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The Identification of Industrial Clusters – Methodical Aspects in a Multidimensional Framework for Cluster Identification

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Abstract

We use a combination of measures of spatial concentration, qualitative input-output analysis and innovation interaction matrices to identify the horizontal and vertical dimension of industrial clusters in Saxony in 2005. We describe the spatial allocation of the industrial clusters and show possibilities of vertical interaction of clusters based on intermediate goods flows. With the help of region and sector-specific knowledge interaction matrices we are able to show that a sole focus on intermediate goods flows limits the identification of innovative actors in industrial clusters, as knowledge flows and intermediate goods flows do not show any major overlaps.

Keywords: industrial clusters, qualitative-input-output-analysis, innovation interaction matrix

JEL classification: O18, R12, R15, R30, R58

Die Identifikation industrieller Cluster– Methodische Aspekte in einem mehrdimensionalen Untersuchungsrahmen

Zusammenfassung

Der Beitrag kombiniert die Nutzung eines Konzentrationsmaßes mit der Qualitativen Input-Output Analyse sowie Innovations-Interaktions-Matrizen zur Identifikation der horizontalen und vertikalen Dimension industrieller Cluster in Sachsen im Jahr 2005. Wir beschreiben unter Verwendung dieser neuen Methodik die räumliche Allokation industrieller Clusterstrukturen und weisen nach, dass bei einer Fokussierung der empirischen Clusterforschung auf Input-Output-Methoden wesentliche Teile des Forschungsnetzwerkes industrieller Cluster unidentifiziert bleiben.

Schlagwörter: industrielle Cluster, Qualitative Input-Output-Analyse, Innovations-Interaktions-Matrizen

JEL-Klassifikation: O18, R12, R15, R30, R58

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1 Introduction

The industrial cluster concept has been widely adopted as a policy tool for promoting regional economic development. Referring in its basic version to a group of similar or linked firms in a defined geographical area (Porter, 1990), the theory soon began to recognize the complexity of interactions in industrial clusters, leading to the development of multidimensional cluster approaches (Gordon and McCann, 2000; Malmberg and Maskell, 2002; Bathelt, 2004; Benneworth and Henry, 2004; Maskell and Malmberg, 2007; Blum, 2008). The success of the industrial cluster concept is based on the shared belief that industrial clusters provide the basis for regional economic growth and prosperity (Spencer et al., 2009). Industrial clusters contribute to regional development by enhancing the competitiveness of clustered firms through Mashallian externalities, a better observability and comparability of competitors or an improved knowledge production and diffusion (Marshall, 1920; Porter, 1990; Malmberg and Maskell, 2002).

Empirical evidence for the existence of positive effects of industrial clusters on regional development is thus based mainly on case-study material (Feser et al., 2005). This situation is closely connected with quite a biased selection of high-tech industries and regional success stories (Wiig and Wood, 1995; Malmberg and Maskell, 2002), leaving aside the analysis of non-spectacular firms, industries and regions (Lundquist and Olander, 1998). As case studies in general produce incomparable results because of methodological differences, agreed empirical methods are needed to identify and map industrial clusters to produce systematic empirical work (Martin and Sunley, 2003).

This paper contributes to the literature on systematic methodologies for the identification of industrial clusters. As theoretical progress highlights industrial clusters as a multidimensional phenomenon, combinations of different approaches in empirical cluster research can capture various aspects pointed out in theoretical contributions (shared labour pools, different types of sectoral interdependence, geographical concentration and so on) to develop richer information about the geography of industrial clusters (Feser et al., 2005). We develop a multiple-step approach by bringing together measures of industrial concentration with input–output methods and innovation interaction matrices to identify clusters from both a horizontal and a vertical perspective. We rely on an approach proposed by Titze et al. (2009) and aim to extent this framework to overcome the limitation of sole focus on market linkages, measured quantitatively or qualitatively in input–output models. With the help of the introduction of innovation interaction matrices developed by DeBresson (1996) and DeBresson and Hu (1999) we refer additionally to the important role of regional knowledge networks, institutionalized through formal cooperation projects.

The paper is structured as follows. After a short review of the relevant literature on cluster theory and identification, we present a multiple-step approach for the identification of regional industrial clusters based on a combination of concentration measures, input–output methods and innovation interaction matrices. We apply this framework to the federal state of Saxony in Germany and describe the regional allocation of industrial clusters, different regional sources of knowledge and their degree of overlap and interaction. The paper concludes with a comparison between the advantages of this new methodical framework and the classical tools of cluster identification.

2 Cluster Theory

Research on industrial agglomerations and clusters has become a central topic in economic geography. Dating back to Marshall's Principles of Economics (1920) theory highlights the role of agglomeration economies arising from a specialising supplier and service industry, local labour market pooling and knowledge spillovers as mechanisms that support regional industry competitiveness and growth.

With the term 'cluster' introduced by Czamanski and Ablas (1979; see also Czamanski, 1971), contributions to this topic increased with the introduction of Porter's diamond model (Cruz and Teixeira, 2009). Porter (1998, p. 199) defines industrial clusters as 'a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities'. With the help of the diamond model he stresses additional advantages such as factor and demand conditions, and conditions that shape firms' strategy, structure and rivalry (Porter, 1990 and 1998). Despite the cluster concept being much criticised (Martin and Sunley, 2003), it has become both empirically and conceptually significant in regional science (Asheim et al., 2006; Vorley, 2008).

Conceptual progress was further undertaken by the knowledge-based theory of spatial clustering (Malmberg and Maskell, 2002). With the help of a multidimensional approach, Malmberg and Maskell (2002) highlight localised learning capabilities as sources of cluster-specific advantages (see also Gordon and McCann, 2000; Malmberg and Maskell, 2002; Bathelt, 2004; Benneworth and Henry, 2004; Maskell and Malmberg, 2007; Blum, 2008 for multidimensional approaches). Regionally concentrated specialised companies linked by value chains benefit from complementary competencies and a higher trust between partners, giving these processes an institutional dimension in the practice of knowledge exchange (Bathelt et al., 2004). Within the same step of the value-chain, the horizontal cluster dimension, companies show similar or substitutive competencies, leading to cognitive proximities enabling mutual learning and motivation. Even if they do not have a direct exchange with their competitors they can benefit from the parallel performance of similar tasks (Malmberg and Maskell, 2002). To avoid a predominantly local focus on industrial clusters and an over-embeddedness in local structures Bathelt et al., (2004) further extended the multidimensional approach and underlined the role of global pipelines to reduce the risks of negative lock-in effects within regional cycles of competencies.

