The Identification of Regional Industrial Clusters Using Qualitative Input-Output Analysis

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Abstract

The ‘cluster theory’ has become one of the main concepts promoting regional competitiveness, innovation, and growth. As most studies focus on measures of concentration of one industrial branch in order to identify regional clusters, the appropriate analysis of specific vertical relations within a value-adding chain is developing in this discussion. This paper tries to identify interrelated sectors via national input-output tables with the help of Minimal Flow Analysis by Schnabl (1994). The regionalization of these national industry templates is carried out with the allocation of branch-specific production values on regional employment. As a result, the paper shows concentrations of vertical clusters in only 27 of 439 German NUTS-3 regions.

Key words: Industrial clusters, Qualitative input-output analysis, Vertical linkages

JEL-classification: C67, O14, L14

Kurzfassung

Industriellen Clustern wird in der ökonomischen Literatur vielfach die Rolle von Motoren der wirtschaftlichen Entwicklung von Regionen zugeschrieben. Dabei existieren unterschiedliche Herangehensweisen innerhalb der empirischen Untersuchung dieses Phänomens. Überwogen bisher spezifische Fallstudien als Untersuchungsdesign, so versuchen neuere Ansätze allgemeingültige Aussagen zur regionalen Wirkung von Clustern zu treffen. Die nachfolgende Untersuchung möchte hier einen Beitrag leisten und analysiert erstmals mit Hilfe der Qualitativen Input-Output-Analyse sowie regionalen Beschäftigtenzahlen vertikale industrielle Verflechtungen auf Ebene der deutschen NUTS-3 Regionen. Erste Ergebnisse zeigen, dass nur 27 von 439 Regionen Ansätze von vertikalen industriellen Cluster aufweisen.

Schlagwörter: Industrielle Cluster, Qualitative Input-Output-Analyse, vertikale Verflechtungen

JEL-Klassifikation: C67, O14, L14

The Identification of Regional Industrial Clusters Using Qualitative Input-Output Analysis

Introduction

This paper explores the potential arising through the application of qualitative input-output analysis (QIOA) to identify regional industrial clusters. It follows a method developed by Schnabl (1994), who uses national input-output tables to discover important qualitative inter-industry linkages. We enhance this method by introducing a framework to regionalize the identified national industry templates and create insights into the spatial allocation of potential vertical industrial clusters in Germany's NUTS-3 regions. To our knowledge, this method has not yet been applied to the subject of industrial clusters. Thus the paper reveals that the method contributes usefully to the identification of potential buyer–supplier linkages within regional industry activities as a starting point for regional planning policy.

Regarding structure, the paper is divided into five parts. After the introduction, the second part reviews the literature concerned with inter-industry linkages and spatial proximity within the cluster concept. The third section describes alternative methods of using nationwide input-output tables for industry cluster analysis. The fourth part describes the technique of qualitative input-output analysis, the selection-criterion for concentrated economic sectors and the regionalization to NUTS-3 level with the help of employment data. The fifth part presents the results obtained from German regions, and develops a classification scheme that characterizes different forms of identified vertical industry clusters. The paper ends with an assessment of how these results can be transferred to regional planning policy, and presents further research questions that emerge with the use of this method.

The Cluster Concept

It is a basic observation that economic activity is concentrated in space and, following this, there is increasing attention being paid to the forces of agglomeration and the role of location in economic development. Theoretical foundations of the analysis of local industry concentrations are given by the concept of agglomerations economies (Marshall 1920), external localization economies (Hoover 1948) and the influential 'cluster theory' developed by Porter (1990). Porter (1998) defines clusters as 'a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities'. This definition is ambiguous, as it is vague in terms of geographical scale and internal socio-economic dynamics, leading to a diversity of further definitions and empirical applications (Martin and Sunley 2003). Following this, there is still a lack of consent as to what defines a cluster. As well as a minimal agreement about the need of spatial proximity, the need for linked industries can be acknowledged in the literature. This paper attempts to contribute to the cluster discussion, and defines clusters from a more functional perspective as 'networks of producers of strongly interdependent firms (including specialized suppliers) linked to each other in a value adding production chain' (Roelandt and Den Hertog 1999). Furthermore, we search for spatial concentrations (the necessity for a critical mass, according to Steinle and Schiele 2002; Walcott 2002) of these benchmark value chains (Feser 2005) at the regional level.

