connectivity matrix **H**			
Step	Filter[a]	Order k[b]	Entropy[c]	0	1	2	3
1	0.00010	11	86.8	420	187	187	4,176
2	0.00182	7	152.1	512	650	650	3,158
3	0.00363	6	181.8	672	964	964	2,370
4	0.00545	5	197.2	972	1,175	1,175	1,648
5	0.00727	5	200.0	1,242	1,232	1,232	1,264
6	0.00908	5	195.3	1,654	1,269	1,269	778
7	0.01090	5	189.9	1,812	1,296	1,296	566
8	0.01271	5	176.5	2,314	1,147	1,147	362
9	0.01453	4	169.9	2,504	1,085	1,085	296
10	0.01635	4	161.2	2,720	1,014	1,014	222
11[a]	0.01816	4	149.5	2,996	907	907	160
12	0.01998	4	146.3	3,068	878	878	146
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
49	0.08718	2	19.1	4,850	59	59	2
50	0.08900	2	NA	4,854	58	58	0

Source: Authors' own calculations.
[a]This filter step has been chosen according to the control measure for the determination of optimal filter rate. The matrix $\mathbf{H}_{res}$ 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.
[c]Values are multiplied by 100 for better readability.

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 I-O analysis (Federal Statistical Office of Germany 2010). Recall that the inverse coefficients from the national I-O analysis reflect average, not actual, flow intensities across space. Here, we employ the more comprehensive concept of interrelationships in forming value-added chains. In a robustness check, we also examine variations in sectoral linkages.

Identifying Potential Regional Clusters of R&D-intensive Industries

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

Table 2. Cluster Templates for German R&D-intensive Industries.

Cluster templates[a]	Related industries[b]
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

Source: Authors' own calculations.
[a]Numbers in parentheses represent the sector codes.
[b]The description of R&D-intensive industries and their related sectors appears in the Appendix.
Note: R&D = research and development.

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 to avoid measuring dispersion instead of concentration. Here, the chosen maximum window size conforms to the $d_{\max}/4$ rule (Kosfeld, Eckey, and Lauridsen 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 (Thuringia), Zwickau/Chemnitz (Saxony), and Teltow-Fläming (Brandenburg).

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 Brunswick (Lower Saxony), Stuttgart, and Karlsruhe (Baden-Wuerttemberg) as well as Upper and Lower Bavaria belong to the sixteen largest automotive clusters in Europe (Blöcker, Jürgens, and Meißner 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