3 The Analysis of Regional Industry Interactions in Clusters

The methodology presented in this paper attempts to integrate the progress made in the theory of empirical cluster research into systematic methodologies. It is possible to distinguish a great number of varying approaches for cluster identification (for reviews, see Bergman and Feser, 1999 and Kiese, 2008, among others). The methodology presented here is in line with methodical approaches on industrial cluster identification, where exogenous information on sectoral interdependence and spatially disaggregated data are combined to analyse patterns of (potential) interaction among industries (Czamanski and Ablas, 1979; Isaksen, 1997; Braunerhjelm and Carlsson, 1999; Feser and Bergman, 2000; Hill and Brennan, 2000; Oosterhaven et al., 2001; Feser et al., 2005; Yang and Stough, 2005; Rosenfeld et al., 2007; Duque and Rey, 2008; Titze et al., 2009).

To indicate sectoral interdependence, these approaches rely on an input–output framework. One drawback of using input–output methods for cluster identification is the limited availability of disaggregated input–output tables at the regional level. This leads to the assumption that similar intersectoral relationships exist at the regional level to those at the national level (Spencer et al., 2009; Titze et al., 2009). Against this background, only a few empirical studies have been able to show that linkages are predominately local (Malmberg and Maskell, 2002). Furthermore, a significant drawback of the input–output method is that other dimensions of sectoral interdependence (exchange of information, joint research and development), where for example, tacit information is exchanged or generated, are captured only incompletely by this methodology (Feser et al., 2005). Simple market linkages governed by price, or captive linkages, contribute to the major part of such interactions.

A focus on knowledge flows can therefore provide additional insights into sectoral interdependence and help to identify sources of knowledge spillover and knowledge production within industrial clusters (Malmberg and Power, 2005). By using innovation interaction matrices it is possible to identify the degree of interaction between industrial sectors in the innovation process (Spencer et al., 2009). They reveal the key location (in a sectoral and spatial perspective) in which knowledge growth originates and knowledge diffuses, and underline the parts of the learning economy in which firms generate knowledge (DeBresson and Hu, 1999). Therefore, using patent data seems to be only the second best option, as Arundel and Kabla (1998) (see also Smith, 2005) show that the average propensity rate for product innovations is 35.9% and even less for process innovations. This paper uses firm-based research and development cooperation project data to overcome these limitations, and outlines their spatial distribution.

4 Identifying Flows of Goods and Knowledge in Industrial Clusters

For the identification of clusters in a multidimensional framework, we suggest a multiple-step approach. We use a concentration measure for the identification of sector- and region-specific industrial clusters (the horizontal dimension of industrial clusters). We determine potential vertical interdependences of the industrial cluster structure by identifying dominant inter-industry linkages based on an input–output framework (the vertical dimension – intermediate goods flows). Finally, we identify innovative inter-industry knowledge flows (vertical dimension – knowledge flows) to get a comprehensive overview of interactions in these industrial cluster structures.

The identification of sector and region specific concentrations of economic activity

Most analyses of industrial clusters are based on the spatial concentration of firms operating in the same industry. In these, independently of the degree of interaction, dynamic effects of local competition arise from the parallel performance of similar tasks carried out by independent firms (Marshall, 1920; Maskell and Malmberg, 2002). A better observability and comparability of local competitors enables learning from successful experimentation of competitors.

To identify the spatial proximate critical mass of relevant industries (Steinle and Schiele, 2002), we use the cluster index of Sternberg and Litzenberger (2004). As a top-down method it avoids problems of arbitrariness and allows systematic comparability of the results between regions and sectors. To apply this index in an input–output framework, we need to apportion the intermediate inputs of an industrial sector ($input_i$) to Germany's NUTS-3 regions according to the regional share of employment in the relevant sector (employment x_{ir} in sector i and region r divided by the total employment in this sector x_i). As a result we find the intermediate input of a certain industrial sector that is obtained from the region r ($input_{ir}$):

(1) $$input_{ir} = \frac{x_{ir}}{x_i} \cdot input_i$$

The cluster index (CI; see Equation (2)) correlates relative enterprise density, relative enterprise status and relative company size (Koschatzky and Lo, 2007).

$$(2) \qquad CI_{ir} = \frac{\dfrac{input_{ir}}{\sum_r input_{ir}}}{\dfrac{z_r}{\sum_r z_r}} \cdot \frac{\dfrac{b_{ir}}{\sum_r b_{ir}}}{\dfrac{a_r}{\sum_r a_r}}$$

In Equation (2), z refers to the number of inhabitants, b to the number of firms and a to the surface area. If the cluster index exceeds a value of one, a spatial concentration and specialisation begins to emerge. As the index controls for firm size, its performance is superior compared to simple measures of specialisation or concentration. None the less, it is not able to reflect the sectoral interdependence of industrial clusters. It is therefore necessary to add linkages between sectors in industrial clusters to the analysis, to gain a more comprehensive view of cross-industry structures and innovation networks.

The identification of dominant inter-industry linkages based on an input–output framework

The identification of dominant industrial value chains aims to give an indication of the vertical relatedness of the identified horizontal cluster structures in a region. By related sectors or vertical relatedness we mean the co-location of successive stages of production in an input–output framework (vom Hofe and Chen, 2006). In a first step we focus on intermediate goods flows provided by official input–output tables. By using qualitative input–output analysis (Schnabl, 1994; for recent applications, see Aroche-Reyes, 2003; Titze *et al*., 2009), we define these intermediate goods flows as being relevant inter-industry linkages that exceed a certain filter rate F. As a result, we generate a binary input–output table W. An intermediate input flow s between the industrial sectors i and j becomes 1 if it passes the filter value, otherwise 0 (see Equation (3)).

$$(3) \qquad w_{ij} = \begin{cases} 1, \text{if } \; s_{ij} > F \\ 0, \text{otherwise} \end{cases}$$

The binary transformation of the input–output table leads to a loss of information. However, this reduction is intentional, because it aims to reduce the complexity of the input–output table by identifying relevant inter-industry linkages. For the determination of the filter rate, Schnabl (1994) developed an endogenous algorithm based on entropy statistics. Titze *et al*. (2009) rely on this procedure and propose a framework to transform the identified national industry templates for the regional level. This procedure is based on three assumptions:

- The classification of products by activity which is generally used in input–output statistics allows the attribution to employment data based on NACE codes.

- The national industry templates are applicable also at the regional level. This leads to the critical assumption that similar intersectoral relationships exist at the regional level as at the national level.

- Sector-specific productivity is not available at a regional level in official statistics. Therefore the productivity in a certain industrial sector is assumed to be exactly equal in all regions. This allows the apportioning of the intermediate inputs to the regional level according to its regional share of employment. However, the region- and sector-specific productivities are likely to exist.