The issue of spatial proximity has been of rapidly increasing importance in the cluster literature since Czamanski and Ablas (1979) made a distinction between industrial complexes and industrial clusters regarding the spatial co-agglomeration of these industry groups. Spatial proximity of interlinked industry activities is regarded as influencing the performance of these sectors, and regional clusters in both the short and long term (Maskell 2001). While the short-term focus points out the temporal and qualitative availability of key inputs and services (Feser and Bergman 2000), the long-term perspective stresses the necessity of interaction with other regional agents (buyers, suppliers, institutions) as sources of competitive advantages through innovation, knowledge spillover and interactive learning (Lucas 1988; Feldman 1999). Temporal and qualitative availability of inputs from specialized suppliers is of increasing importance as industries are restructuring their relationships with members of the value chain, focusing on core competencies and permitting greater co-ordination in design and production (Feser and Bergman 2000). Larsson (2002) and Frigant and Lung (2002) highlight that new production concepts such as Just-in-Time (JIT) or modular production focus on reliability so much that temporal and spatial proximity becomes of strategic importance. While these studies focused on the vehicle industry, Cannon and Homburg (2001) use a wider sample of firms, and stress the pecuniary advantages arising from the geographical closeness of suppliers' facilities to customers' buying locations, thus lowering the customer firms' costs.

Additionally, long-run empirical studies tend to emphasize that agents that are concentrated spatially benefit from knowledge externalities (Marshall, 1920). These knowledge spillovers appear to be spatially bounded (Jaffe *et al*., 1993; Audretsch and Feldman 1996), as closer proximity allows more frequent face-to-face contact, facilitating the exchange of knowledge and fostering transfer skills and innovation (Knoben and Oerlemans 2006). Oerlemans and Meeus, (2005) indicate that these interactions along the value chain could be even more important, since business agents (buyers and suppliers) embody the most valuable product-related technical knowledge and therefore affect the innovative and economic performance of the firm. This might be necessary not only for tacit knowledge but also for codified knowledge, as the assimilation of both still require tacit knowledge, and thus spatial proximity (Howells 2002; Boschma 2005).

The effect of spatial proximity alone has been challenged in the recent literature on innovation, inter-firm collaboration and firm performance. Torre and Rallet (2005) stress the fact spatial proximity on its own cannot create interaction or collaboration, and that other forms of proximity (organized proximity, temporal spatial proximity, for example) could have increasing importance for successful interaction. Spatial proximity may act in a complementary way in building and increasing institutional, social, organizational or cognitive proximity (Boschma 2005). Oerlemans and Meeus (2005) point out that local connectivity on its own may even be problematic for firm performance, as firms with both intra- and inter-regional innovative ties with buyers and suppliers tend to outperform other firms in the same sector in innovated processes, products and sales. To capture these additional forms of proximity, we choose to focus on inter-industry flows, as intermediate flows of goods are indicators of inter-firm interactions encouraging company performance.

The Analysis of Regional Industry Interactions in Clusters

For the generation of information about vertical industry linkages it is necessary to use input-output tables. The literature offers several approaches to solve this problem. The basic commonality is the division of inter-industry linkages into important and unimportant flows of goods. Recent literature focuses mainly on four concepts. An elementary cluster analysis is proposed by Bijnen (1973). He focuses only on the strongest inter-industry linkages as main points of interest, while neglecting possibly weaker but also important linkages (see also Bellet *et al*. 1989 – 'Direct Flow Analysis'; Peeters *et al*. 2001 – 'Method of the Maxima'). Feser and Bergman (2000) use principal components factor analysis where measures of direct and indirect linkages calculated from inter-industry trade information were treated as variables to measure the relative strength of a given industry and a derived factor. As this approach is not based on the absolute or even the relative size of transactions between the sectors, they use the similarity of intermediate purchases and sales structure to group different industries into one cluster (Oosterhaven *et al*., 2001). Thus highest-loading industries were treated as members of an industrial cluster (see also Vom Hofe and Dev Bhatta 2007; Kelton *et al*. 2008, for recent applications).