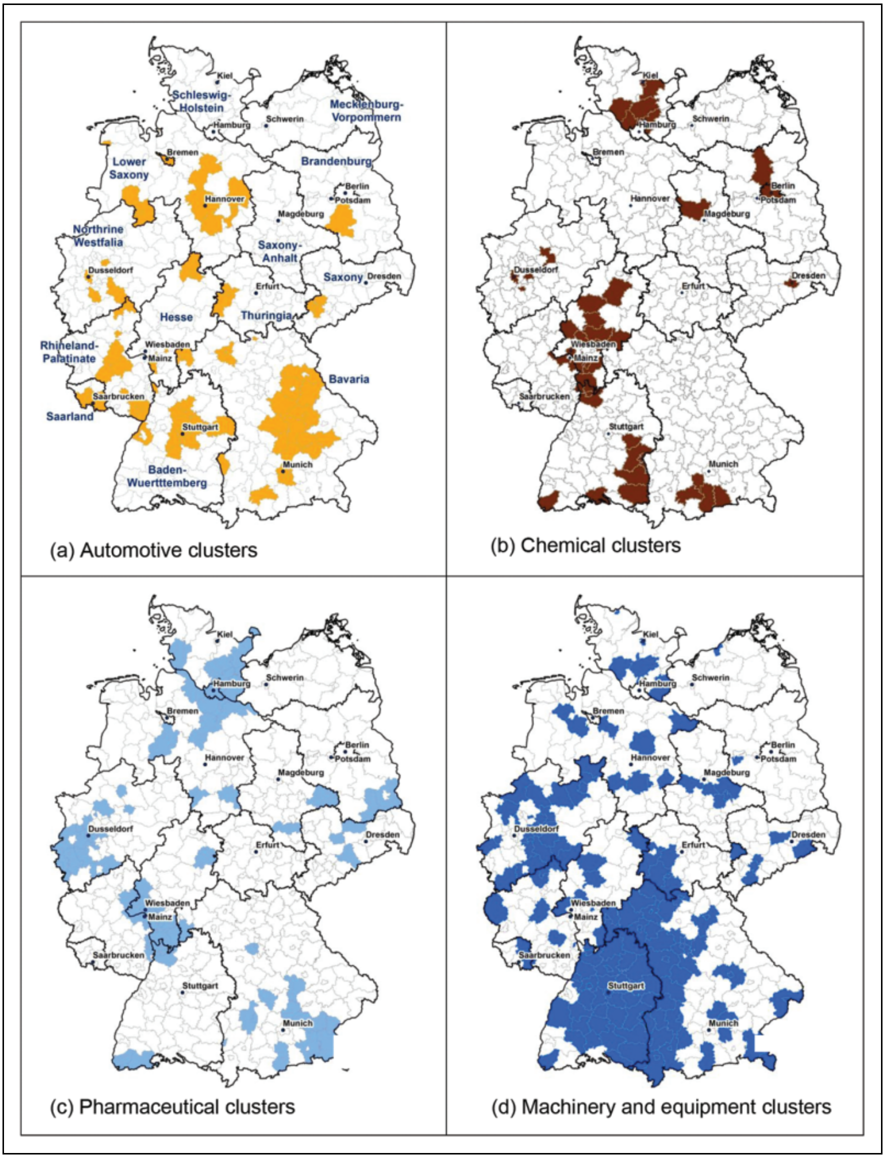

Figure 1. Regional research and development clusters I: nonelectrical industries.
Source: Authors' own illustration.

of these regional clusters. The European Cluster Observatory relies on relatively large spatial units, generally on NUTS-2 level. For six of the sixteen German federal states, information is only used at the NUTS-1 level.[10] Although the data are often available for comparable "Statistical Regions" (Regional Database Germany), the European Cluster Observatory only makes use of official NUTS-2 level data. The drawback to this level of analysis is that local economic differentiation is obscured due to the large size of statistical units.

As we mentioned in the Introduction, there is still strong political interest in the support and the development of industrial clusters. Particularly in regions showing structural weaknesses, the emergence of (high-tech) clusters is regarded as promising. A specific subject of research within this context is the development of the East German economy. To date, East Germany has not been able to catch up to the West German economy in terms of productivity. The remaining gap is mainly traced back to structural shortcomings, especially (less connected) small firms and the lack of headquarters (Heimpold and Titze 2014). Furthermore, the transformation process in the early 1990s came along with the disruption of value chains (Albach 1994). Nevertheless, selected industries in East Germany have recovered, and some of these might be potential candidates for cluster policy. For the automotive industry, the spatial scan method reveals clusters in the federal states of Saxony and Thuringia that have not been detected with the traditional mapping technique of the European Cluster Observatory.

However, both automotive clusters in East Germany are discovered by case studies. The potential international significance of these clusters is highlighted in a benchmarking study of European automotive clusters (AutoAnalysis and Automotive Sweden 2005). In the Thuringian automotive cluster around Eisenach, approximately 7,000 employees work in nearly sixty vehicle producers and suppliers. Three main vehicle manufacturers are located within the cluster, along with suppliers of drives and metal parts, electronics, plastics and rubber parts, body parts, and superstructure as well as other equipment. The high significance of this regional value-added chain as a location of the car industry is also corroborated in Kaufmann's (2009) case study. This holds a fortiori for the automotive cluster in the Chemnitz/Zwickau region, which includes approximately 13,000 employees from more than 100 enterprises. The Saxon automotive supplier network encompasses parts manufacturers, service firms, and equipment manufacturers (AutoAnalysis and Automotive Sweden 2005). Such clusters may go undetected if spatial units are too large and spatial interaction is ignored.