With these assumptions in mind, Titze *et al*. (2009) are able to calculate intra-regional input–output tables *W* using the following equation:

(4)

$$w_{irjs}^{1} = \begin{cases} 1, \text{if } \; t_{ij}^{1} > F_{opt} \quad \middle| \; i, j \in M\{\text{concentrated industrial sectors}\} \cap r, s \in M\{\text{important production locations}\} \\ 0, \text{otherwise} \end{cases}$$

Equation (4) refers to the identification of the vertical dimension of industrial clusters in a particular region. It outlines that an intermediate input flow *t* between sectors *i* and *j* becomes a relevant vertical interaction in industrial clusters if it exceeds the optimal filter value F_{opt}, and if the respective regions possess important production locations of concentrated economic sectors according to the cluster index of Sternberg and Litzenberger (2004). The matrix *W* has the dimensions *i* x *r* and *j* x *s* with $i,j = 1, \ldots, n$ industrial sectors and $r,s = 1, \ldots, m$ regions.

Because of its structure, the matrix *W* allows the development of local (within the region) and regional (linkages beyond administrative boundaries) structural graphs, which can be interpreted as a regional cluster with a vertical dimension based on intermediate flows of goods. Nevertheless, attention must be paid to how these results are interpreted. The identified regional structural graphs do not show real value chains. The aim of this approach is to use the benchmark chains in combination with the measures of spatial concentrations to identify the vertical dimension of the industrial cluster that can be studied in detail. These templates present inter-industry relations that might occur from the production technique point of view.

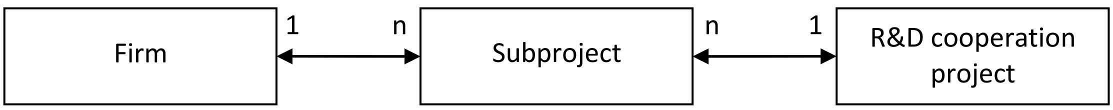
The identification of inter-industry knowledge flows based on innovation interaction matrices

Beyond inter-industry intermediate goods flows a focus on knowledge flows can contribute to the exploration of the nature of production and diffusion in industrial clusters. Theoretical contributions point out that inter-firm communication and interactive processes of localised learning play important roles in processes of innovation and growth (Lundvall, 1992; Gordon and McCann, 2000; Bathelt *et al*., 2004). With respect to industrial clusters, Baptista and Swann (1998) find that firms are more likely to innovate if they are located in a region with a strong presence of firms in the same industry. In addition, Bathelt *et al*. (2004) point out that, by sharing knowledge in industrial clusters, firms are able to combine and recombine resources continuously to generate new knowledge and innovations. This allows firms to specialize within the cluster and results in the improvement in localised capabilities that are available to cluster firms (Maskell and Malmberg, 1999a, 1999b).

To identify inter-industry knowledge flows in industrial clusters we use innovation interaction matrices derived from a firm-based dataset of R&D cooperation projects. Innovation interaction matrices are able to provide indications regarding the degree of interdependence of different sectors in the innovation process of industrial clusters, as well as within an individual sector (Spencer *et al*., 2009). Within this framework, innovative interaction between firms engaged in joint research projects is an indicator of an increase in their level of technological knowledge (DeBresson, 1996).

An innovation interaction matrix in our case is a square matrix of firms engaged in joint R&D cooperation projects. Figure 1 explains the structure of these cooperation projects. Each project consists of at least two participants.

Figure 1:
Structure of the R&D cooperation projects under analysis



Source: Authors' own illustration.

As a first step we create a cross-table which includes the coordinator in the rows and the participants in the columns (see Table 1). To avoid false linkages we analyse the interaction at the project level.

Table 1:
The original cooperation matrix – an example

Involved partners in the project / 'Coordinator' of the project	Project Member 1	Project Member 2	Project Member 3	...	Project Member n
Project Member 1		1	1	0	0
Project Member 2	0		0	0	0
Project Member 3	0	0		0	0
...	0	0	0		0
Project Member n	0	0	0	0	

Source: Authors' own illustration.

We can transform Table 1 into a structural graph, which is shown in Figure 2. In the second step, we add the transposed matrix C' to the origin cooperation matrix C to describe the bi-directional exchange of knowledge between the project partners.

(5) $C^1 = C + C'$

In our example, we can denote knowledge flows between the coordinator and project members 2 and 3. However, Equation (5) does not contain the information that the generated knowledge diffuses among all project partners. As we can assume a knowledge flow between members 2 and 3, we solve the problem by calculating the product of the matrix C^1 with itself.

(6) $C^2 = C^1 \cdot C^1$

Figure 2 shows the indirect relation between members 2 and 3. As a result, we get the matrix C^2 which illustrates a so-called path length of 2 while C^1 only includes a path length of 1. In the third step, we add the matrix C^2 to matrix C^1 and we show the knowledge flows – respectively, the dependence – between all involved partners in the R&D cooperation project (see Figure 2, diagram 4).

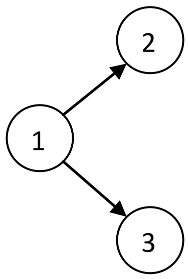
(7) $C^D = C^1 + C^2$

Every firm engaged in a cooperation project is classified by industrial sector. In the final step, we aggregate the matrix CD to a final matrix which in its sectoral disaggregation is compatible with the official input–output statistics. This matrix is denoted by CF, with the dimensions i x r and j x s, i,j = 1, ..., m and r,s = 1, ..., n. The indices i,j represent one of the industrial sectors and r,s stand for the regions under analysis. Because knowledge flows occur in both directions, the matrix CF is symmetrical.

The comparison of the derived innovation interaction matrix with the dominant inter-industry flows allows the identification of the similarity of locations (in a spatial and sectoral perspective) of innovative and general economic activity in industrial clusters. Furthermore, we are able to determine which economically active channels sustain innovative activities, and where innovative activity is occurring despite low levels of economic activity (DeBresson and Hu 1999).

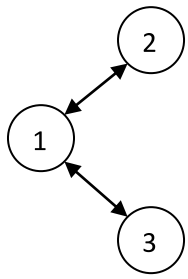
Figure 2:
Knowledge flows between partners in an R&D project

1. Structure of the cooperation matrix *C*:



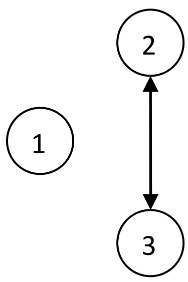
Content of the structural graph:
- Member 1 acts as the ‘coordinator’ of the supported R&D cooperation project
- Members 2 and 3 are involved in the relevant project

2. The addition of C with its transposed matrix *C*' leads to C^1:



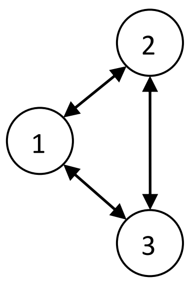
Content of the structural graph:
- Knowledge spillovers flow in both directions

3. $C^2 = C^1 \cdot C^1$ shows the (indirect) relation between firm 2 and firm 3:



Content of the structural graph:
- If member 2 and 3 are involved in the same project we also can assume a knowledge flow between 2 and 3

4. $C^D = C^1 + C^2$ shows the dependence between all firms involved:



Content of the structural graph:
- This includes all knowledge flows in the project

Source: Authors’ own illustration.