Oosterhaven *et al*., (2001) use intra-regional intermediate sales matrices. They introduce three criteria to determine which direct linkages are important for potential cluster building. First, absolute intermediate transaction size should be larger than the average intermediate transactions size. Further, the relative importance of intermediate transactions is covered through an above-average intermediate input coefficient and an above-average intermediate output coefficient, thus stressing the importance of intermediate purchases and sales. Oosterhaven *et al*. (2001) point out that the absolute size is the most important criterion, as it looks directly at the strength of the linkages, but they do not take absolute and relative indirect effects into account, which seems to be of increasing importance as the absolute size of intermediate transactions is increasing.

Another method to measure inter-industry linkages is presented by Dietzenbacher (1992); for a recent application, see Midmore *et al*. (2006)), who use an eigenvector method associated with a dominant eigenvalue of the direct coefficients matrix in a search for key industrial sectors. The focus of this method lies in the ranking of regional industries in terms of forward and backward linkage potential with the help of industry weights that filter out the effects of different primary input intensities in supplying industries (Midmore *et al*. 2006). Another contribution that has not yet been applied to the cluster concept was developed by Schnabl (1994). This method of qualitative input-output analysis is now discussed in further detail.

Methodology

The basic principle of qualitative input-output analysis is the differentiation of important and unimportant intermediate flows of goods within the national input-output framework. For practical purposes, we shall only take into account those inputs that exceed a developed endogenous filter rate. This method transforms quantitative information about the relative or absolute importance of these inter-industry transactions into qualitative information. On the one hand, this contributes to a loss of information; but on the other, it leads to the selection of required relevant input flows and creates insights into the core structures of intermediate purchases and sales relations. Mathematically, we carry out a binary transformation of input flows between two industries, i and j. An input flow s_{ij} becomes 1 if it exceeds a filter rate F, and 0 otherwise. This transforms the basic input-output table into the so-called adjacency matrix W:

$$w_{ij} = \begin{cases} 1, \text{if } s_{ij} > F \\ 0, \text{otherwise} \end{cases} \tag{1}$$

In this paper, we are interested primarily in inter-industry linkages. For our purposes, the examination of intra-industry linkages ($i = j$) is of secondary importance. Thus the elements of the main diagonal are fixed at 0. The fundamental question arising is: what is the optimum threshold value determining the value of the filter rate F? This includes the question of which input flows are relevant. In our paper we use minimal flow analysis (MFA) to detect the optimal filter rate F_{opt}. This method was substantially developed by Schnabl (1994). The optimal filter rate will be calculated using an iterative process. The initial point is the layer-wise separation of the input-output information. Basically, relation (2) is essential, whereas x is the vector of production values, C stands for the Leontief inverse matrix, and y equals the vector of total demand.

$$x = C \cdot y \tag{2}$$

The Leontief inverse can be written as Eulerian series, in which I is the unit matrix and A is the matrix of input coefficients.

$$x = C \cdot y = \left(I + A + A^2 + A^3 \ldots\right) \cdot y \tag{3}$$

The real total demand vector y can be replaced by a synthetic vector. This shows the potential of this method. With the application of the real final demand vectors, absolute values of intermediate good flows can constitute the major research interest, while, using synthetic vectors, the relative importance of inter-industry transactions determines the relevant threshold value and input flows. In this paper we have chosen to use a synthetic vector, because the calculated structure reflects the technical relations and relative importance of the sector. After diagonalization, this vector corresponds to the unit matrix I. The real total demand vector would distort the desired technical structure (Schnabl 1994).

The next step is to develop a set of transaction matrices, based on the decomposition of the Leontief inverse with the help of Eulerian series. We find the transaction matrix T, where the matrix of input coefficients is multiplied by the diagonal matrix $<x>$ of the vector of production values x.

$$T = A \cdot \langle x \rangle \tag{4}$$

According to relation (3), we can separate (4) into the following layers:

$$\begin{aligned} T_0 &= A \cdot \langle y \rangle \\ T_1 &= A \cdot \langle A \cdot y \rangle \\ T_2 &= A \cdot \langle A^2 \cdot y \rangle \\ T_3 &= A \cdot \langle A^3 \cdot y \rangle \quad etc. \end{aligned} \tag{5}$$

The exponentiation of the matrix of input coefficients continues until no elements t_{ij}^k of matrix T_k exceed a given filter level F. This transformation leads to binary layer specific adjacency matrices W_k, with

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

Using Equation (7), it is possible to reproduce the quantitative layer-wise information included in the Leontief inverse into qualitative information in the adjacency matrix.

$$W^k = \begin{cases} W_k \cdot W^{k-1}, \text{if } k > 0 \\ I, \text{if } k = 0 \end{cases} \tag{7}$$

W^k represents the connection between layer-wise varying adjacency matrices W_k, while including the increasing irrelevance of the flow of intermediate goods between the sectors i and j at higher levels of k. Executing this step, we can show the indirect information of the input-output table (see Table 1).