Although the Saarland cluster is rated only a two-star cluster, it also belongs to the aforementioned group (European Commission 2011). Employment concentration in automobile production proves to be significant within a slightly reduced area of this small German federal state. In addition, though 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 triborder region of Rhineland-Palatinate, Baden-Wuerttemberg, and Hesse (see Figure 1b). 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. Coherent chemical clusters are found around Ulm/Biberach and Weilheim-Schongau/Starnberg. Scattered centers of chemical production are located in the Rhine-Ruhr area. Although 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 Figure 1b and c reveals some overlap in regional clustering in the value-added chains of the chemical and pharmaceutical industries. This is particularly the case for the Rhine-Main cluster with the city of Ludwigshafen as the core of the pharmaceutical industry. Compared with the manufacture of chemical products, the manufacture of pharmaceuticals is more pronounced in the Rhine-Ruhr cluster. Moreover, the northern pharmaceutical cluster covers Hamburg as well as some neighboring districts of Lower Saxony. Except for their boundaries, these centers of pharmaceutical production as well as those in southern Baden-Wuerttemberg and Upper Bavaria are also detected by cluster mapping. The spatial scan method also highlights 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 (see Figure 1d). 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 centers of mechanical engineering in the figure are well in line with the star clusters. Yet the spatial scan method highlights nonclustering areas in the Free State of Bavaria, which have not emerged from the traditional mapping technique.

Hot spots of IT activity are illustrated in Figure 2a. The three-star clusters of the European Cluster Observatory around Karlsruhe, in Upper Bavaria, and in 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.[11] However, the cluster boundaries of the star rating method appear to be fuzzy. Moreover, significant clustering of IT activity also emerges in the regions of Berlin, Hamburg, Hanover, Bremen, and the Saxony Triangle.

Figure 2b–d reveals that the centers of production activity of the sectors "electrical machinery and apparatus," "radio, television, communication equipment," and "medical, precision, and optical instruments" are located most notably in southern Germany and North-Rhine Westphalia. In contrast to both other sectors, the southern 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.