5 Data Sources

We now apply the proposed framework to the Free State of Saxony in Germany. The analysis is undertaken for the year 2005. For the calculation of the cluster index of Sternberg and Litzenberger (2004), employment data for 2005 have been provided by the German Federal Employment Office. The data for the number of persons (2005) and the physical extent (2004) of the areas have been taken from the German Federal Statistics Office's regional databases. The number of firms (2005) stems from the German Federal Employment Office. With respect to the specific East German economic characteristics, we include only the 112 NUTS 3 regions in the New Laender ($r \in \{1,...,112\}$) to calculate the cluster index of Sternberg and Litzenberger (2004).

The identification of dominant inter-industry linkages is based on the German Federal Statistical Office's input–output table for 2005. Because the important production locations will be matched with dominant inter-industry linkages, we apply the 71 industrial sectors (2- or 3-digit NACE codes) of the German input–output table. These 71 sectors form the most disaggregated level that is provided by the official German input–output statistics.

The construction of the knowledge interaction matrices relies on two firm-based datasets, which have been provided by the Development Bank of Saxony (SAB), the Saxon State Ministry for Economic Affairs and Labour, and the Federal State of Germany. The dataset provided by the Development Bank of Saxony (SAB) and the Saxon State Ministry for Economic Affairs and Labour contains data regarding EU co-financed R&D projects between firms and/or scientific institutions (universities; public or private research institutions) in Saxony. Applying this specific support programme,[1] eligible recipients receive non-repayable grants to encourage regional R&D activities (Günther *et al*. 2008). The Saxon programme's framework requires an innovation in a comprehensively defined set of natural scientific technology's field. This dataset is extended by cooperation data provided by German ministries at the federal level. The database ('Förderkatalog') contains data about cooperation projects between Saxon firms and/or

1 In the relevant R&D programme, there are no restrictions relating to the field of technology. An R&D project is eligible if it belongs to the following technological fields: materials science, physical and chemical technologies, biological research and biological technology, microsystems technology, information technology, manufacturing technology, energy technology, environmental technology or medical technology. According to this definition, almost all technologies can be supported. Regarding the industrial sectors in an eligible technological field that are capable of innovating, we have to note that this does not apply to all of the above-mentioned 71 industrial sectors listed in the German input–output table. Against this background, we have chosen those industrial sectors that have a scientific or technological background to the eligible technology fields. In detail, we selected 46 industrial sectors as being capable of innovating in the relevant technology areas. The sectors under analysis are the primary sector, the secondary sector (excluding the construction industry, codes 45.1–45.2 and 45.3–45.5) and selective industries belonging to the service sector, especially computer and related activities (code 72), research and development (code 73), business activities (code 74), education (universities, code 80). The total number of projects for analysis was 303.

scientific institutions. These federal-level programmes were financed by the Federal Ministry of Education and Research (BMBF), the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU), the Federal Ministry of Economics and Technology (BMWi) and the Federal Ministry of Food, Agriculture and Consumer Protection (BMELV).[2] The outstanding advantage of these datasets is that they allow the determination of cooperation at the firm level.

The datasets involves grant-aided projects during the period 2000–2005. In the relevant period, 610 cooperation projects were supported. As there are other support programmes (at the federal level or programmes that are financed directly by the European Union) besides this R&D-supporting scheme, the analysis focuses on the internal linkages of cluster-related firms in the Federal State of Saxony. We therefore included only those cooperation projects where at least two of the project partners were located in Saxony. Using these two datasets, we capture most of the supported R&D cooperation projects (Günther *et al*., 2008).

6 Empirical Findings

Sector and region-specific concentrations – identifying the horizontal cluster dimension

The first step of the analysis is the identification of industrial clusters using the cluster index of Sternberg and Litzenberger (2004). Sternberg and Litzenberger (2004) propose a cluster index of 4 as a minimum requirement for the first signs of (horizontal) industrial clusters. Within our static research design we aim to identify the most important production locations. We therefore choose a relatively high cluster index of 64, meaning parameter values are at least four times higher than the average values of the area under analysis. Applying this threshold value, we identify 30 relevant locations of production in the State of Saxony showing horizontal clusters (see Figure 3).

2 Data were obtained from the official Förderkatalog (www.foerderkatalog.de/), which includes around 110,000 completed and ongoing research projects in Germany. The database includes project-based information listing the firm’s name, location, amount of money obtained for each project member, and a detailed project description. We included only those cooperation projects where at least two project partners were located in Saxony and which began between the years 2000 and 2005 (total number 307). Project data included R&D project support and R&D contracts of the Federal Ministry of Education and Research; project support in the field of energy research and energy technologies by the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety; R&D projects with direct project funding in the areas of energy, aeronautics research, multimedia, aerospace and InnoNet by the Federal Ministry of Economics and Technology; and R&D projects or direct project funding of the Federal Agency for Agriculture and Food and the Agency of Renewable Resources by the Federal Ministry of Food, Agriculture and Consumer Protection.

Figure 3:
Horizontal dimension of industrial clusters in the Free State of Saxony

Source: Authors' own illustration.

Most of the identified horizontal clusters are located in the urban districts of Dresden and Leipzig and in the southern regions of Saxony. In total, we are able to identify industrial clusters in 21 of the 71 industrial sectors under analysis; 13 of these 21 sectors belong to the secondary sector, while seven are classified in the service sector and one in the primary sector. The number of inter-regional intra-sectoral links (see Table 2), indicating cognitive proximity and enabling knowledge-enhancing mechanisms such as observation, comparison or rivalry to act additionally at the regional level (Malmberg and Maskell, 2002) are limited. Only the textile and apparel industry in the south-west of Saxony and the IT service industry in the three larger urban centers are characterized by a larger number of locations with industrial clusters.

The spatial allocation of the identified clusters on this highly aggregated level differs with regard to the secondary and tertiary sectors. Overall, 45% of Saxon regions host industrial clusters. While the secondary sector's important production locations are spread throughout the federal state, the service sector's clusters locate only in the agglomerations of Dresden, Leipzig and Chemnitz (see Figure 3).

Table 2:
Horizontal cluster structures in Saxony: structural indicators

	Number	Percentage
Total Saxon regions	29	
Regions with industrial clusters	13	44.8
in the primary sector	1	3.4
in the secondary sector	12	41.4
in the tertiary sector	3	10.3
Total number of horizontal clusters	30	
Connected horizontal clusters	11	36.7
Isolated horizontal clusters	19	63.3
Maximum number of horizontal relations	3	–

Source: Authors' own calculations.