In this (first) product (respectively, adjacency) matrix we can find a direct relation from sectors 1 to 2, but no direct link exists from sectors 1 to 3. Given that sector 2 is related directly to 3, we can denote an indirect link from sector 1 to sector 3 via sector 2.

Table 1:
Indirect inter-industry linkages – an example

	Industry consuming				
Industry producing	1	2	3	...	m
1		1	0		1
2	1		1		0
3	0	0			0
...					1
m	1	0	1	1	

Source: Czayka (1972).

In the next step, we calculate the so-called dependence matrix D by adding the product matrices W^k layer-wise. We use Boolean addition (marked by #) as it is important to know whether a direct or indirect connection exists, but not how many steps are needed to fulfil the filter criterion.

$$D \; = \# \left(W^1 + W^2 + W^3 + \ldots \right) \tag{8}$$

Finally, we derive the connectivity matrix H.

$$H = D + D' + D \tag{9}$$

Equation (9) now generates information about the kind of relation between two sectors. Elements of D take only values of 0 or 1, therefore the set of elements h_{ij} in the connectivity matrix H is restricted to values between 0 and 3. The meaning of these elements can be interpreted as follows:

- 0, no link between sector i and j exists, i and j are isolated;
- 1, a weak relation between the sectors i and j is identified; for example, to reach sector j (starting from i) we 'travel' in the wrong direction;
- 2, a uni-directional relation exists between sector i and j, meaning i supplies j; and
- 3, we can denote a bilateral relation between the two sectors, which means that sector i supplies j and i receives from j.

For the purpose of this paper, the uni-directional and the bilateral relations are important. Regarding Equation (6) we see that the value of the filter rate F determines both kinds of relations. We are coming back to the question: what is the right filter rate F? Using minim, the information measure according to Shannon and Weaver (1949) and second, the average value of the elements of the so-called resulting connectivity matrix H_{res}.

Following Shannon and Weaver (1949) we calculate the optimal filter rate F by maximizing the information content of the connectivity matrix H. To measure the information content they used the entropy E. E is maximized when the probability of occurrence is equal for each element (in our case: 1, 2 and 3). Starting with a low filter rate we can denote a high share of uni-directional (h_{ij} = 2) and bilateral relations (h_{ij} = 3). With increases in the filter rate, the bilateral relations become uni-directional or weak relations (h_{ij} = 1). At the highest filter level, all relations are isolated (h_{ij} = 0). To determine E we first calculate the final filter rate F_f. This breaks up the last bilateral linkage (h_{ij} = 3). Second, we apportion the filter into 50 equidistant filter steps l. Third, we calculate the entropy E_l for each of the 50 filter steps, using Equation (10). The variable p indicates that the probability for an element h_{ij}, n is determined by the co-domain of h_{ij}, and log_2 notes the logarithm dualis.

$$E_l = \sum_n \left(p_{l\,n} \cdot \log_2 \left(\frac{1}{p_{l\,n}} \right) \right) \tag{10}$$

The optimum filter step l represents the maximal entropy E.

$$\max E_l \forall_{l=1,..,50} \tag{11}$$

Schnabl (1994) recommended using a second method to decide on the optimal filter rate. In this paper we use the average value of the elements $h_{ij_{res}}$ of the resulting connectivity matrix H_{res}. This matrix is calculated as follows:

$$H_{res} = \left(\sum_{k=1}^{50} H_l \right) - 100 \tag{12}$$

The optimal filter step l_{opt} is derived from the sum of elements $h_{ij_{res}}$ greater than 0, divided by the number of elements greater than 0. We finally apply the average of the two measured filter steps as the optimal filter rate.