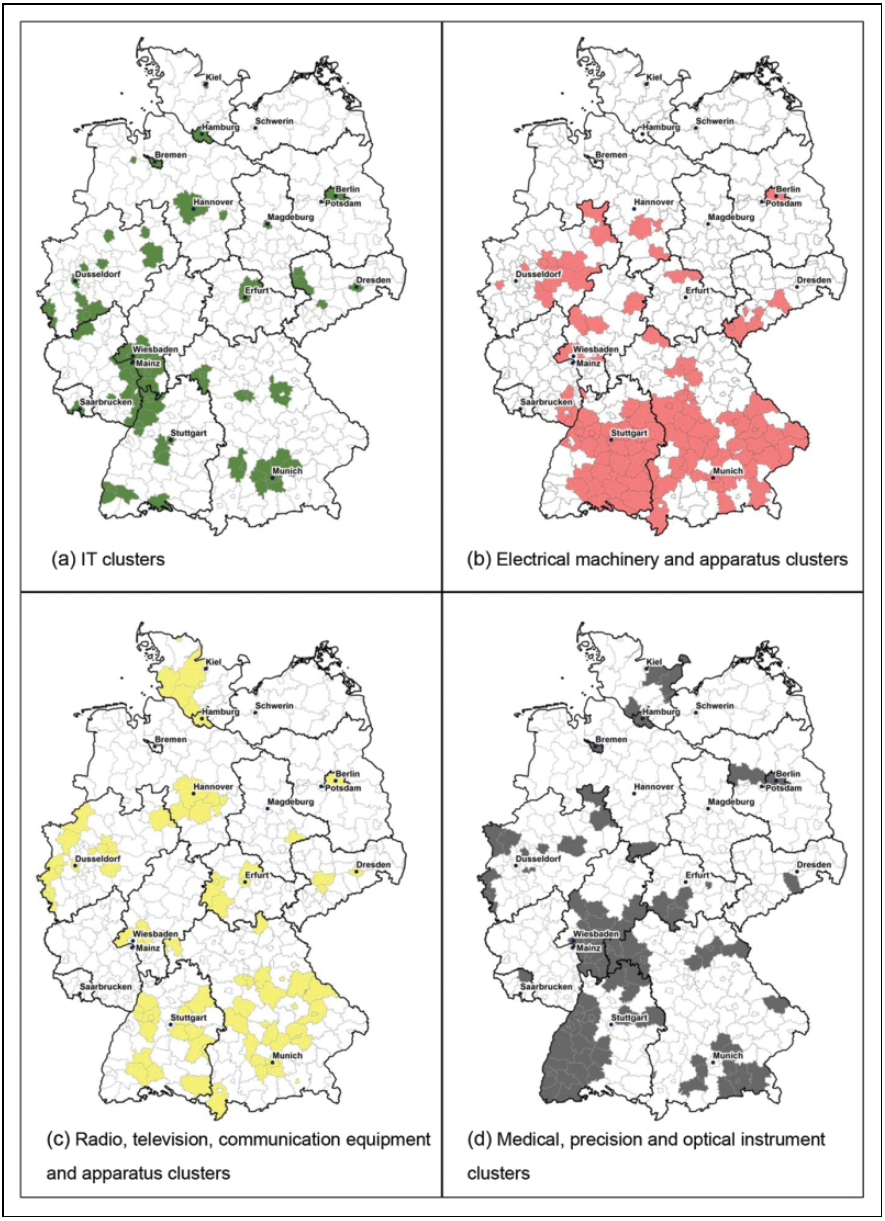

Figure 2. Regional research and development clusters II: electrical industries.
Source: Authors' own illustration.

Robustness of Cluster Structures

In identifying potential regional clusters using the method of spatial scanning, both regional and national employment data have been used. Although 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, they will differ from region to region. Local clusters, for example, 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. Conversely, 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.

Table 3 illustrates the robustness of cluster structures with respect to the utilization of inverse or I-O coefficients. We do not observe different numbers of clusters in any of the cases. The two methods produce exactly the same regional clusters for the value-added chains in the automotive and IT industries. A change in size in a single cluster is observed in the manufacture of machinery and equipment, the manufacture of radio, television, and communication equipment and apparatus, and the 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 in one cluster, respectively. Although the geographical extent of two clusters will expand for the value-added chain of the 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 the manufacture of pharmaceuticals, overall the sizes of four regional clusters vary in the manufacture of chemicals and chemical products.

Not only is the fuzziness of regional clusters introduced by potential differences in the importance of direct and indirect linkages between industries, but it also accrues from varying spatial concentrations of suppliers and customers around the core industries. In particular, in anticipating more pronounced spatial spillovers, companies from related industries may be more strongly localized in regional clusters. Such behavior is simulated by doubling the inverse coefficients in defining regional value chains. Table 4 summarizes alterations in cluster detection involved in this approach.

For most R&D-intensive industries, no substantive changes arise. However, the formation of regional value-added chains by doubling the inverse coefficients leaves one undetected cluster in each of three core industries. In addition, the isolated cluster of Dresden remains undetected in the manufacturing of chemicals and chemical products, while the single cluster of Berlin is not identified in the

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

Source: Authors' own calculations.
Note: I-O = input and output; IT = information technology.

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. However, none of the three undetected potential clusters belongs 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 industries, however, somewhat more noticeable differences occur. Although the number of potential clusters is virtually unaffected in the 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 the manufacture of pharmaceuticals. This effect is due mainly to the strong relatedness of the two industries, which 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.

Table 4. Alterations in 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

Source: Authors' own calculations.
Note: IT = information technology.

Conclusion

The EU and national regional development and innovation policy draw in large part on advantages ascribed to regional clusters. Although the concept of a cluster resides in 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 to establish dominant links between industries to form cluster templates. Likewise, different approaches have been considered in locating industrial clusters.

The focus of this article has been on identifying potential clusters of R&D-intensive industries with an application to Germany. For this purpose, we have introduced a two-step procedure. In the first step, we form national cluster templates of

R&D-intensive core industries with the aid of QIOA. Dominant I-O linkages between the core industries and related sectors are deduced using a filter rate that is endogenously developed with 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. We identify potential regional clusters using the technique of spatial scanning, which 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 based on the national I-O table provides regional planning agencies with information on parts missing from regional value-added chains. This illustrates 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 Gi* 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. In contrast, much empirical evidence of varying scales of industrial clusters exists. With 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.