Sector and region-specific inter-industry linkages – identifying the vertical cluster dimension

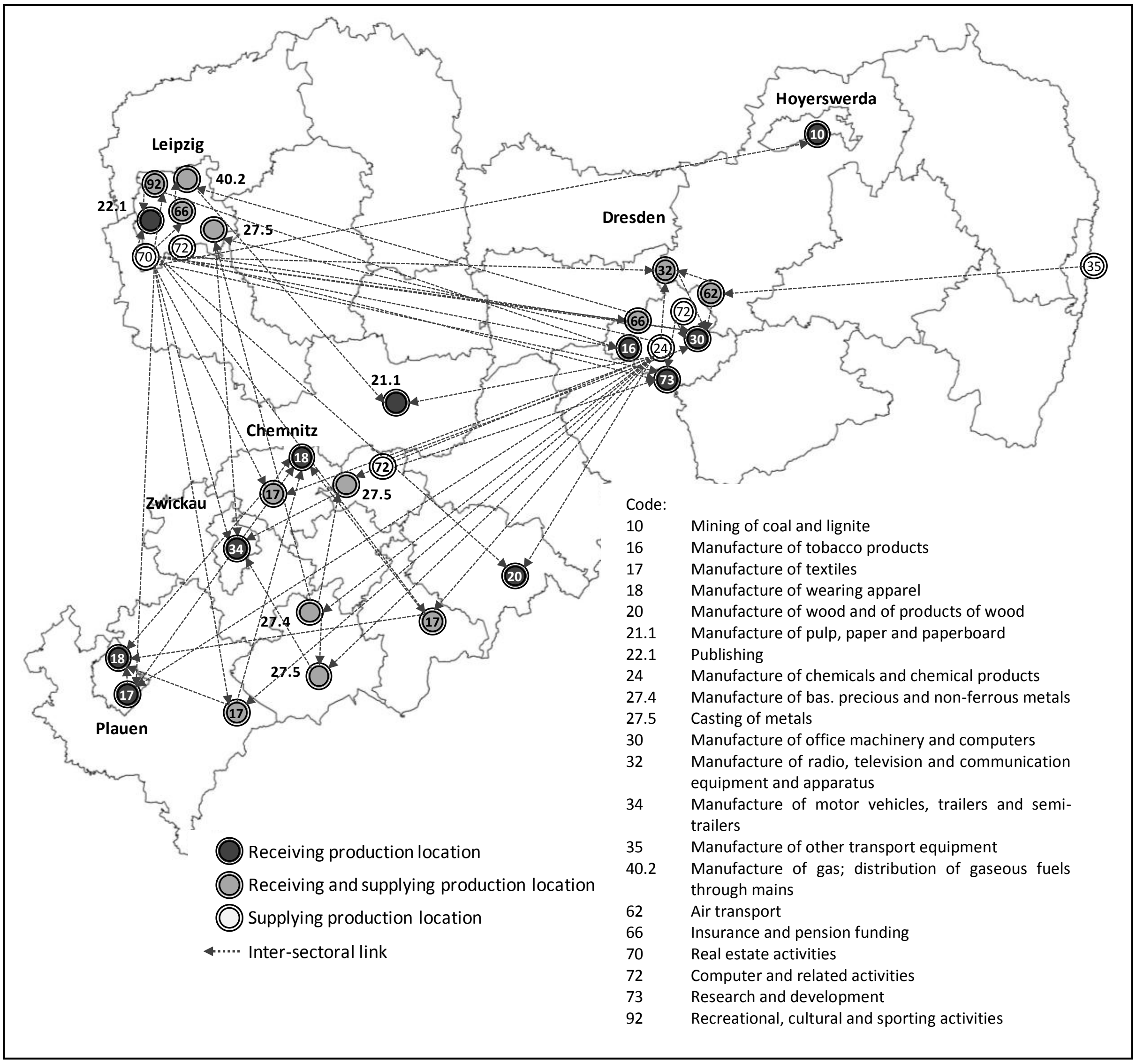
To identify the degree of vertical relatedness of the identified industrial cluster structures we apply qualitative input–output analysis using the German input–output table for the year 2005. Following the procedure proposed by Schnabl (1994), we calculate the optimum filter rate for the identification of relevant vertical inter-industry linkages. The optimum filter rate in terms of input coefficients is 0.01196 (or 1.2%).

Applying this filter rate leads to a reduction in the number of inter-industry relations under analysis from 4,970 (71 x 71 - 71 – reflecting 71 sectors of the input–output table; elements of the main diagonal are excluded) to 419. These 419 relevant linkages are used as basis for the industry templates at the regional level, reflecting a relevant degree of vertical relatedness of the identified cluster structures. By using the proposed framework of Titze et al. (2009) we are able to transform the national industry templates to the regional level.3 Keeping in mind the assumption that similar inter-sectoral relation-

3 The following example may illustrate this procedure. The Dresden region possesses, among other things, important production locations in the fields of Office machinery and computers (NACE code 30) and radio, television

ships exist at the regional level as at the national level, we do not identify real buyer–supplier relations but relevant vertical relations that may occur according to the relations shown in the input–output table. This procedure therefore cannot replace a bottom-up approach. It regards all identified regional inter-industry relations as potential vertical linkages, shown in Figure 4 as dashed lines.

Figure 4:
Vertical dimension of industrial clusters in Saxony (intermediate goods flows)



Source: Authors' own illustration.

In Figure 4 we see that, from an input–output point of view, no vertically isolated clusters exist in Saxony. All clusters show potential vertical linkages with other clusters at

and communication equipment (NACE code 32). We assume the regional link between these two industrial sectors because qualitative input–output analysis detected the intermediate input between both sectors as a dominant value chain.

the local or regional level. The average number of potential vertical linkages is 1.83 (see Table 3). This indicates a limited number of complementary cooperation possibilities along the value adding production chain. While specialization of economic activity has occurred in Saxony, interaction and exchange along concentrated industrial structures is restricted. This is because the regional specialization in sectors showing low input–output relatedness makes it difficult to foster learning dynamics based on the complementary capabilities of local or regional firms.[4]

Table 3:
Vertical cluster structures in Saxony: structural indicators

	Number	Percentage
Vertically isolated clusters	0	–
Vertically connected clusters	30	100
Total vertical linkages	55	–
Average number of vertical linkages	1.83	
Max. indegree by cluster[a]	6	
Max. outdegree by cluster[b]	15	

Source: Authors' own calculations.

Notes: [a] Max. indegree measures the maximum number of receiving relations of one industrial cluster. [b] Max. outdegree measures the maximum number of supplying relations of one industrial cluster. The average number of vertical linkages is calculated by dividing the total number of linkages by the number of industrial clusters.