The Identification of Spatial Concentrations of Industrial Sectors

Identifying vertical industry linkages is the first step in industry cluster analysis. In this section, we present the concept used to identify a spatial proximate critical mass of relevant industries (Steinle and Schiele, 2002; Walcott, 2002). Therefore, we have to transfer the information about intermediate inputs to geographic units. We portion the intermediate input of a certain 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).[1] As a result, we receive the intermediate input of a certain industrial sector, which is obtained from a region ($input_{ir}$).

$$input_{ir} = \frac{x_{ir}}{x_i} \cdot input_i \tag{13}$$

With the help of concentration indices we can identify industrial sectors and regions that are characterized by a concentrated delivery of intermediate inputs. To calculate, we draw on the Gini coefficient, the Herfindahl index and the concentration rate. Although alternative measures of concentrations (Ellison and Glaeser 1997; Duranton and Overman 2005) have been used in recent literature, we consider these concentrations to be reasonable for the characterization needs of different forms of identified clusters. This includes, for example, clusters in the form of hub and spokes, where the spatial concentration of inputs is created by small numbers of major firms realizing internal economies of scale but being important for spatial proximate concentrate suppliers (Markusen 1996). The Gini coefficient considers the total number of regions N, the rank of the region r, and the share s of intermediate inputs that are delivered from the region in a certain industrial sector (according to Suedekum 2006).

$$Gini_i = \frac{N}{N-1} \cdot \left[\frac{2}{N} \cdot \frac{\sum_{r=1}^{N} (r \cdot s_{ir})}{\sum_{r=1}^{N} s_{ir}} - \frac{N+1}{N} \right] \text{ with } s_{ir} = \frac{input_{ir}}{input_i} \tag{14}$$

Another concentration measure that is principally used in the literature is the Herfindahl index, H. This results from the sum of squares of regional intermediate input deliveries divided by the square of the total intermediate input deliveries in a certain industrial sector i.

1 Although regional sectoral turnover would be a more appropriate indicator we have chosen to use employment data. Official statistics do not support regional turnover analysis because of data restrictions at this spatial scale.

$$H_i = \frac{\sum_{r=1}^{N} input_{ir}^2}{input_i^2} \text{ with } input_i = \sum_{r=1}^{N} input_{ir} \tag{15}$$

The two concepts of measurement discussed here describe whether a certain industrial sector is concentrated or not. However, we do not receive information about regions belonging to the important production locations in Germany. For this purpose, the concept of concentration rate is suitable. In this paper, a certain industrial sector belongs to set of concentrated industrial sectors when a maximum of twenty-five regions account for 50 per cent of total intermediate input deliveries. Furthermore, these twenty-five regions are regarded as being important production locations in Germany.

$$i \in M\{\text{concentrated industrial sectors}\} \text{ if } \left(\sum_{\mathrm{r}=1}^{25} input_{ir} \right) > 0{,}5 \cdot input_i \tag{16}$$

To transfer the identified industrial structure and concentration rates to the regional level, we deal repeatedly with Equations (6) and (16). Applying the derived optimum filter rate, the first adjacency matrix w_{ij}^1 offers insights into the relevant direct inter-industry linkages, while *D* gives a summary of relevant direct and indirect relations. For this purpose, regional cluster structures are derived by Equation (17), focusing on spatial proximate direct inter-industry linkages.

$$w_{ijr}^1 = \begin{cases} 1, \text{if } t_{ij}^1 > F_{opt} & \big| i, j \in M\{\text{concentrated industrial sectors}\} \cap r \in M\{\text{important production locations}\} \\ 0, \text{otherwise} & \end{cases} \tag{17}$$

The following example illustrates this concept. The left-hand side of Figure 1 shows a potential national industrial structure and the corresponding structural relations. In the (exemplary) region (to the right in Figure 1) only sectors 2 and 3 are concentrated. For this reason, the links from sector 1 to 2 and from 3 to m drop out. Thus the national industrial structure acts as a template for the regional economic structure, showing regional specializations within different value chains.

At this point we need to pay attention to how this structural graph can be interpreted. The regional structural graph does not show the real supply chains. We assume these industrial linkages to exist from a production engineering point of view, helping regional agents to understand potential inter-industry relations, which might benefit from spatial proximity, as indicated by cluster theory and empirical studies (particularly case studies). On the other hand, potentially missing parts of value chains can be identified at the regional level, with further implications for regional planning policies. We now want to turn to the application of the presented method for Germany's NUTS-3 regions.