Policy makers and regional development agencies have increasingly embraced the view of strong regional clusters in response to economic globalization. The notion that countries and regions with enterprises organized in clusters have a competitive advantage is closely linked 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, until 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 to valid evaluation of clustering effects has been the fuzziness in establishing the borders of regional clusters. Beyond the industrial overlap in one special case, the hybrid methodology employed in cluster identification that we introduce herein meets a high degree of robustness. Thus, we expect this approach to provide a sound basis for evaluating the impact of industrial clusters on sectoral performance and regional development.

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	Manufacture of basic iron and steel and of ferro-alloys
27.3	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, television 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).

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Notes

1. Schnabl (1994) recommends that the maximum step number L be 50.

2. If the maximum number of filter steps is set at 50, the matrix $\mathbf{H}_{cum}$ 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).
3. Sum of the elements of the matrix $\mathbf{H}_{res}$ divided by the number of non-zero elements.
4. Areas of high industrial activity discovered by these methods will mostly not represent regional cluster according to Porter's theory as relatedness between industries is usually ignored.
5. Recently, Murray, Grubesic, and Wei (2014) generalized this approach by addressing spatial contiguity explicitly in cluster detection without the use of arbitrarily shaped scan windows.
6. This work uses SatScan software (Kulldorff 2010) for performing spatial scan tests. Instead of presetting the upper limit for the size of the scanning window by maximum percentage of the population at risk, according to Kosfeld, Eckey, and Lauridsen (2011) the maximum distance is set to 220 km.
7. The threshold of 1,000 employees used here is in accordance with traditional cluster mapping of the European Cluster Observatory (European Communities 2008).
8. The analysis is carried out for the so-called standard structure. In this case, the total demand vector in equation (5) will be replaced by a synthetic vector that is given in the simplest case by the summing-up vector ι. In doing so, the core matrix reveals its technological structure and is not "biased" through total demand (see Schnabl 1994, 2000).
9. As an alternative to using a fraction of the maximum distance d_{max} between the centers of the regions, the maximum cluster size can be determined by the median or average distance (cf. Duranton and Overman 2005).
10. These are the federal states of Brandenburg, Mecklenburg-Western Pomerania, Saxony-Anhalt, Thuringia, Schleswig-Holstein, and Saarland.
11. In the IT sector, no region is rated as a two-star cluster by the mapping method of the European Cluster Observatory (European Commission 2011).

References

Abdi, H. 2007. "The Bonferroni and Sidak Corrections for Multiple Comparisons." In *Encyclopedia of Measurement and Statistics*, edited by N. Salkind, 103–7. Thousand Oaks, CA: Sage.

Albach, H. 1994. *The Transformation of Firms and Markets: A Network Approach to Economic Transformation Processes in East Germany*. Stockholm, Sweden: Almqvist & Wiksell.

Aldstadt, J. 2010. "Spatial Clustering." In *Handbook of Applied Spatial Analysis—Software Tools, Methods and Applications*, edited by M. M. Fischer and A. Getis, 279–300. Berlin, Germany: Springer.

Anselin, L. 1995. "Local Indicators of Spatial Association—LISA." *Geographical Analysis* 27:93–115.

AutoAnalysis, and Automotive Sweden. 2005. *Benchmarking of European Automotive Clusters, Stage 1*. Accessed November 16, 2014. http://www.clusterforum.org/en/case_studies.html.

Besag, J., and J. Newell. 1991. "The Detection of Clusters in Rare Diseases." *Journal of the Royal Statistical Society, Series A* 154:143–55.

Blöcker, A., U. Jürgens, and H.-R. Meißner. 2009. *Innovationsnetzwerke und Clusterpolitik in europäischen Automobilregionen*. Münster, Germany: LIT.

Bon, R. 1989. "Qualitative Input-output Analysis." In *Frontiers in Input-output Analysis*, edited by R. E. Miller, K. R. Polenske, and A. Z. Rose, 222–31. Oxford, UK: Oxford University Press.