The regional analysis shows that the two main Saxon agglomerations, Dresden and Leipzig, are determined by a relatively high number of industrial clusters. While the major part of Saxon regions do not show any potential for related local cluster activities, Table 4 shows that these possibilities are present in the two agglomerations and in the south of Saxony (in the textile industry in the districts of Plauen, Aue-Schwarzenberg and Chemnitzer Land). Moreover, Dresden and Leipzig show a high potential for interactions with other industrial clusters in other regions. Differences in the cluster structures of these two agglomerations can be identified in the directedness of the intermediate goods flows of their cluster activities. While Dresden shows a balanced interaction of supplying and receiving input–output relations, Leipzig is characterized by a high

4 Applying the proposed calculation scheme, we identify potentials for input–output relatedness between sector 35 (Manufacture of other transport equipment) and sector 62 (Air transport). Basically, this relation is consistent with technical buyer–supplier relations in reality. However, because of the statistical classification, this sector can be divided into three subgroups: 35.1 (Building and repairing of ships and boats), 35.2 (Manufacture of railway locomotives) and 35.3 (Manufacture of aircraft). The aggregated treatment of these three sectors in the input–output framework may therefore lead to a mismatch of the output of sector 35 with the input of the sectors with NACE Code 60.1 (Transport via railways), 61 (Water transport) and 62 (Air transport).

outdegree of the identified cluster structure, which means that the clusters there are supplier-dominated.

Table 4:
Vertical cluster structures in Saxony: regional allocation

Region	Number of industrial clusters in the region	Number of intra-regional vertical relations between clusters	Number of inter-regional vertical relations between clusters	
			Supplier relations	Receiving relations
Dresden	8	6	11	11
Leipzig	7	5	17	3
Chemnitz	2	0	3	2
Plauen	2	1	1	5
Chemnitzer Land	2	1	1	5
Aue-Schwarzenberg	2	1	3	2
Zwickau	1	0	0	4
Annaberg	1	0	2	2
Vogtlandkreis	1	0	2	2
Mittlerer Erzgebirgskreis	1	0	0	2
Mittweida	1	0	0	2
Goerlitz	1	0	1	0
Hoyerswerda	1	0	0	1

Source: Authors' own calculations.

Regional innovative knowledge flows in and to industrial clusters – widening the vertical dimension

Firms learn from each other when they interact (Freeman 1982, 1991). As well as learning dynamics based on rivalry, observation or comparison, the exchange of complementary knowledge through close collaboration can enhance the knowledge base of firms in industrial clusters (Malmberg and Maskell, 2002). As the cluster concept highlights the combination of agglomeration effects and localized inter-organization linkages for the innovativeness of firms, the identification of the structure of spatial proximate knowledge networks in industrial clusters is a major component in explaining the innovativeness of clusters and cluster-inherent firms (Knoben, 2009).

With the help of the 610 cooperation projects under analysis (with 4,614 interactions overall) we create an innovation interaction matrix for Saxony. This matrix contains 29 x 71 (29 Saxon regions with 71 sectors in each case) rows and columns. In the matrix, 734 out of 4,614 innovative interactions (15.9%) take place within or in connection with the identified cluster structure. Regarding the 30 industrial clusters under analysis, only 15 (50.0%) are engaged in local or regional innovative interactions, while the other half of the industrial clusters do not participate in local or regional cooperation projects. Looking at the participation rate of regions in innovative interactions, all regions apart from three are involved in cooperation projects with the industrial cluster structure (see Table 5).

Table 5:
Knowledge flows to industrial clusters: structural indicators

	Number	Percentage
Total number of cluster	30	–
Clusters engaged in innovative interactions	15	50.0
Clusters not engaged in innovative interactions	15	50.0
Total number of regions	29	–
Regions active in knowledge production for industrial clusters	26	89.7
Inactive regions	3	10.3

Source: Authors' own calculations.

Taking a closer look at the fifteen clusters engaged in innovative interactions, Table 6 shows the regional structure of knowledge flows within industrial clusters and between clusters, and other non-spatially concentrated sectors. Thus we distinguish between local (within the cluster or the same district) and regional (between different districts) interactions. We find that only a small amount of knowledge interaction takes place at the local level within the industrial clusters under analysis. More important factors for the knowledge generation are interactions with other sectors within the same region (24.7%) and other sectors outside the region (56.3%). This means that complementary knowledge, enabling learning and fostering innovation, is likely to be found not only in clusters but also in other sectors within the same region or outside the region. Thus the number of regions involved varies with the size of the innovation network of the identified clusters. The clusters in Chemnitz, Zwickau, Leipzig and the textile clusters around the regions of Plauen, Chemnitzer Land, Vogtlandkreis and Annaberg show only small-scale innovation networks with a limit of ten regions involved in knowledge generation. In contrast to this, the larger innovation networks of the clusters in Dresden (Clusters 11 to 13 in Table 6) are able to use knowledge sources in a greater number of Saxon regions.

Table 6:
Knowledge flows to industrial clusters: regional indicators

Cluster number	Region	Core activity of the cluster	Characteristics of knowledge flows – interactions: Within the cluster (%)	With other clusters (%)	With other sectors within the same region (%)	With other sectors outside the region (%)	Number of regions involved in knowledge network
1	Chemnitz	72	7.8	6.5	40.3	45.5	14
2	Plauen	17	0.0	26.7	6.7	66.7	9
3	Zwickau	34	15.4	0.0	0.0	84.6	8
4	Annaberg	17	0.0	14.3	0.0	85.7	6
5	Chemnitzer Land	17	0.0	28.6	0.0	71.4	6
6	Chemnitzer Land	18	0.0	16.7	0.0	83.3	4
7	Vogtlandkreis	17	0.0	23.1	7.7	69.2	10
8	Aue-Schwarzenberg	27.4	0.0	25.0	0.0	75.0	4
9	Dresden	24	0.0	0.0	0.0	100.0	5
10	Dresden	30	0.0	20.0	0.0	80.0	3
11	Dresden	32	12.8	13.6	29.6	44.0	14
12	Dresden	72	5.6	16.7	30.6	47.2	10
13	Dresden	73	10.9	7.2	23.7	58.3	24
14	Leipzig	27.5	0.0	0.0	60.0	40.0	3
15	Leipzig	72	0.0	0.0	12.5	87.5	4
Average			9.5	9.5	24.7	56.3	8.3

Source: Authors' own calculation.

Notes: Description of the core activity of the industrial cluster: 17 – Manufacture of textiles; 18 – Manufacture of wearing apparel; 24 – Manufacture of chemicals and chemical products; 27.4 – Manufacture of basic precious and non-ferrous metals; 27.5 – Casting of metals; 30 – Manufacture of office machinery and computers; 32 – Manufacture of radio, television and communication equipment and apparatus; 34 – Manufacture of motor vehicles, trailers and semi-trailers; 72 – Computer and related activities; 73 – Research and development.

As our goal is to contribute to the discussion on adequate methods for the identification of industrial clusters, we further analyse the overlap of the identified regional potentials for intermediate goods flows with the structure of innovation interactions to obtain a more comprehensive view of the interactions in the Saxon industrial clusters. Out of the overall 4,614 innovation interactions, 15.9% take place within industrial clusters, and 15.3% along dominant input–output linkages (see Table 7).