Brachert, M., M. Titze, and A. Kubis. 2011. "Identifying Clusters from a Multidimensional Perspective: Methodical Aspects with an Application to Germany." *Papers in Regional Science* 90:419–40.

Brenner, T. 2006. "Identification of Local Industrial Clusters in Germany." *Regional Studies* 40:991–1004.

Christensen, T. A., G. Meier zu Köcker, T. Lämmer-Gamp, M. S. Thomsen, and K. Oleson. 2011. "Cluster and Network Policy Programmes in Europe." In *NGP Cluster Excellence Conference*, May 2011, Copenhagen, Denmark.

Cruz, S. C. S., and A. A. C. Teixeira. 2010. "The Evolution of the Cluster Literature: Shedding Light on the Regional Studies–regional Science Debate." *Regional Studies* 44:1263–88.

Delgado, M., M. E. Porter, and S. Stern. 2014. "Defining Clusters of Related Industries." Working Paper 20375, National Bureau of Economic Research, Cambridge, MA.

Duranton, G., and H. G. Overman. 2005. "Testing for Localization Using Micro-geographic Data." *Review of Economic Studies* 72:1077–106.

European Commission. 2011. *Star Clusters in Germany, Europa INNOVA, European Cluster Observatory, Center for Strategy and Competitiveness (CSC), Stockholm School of Economics, Stockholm*. Accessed August 22, 2012. 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, Europe.

Federal Statistical Office of Germany. 2010. "Volkswirtschaftliche Gesamtrechnungen—Input-Output-Rechnung 2006." Fachserie 18, Reihe 2. Wiesbaden, Germany: Federal Statistical Office of Germany.

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

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

Feser, E., H. Renski, and J. Koo. 2009. "Regional Cluster Analysis with Interindustry Benchmarks." In *Targeting Regional Economic Development*, edited by S. Goetz, S. C. Deller, and T. R. Harris, 213–40. New York: Routledge.

Feser, E., and S. Sweeney. 2000. "A Test for the Coincident Economic and Spatial Clustering of Business Enterprises." *Journal of Geographical Systems* 2:349–73.

Feser, E., and S. Sweeney. 2002. "Theory, Methods and a Cross-metropolitan Comparison of Business Clustering." In *Industrial Location Economics*, edited by P. McCann, 222–57. Cheltenham, UK: Edward Elgar.

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

Getis, A. 2010. "Spatial Autocorrelation." In *Handbook of Applied Spatial Analysis—Software Tools, Methods and Applications*, edited by M. M. Fischer and A. Getis, 255–78. Berlin, Germany: Springer.

Glaeser, E. L., H. D. Kallal, J. A. Scheinkman, and A. Shleifer. 1992. "Growth in Cities." *Journal of Political Economy* 100:1126–52.

Grenzmann, C., A. Kladobra, and B. Kreuels. 2009. *FuE-Datenreport 2009—Tabellen und Daten*. Essen, Germany: Stifterverband für die Deutsche Wissenschaft.

Guillain, R., and J. Le Gallo. 2010. "Agglomeration and Dispersion of Economic Activities in Paris and Its Surroundings: An Exploratory Spatial Data Analysis." *Environment and Planning B: Planning and Design* 37:961–81.

Heimpold, G., and M. Titze. 2014. "Economic Development in East Germany since German Unification. Results, Shortcomings and Implications for Economic Policy." In *Competitiveness in the European Economy*, edited by S. Collignon and P. Esposito, 184–96. Abingdon, New York: Routledge.

Hoover, E. M. 1948. *The Location of Economic Activity*. New York: McGraw-Hill.

Jacobs, J. 1969. *The Economy of Cities*. New York: Random House.

Kaufmann, R. 2009. "Automobilzulieferer und Automobilhersteller in Thüringen—Eine unter-nehmensbezogene Analyse. Thüringer Statistisches Landesamt." Accessed November 16, 2014. http://www.statistik.thueringen.de/analysen/Aufsatz-06a-2009.pdf.

Ketels, C., G. Lindqvist, and Ö. Sölvell. 2006. *Cluster Initiatives in Developing and Transition Economies*. Stockholm, Sweden: Center for Strategy and Competitiveness.

Kiese, M., and M. Wrobel. 2011. "A Public Choice Perspective on Regional Cluster and Network Promotion in Germany." *European Planning Studies* 19:1691–712.

Kosfeld, R., H.-R. Eckey, and J. Lauridsen. 2011. "Spatial Point Pattern Analysis and Industry Concentration." *Annals of Regional Science* 47:311–28.

Kronenberg, T. 2010. "Erstellung einer Input-Output-Tabelle für Mecklenburg-Vorpommern." *AStA—Wirtschafts-und Sozialstatistisches Archiv* 4:223–48.

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* 3:206–28.

Kulldorff, M. 1997. "A Spatial Scan Statistic." *Communications in Statistics: Theory and Method* 26:1481–96.

Kulldorff, M. 2010. "SatScan^{TM} User's Guide for Version 9.0." Accessed August 22, 2012. http://satscan.org/.

Kulldorff, M., and N. Nagarwalla. 1995. "Spatial Disease Clusters: Detection and Inference." *Statistics in Medicine* 14:799–810.

Lazzaretti, L., S. R. Sedita, and A. Caloffi. 2013. "Founders and Disseminators of Cluster Research." *Journal of Economic Geography* 14:21–43.

Marcon, E., and F. Puech. 2003. "Evaluating the Geographic Concentration of Industries Using Distance-based Methods." *Journal of Economic Geography* 3:409–28.

Marshall, A. (1890) 1920. *Principles of Economics*. 8th ed. London, UK: McMillan.

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

Menzel, M.-P., and D. Fornahl. 2010. "Cluster Life Cycles—Dimensions and Rationales of Cluster Evolution." *Industrial and Corporate Change* 19:205–38.

Murray, A. T., T. H. Grubesic, and R. Wei. 2014. "Spatially Significant Cluster Detection." *Spatial Statistics* 10:103–16.

Neill, D. B. 2006. "Detection of Spatial and Spatio-temporal Clusters." PhD dissertation, Technical Report CMU-CS-06-142, Department of Computer Science, Carnegie Mellon University, Pittsburgh, PA.

Openshaw, S., M. Charlton, C. Wymer, and A. W. Craft. 1987. "A Mark I Geographical Analysis Machine for the Automated Analysis of Point Data Sets." *International Journal of Geographical Information Systems* 1:335–58.

Ord, J. K., and A. Getis. 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: Oxford Research.

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

Popa, I., and C. Vlăşceanu. 2013. "Cluster Policies in the European Union—Engines for Sustainable Economic Development and Competitiveness." *Annals of the University of Oradea, Economic Science Series* 22:1581–87.

Porter, M. E. 1990. *The Competitive Advantage of Nations*. New York: The Free Press.

Porter, M. E. 1998a. "Clusters and the New Economics of Competition." *Harvard Business Review* 76:77–90.

Porter, M. E. 1998b. *On Competition*. Boston, MA: Harvard Business School Press.

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* 37:549–78.

Romer, P. 1986. "Increasing Returns and Long-run Growth." *Journal of Political Economy* 94:1002–37.

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*. Munich, Germany: Oldenbourg.

Schnabl, H., and Y. Kohei. 2003. "Structural Development of Germany and Japan 1980–1995." *Journal of Applied Input–Output Analysis* 9:93–115.

Scholl, T., and T. Brenner. 2012. "Detecting Spatial Clustering Using a Firm-level Cluster-index." Working Papers on Innovation and Space, Philipps University Marburg, Marburg, Germany.

Shannon, C. E., and W. Weaver. 1949. *The Mathematical Theory of Communication*. Urbana: University of Illinois Press.

Sternberg, R., and T. Litzenberger. 2004. "Regional Clusters in Germany—Their Geography and Their Relevance for Entrepreneurial Activities." *European Planning Studies* 12: 767–91.

Sweeney, S., and E. Feser. 1998. "Plant Size and Clustering of Manufacturing Activity." *Geographical Analysis* 30:45–64.

Titze, M., M. Brachert, and A. Kubis. 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, Belgium.

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

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