Table 7 further compares the knowledge flows within and to industrial clusters with dominant input–output linkages between industrial clusters. It shows that only a small proportion of knowledge flows occur along the value chain of industrial clusters. Only 10.6% take place along the dominant input–output linkages. The major part is characterised by sole knowledge flows rather than dominant input–output linkages. A sole focus in empirical cluster research on the identification of vertical relations based on intermediate goods flows may therefore limit the comprehensive identification of the cluster's knowledge network as these non-clustered activities play an important part in enhancing the knowledge base of local cluster structures.

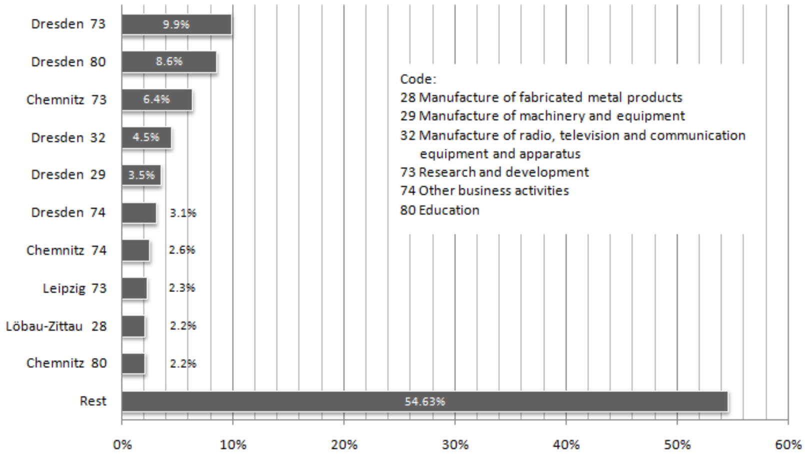
Table 7:
Comparing knowledge and intermediate goods flows in Saxony's industrial clusters

	Number	Percentages
Overall knowledge flows	4 614	–
along dominant input–output linkages	708	15.3
within industrial clusters	734	15.9
Overall knowledge flow relationships in industrial clusters	734	–
along dominant input–output linkages	78	10.6
sole knowledge flows	656	89.4

Source: Authors' own calculations.

Figure 5 now presents the central sources of knowledge for industrial clusters in Saxony. The illustration allows us to further distinguish between the important knowledge sources for each of the seven clusters. The most important region–sector combinations engaged in cooperation projects are the research and development sector and the university and specialized colleges of higher education in Dresden (NACE 73, NACE 80). They participate in 18.5% of the overall cooperation projects, and interact with 9 out of the 15 industrial clusters under analysis. This shows the high importance of private and public R&D facilities for innovations. The next two important region–sector combinations are the research and development sector (NACE 73, interaction with 13 more clusters) in Chemnitz and the cluster of the manufacture of electronic components (NACE 32, interaction with 2 more clusters) in Dresden.

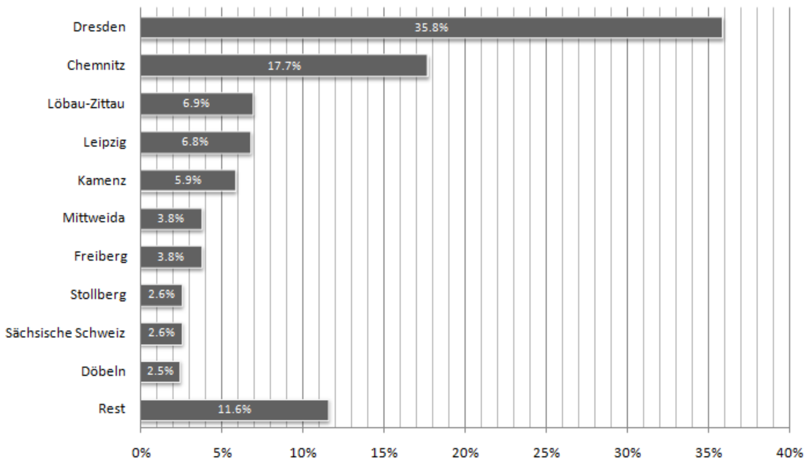
Figure 5:
Central sources of knowledge for industrial clusters in Saxony – Most important region-sector combinations cooperating with industrial clusters (in percent)



Source: Authors' own illustration.

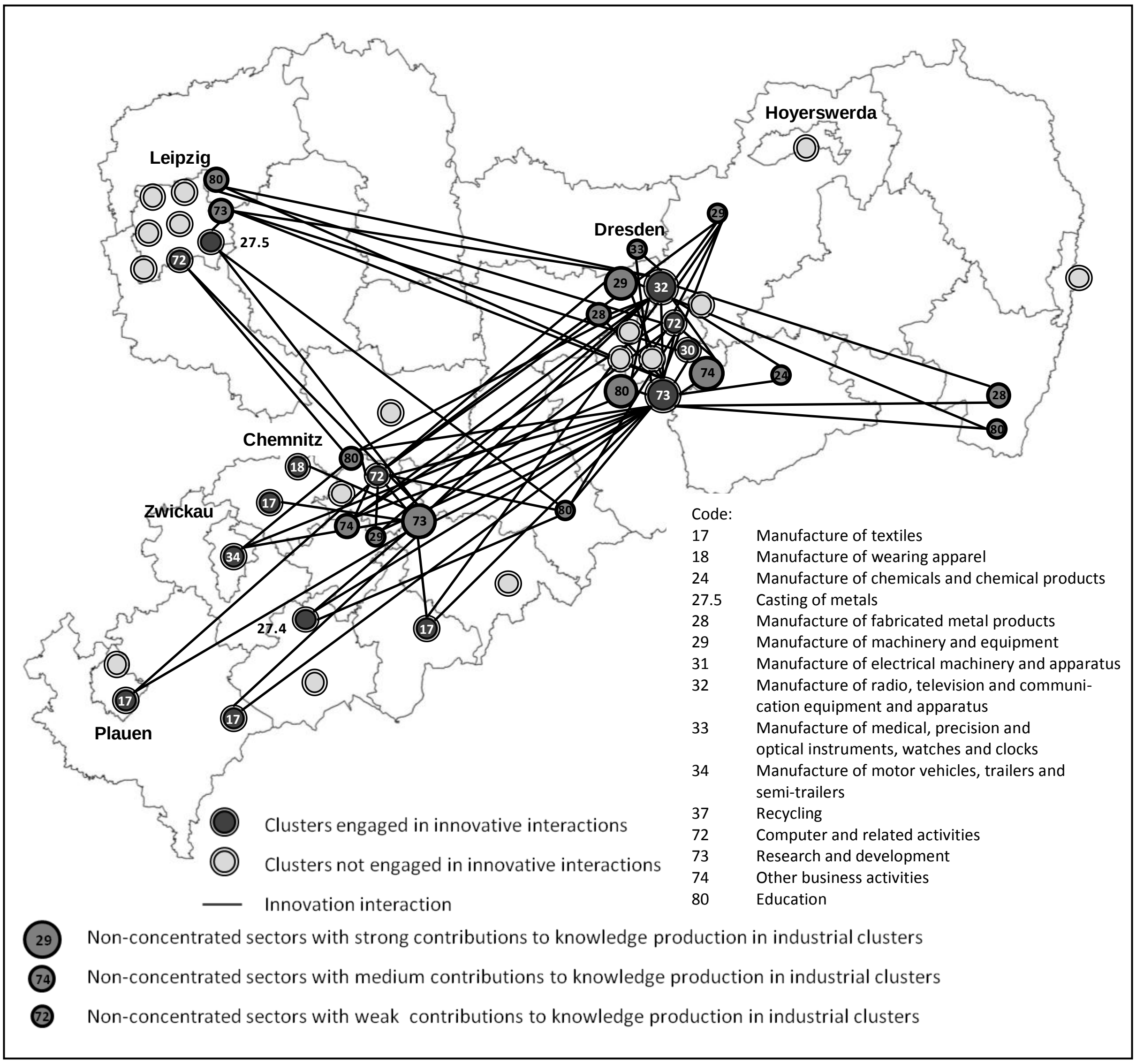
Figure 6 further highlights the dominant role of the Dresden region for knowledge production. The region is involved in 35.8% of all innovation interactions in industrial clusters in Saxony. Other important regions are Chemnitz (17.7%), Löbau-Zittau (6.9%) and Leipzig (6.8%). However, with respect to the number of industrial clusters identified in the region, the participation of Leipzig in the processes of knowledge generation appears to lag behind Dresden and Chemnitz. Overall, these four locations contribute to 67.3% of all innovation interactions.

Figure 6:
Central regions of knowledge production for industrial clusters in Saxony - Regional share of co-operations with industrial clusters



Source: Authors' own illustration.

Figure 7:
Vertical dimension of industrial clusters in Saxony (innovation interactions)



Source: Authors' own illustration.

Notes: The illustration of the locations involved in knowledge production is limited to the 20 most important sector–region combinations (representing 60% of all innovation interaction in Saxon industrial clusters). Overall, 158 sector–region combinations were involved in innovation interactions. Strong contributions to knowledge production within industrial clusters are indicated in Figure 7 when sectors contribute to more than 3% of the overall knowledge interactions, medium contributions are made when sectors contribute to more than 2% of overall knowledge interaction.

Figure 7 presents the spatial structure of innovation interactions in Saxony. The figure is limited to the 20 most important sector–region combinations that contribute to knowledge production and knowledge diffusion. However, it becomes clear that the innovative potential of industrial clusters relies greatly on intense research and development interactions with other regions and other sectors. Regarding Saxony, there seem to be strong sectoral interdependencies between Dresden and Chemnitz, the two leading manufacturing sites in this region. In combination with Table 6 we further identify different structural characteristics (regional participation, number of interactions and so on) of knowledge networks in industrial clusters. Peripheral clusters (for example, textiles and wearing apparel) thereby seem to rely on the knowledge base of those two centres. The third other urban area in this region, Leipzig, shows only minor innovation interaction with the surrounding regions. This can, on the one hand, be traced back to the sectoral structure of the industrial clusters in the region (publishing, energy distribution services, cultural activities, insurances), which show different innovation characteristics that might not be captured by the selected R&D project databases. On the other hand, it shows clearly that the region lacks a strong manufacturing base, and a strong technical university or public and private research institutes (as there are in Chemnitz and Dresden) that are integrated with the innovation network of Saxony.

7 Conclusions

One problem with the industrial cluster literature is the suggested overlap of the space of place and the space of flows (Boschma and Ter Wal, 2007). This is combined with the assumption that knowledge externalities are spatially bounded because knowledge networks are limited to the boundaries of the cluster. Empirical cluster research has to tackle these assumptions. Therefore, in a first step, adequate methodologies for the identification of industrial clusters are needed. This article proposed a multidimensional approach to overcome the limitation of traditional regional tool kits in cluster research. With the help of the combination of measures of spatial concentrations, qualitative input–output analysis and innovation interaction matrices, we were able to overcome the limitations of the sole utilization of these approaches and contribute to a more comprehensive identification of the structures within industrial clusters. While this approach is not able to reflect (important) external linkages of the identified clusters, it shows that significant extra-cluster linkages were likely to exist at both local and regional levels. These linkages include relatedness of input–output flows and, even more important, the regional sourcing of knowledge. Thus most innovation interaction for knowledge generation does not take place within the traditional boundaries of the industrial clusters identified when using concentration measures alone. Cross-sectoral cooperation, based on complementary knowledge is one of the major sources of knowledge for industrial clusters. In our research design they contribute to around 90% of all innovation interaction in Saxony. Furthermore, the determination of the directedness and the connectedness of input–output flows of the identified cluster structures allows for deeper insights into potential interactions along the value chain.

The analysis for Saxony shows that while the Free State has been characterised by strong structural change since the beginning of the 1990s, the regions were able to build up important specialisations of economic activities. Regarding the East German region specifically, in total 30 industrial clusters could be identified in Saxony. While the cluster structures show a low degree of potential vertical interaction, no vertically isolated clusters exist in the Saxon cluster network. Out of the 30 industrial clusters identified, only 15 are engaged in innovative interactions. Taking a closer look at these 15 industrial clusters we can show differences in the size and regional participation in knowledge networks of the clusters. Regarding the structural indicators of the knowledge network of the industrial clusters, non-clustered activities make major contributions to knowledge generation and diffusion. This makes it clear that traditional approaches in empirical clusters research are limited when identifying industrial clusters in a comprehensive manner. Multidimensional approaches are needed, which are able to reshape the boundaries of industrial clusters and adequately reflect industrial cluster structures.

However, this methodology has important limitations that restrict the interpretation of the results. First, the assumption that similar inter-sectoral relationships exist at both regional and national levels led to a situation where we were not able to identify real buyer–supplier relations but only the relevant vertical relations that occur according to the interaction shown in the input–output table. This procedure therefore cannot replace a bottom-up approach. Second, no measure of spatial concentration is able to reflect all the theoretically relevant dimensions of localization (see also Feser *et al*. 2005). Third, for the creation of the innovation interaction matrix, we relied on only two sources of cooperation projects in Saxony. Firms are also able to use other sources of innovation, thus leading to possible bias in the results. However, it is our aim to develop a multidimensional approach for the systematic identification of industrial clusters by the use of a combination of different methods. With the integration of innovation interaction matrices we are able to enrich information about the spatial structures of industrial clusters by showing the limited degree of overlap of intermediate goods flows and knowledge flows, and the part that non-clustered activities play in knowledge generation at both local and regional levels.

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