Figure 1:
The transfer of industrial structures and concentration rates to regions

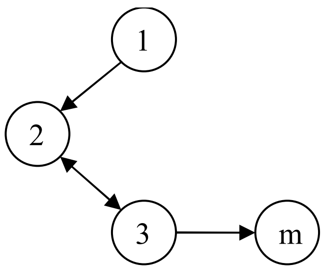
National industrial structure

	1	2	3	…	m
1		1	0		0
2	0		1		0
3	0	1			1
…					0
m	0	0	0	0	

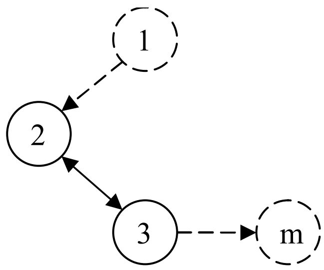
Regional structure (bold numbers = concentrated industrial sectors in that region)

	1	**2**	**3**	…	m
1		$\boxed{0}$	0		0
2	0		1		0
3	0	1			$\boxed{0}$
…					0
m	0	0	0	0	

Structural graph



Regional structural graph



Source: Authors' own illustration.

Germany's Regional Vertical Industry Clusters

Data and assumptions

To analyse inter-industry linkages, we use data from the German *Input-Output Table 2003* (Statistical Office of Germany, 2007). This table includes seventy-one industrial sectors (CPA – Classification of Products by Activity). We excluded imports from the analysis as our aim is to detect regional production linkages. We calculate the concentration of industrial sectors (NACE codes) using the data for the year 2003 from the German Federal Employment Office at the NUTS-3-level (districts, district-free cities). Our analysis is based on three fundamental assumptions. First, we assume that the CPA classification is nearly equivalent to the NACE code. The second assumption concerns the (technical) production structure in the NUTS-3 regions. We suppose that the national industry templates are applicable to the regional level, meaning that fundamental relations between different economic sectors are identical. Following this, the production process of an automobile in terms of input coefficients in Stuttgart is (nearly) equivalent to that in Bremen or Zwickau. Third, we suppose that productivity is approximately equal in all German NUTS-3 regions in a certain industrial sector, allowing us to portion the intermediate inputs to the NUTS-3 regions according to its regional share of employment in the relevant industrial sector.

Regional inter-industry linkages

According to the method mentioned above, we first need to identify the optimum filter rate for German input-output in 2003. The results presented in Table 2 show entropy *E* for the 50 equidistant filter steps. For reasons of simplification, irrelevant filter steps have been taken out of the description.

Table 2:
Filter steps and entropy

Filter step	Filter	Entropy	Number of different inter-industry linkages				Sum of overall connections possible
			Isolated	Weak uni-directional	Uni-directional	Bilateral	
1	0.0001	57.51	487	192	192	4,170	4,970
2	0.0016	108.74	543	559	559	3,380	4,970
3	0.0031	139.86	735	913	913	2,480	4,970
4	0.0047	150.07	895	1,125	1,125	1,896	4,970
5	0.0062	151.59	1,163	1,280	1,280	1,318	4,970
6	0.0078	148.85	1,355	1,325	1,325	1,036	4,970
7	0.0094	141.37	1,743	1,289	1,289	720	4,970
8	0.0109	134.51	2,019	1,246	1,246	530	4,970
9	0.0125	125.23	2,395	1,139	1,139	368	4,970
10	0.0141	120.42	2,559	1,092	1,092	298	4,970
...	...	...	...	...	...	...	...
49	0.0749	22.79	4,843	98	98	2	4,970
50	0.0765	-	4,849	96	96	-	4,970

Source: Data use from Statistical Office of Germany 2003; calculations IWH.

Entropy level is maximized at filter step 5, but according to Schnabl (1994) it is reasonable to use a second criterion for the identification of the optimum filter rate. The average value of the resulting connectivity matrix H_{res} indicates filter step 8 as optimum. The average of these two values leads us to filter step 7 as the optimum filter, with the value 0.0094. With the help of this filter we calculate the first layer adjacency matrix containing 524 inter-industry relations. Differences among the values in the Table 2 are caused by indirect effects between sectors, leading to more inter-industry linkages.

Regional concentrated economic sectors

In the next step we identify regionally concentrated economic sectors with the help of different concentration measures (see Table 3). Out of the original seventy-one industrial sectors, a set of twenty-seven regional concentrated sectors could be identified.

Table 3:
Regionally concentrated economic sectors

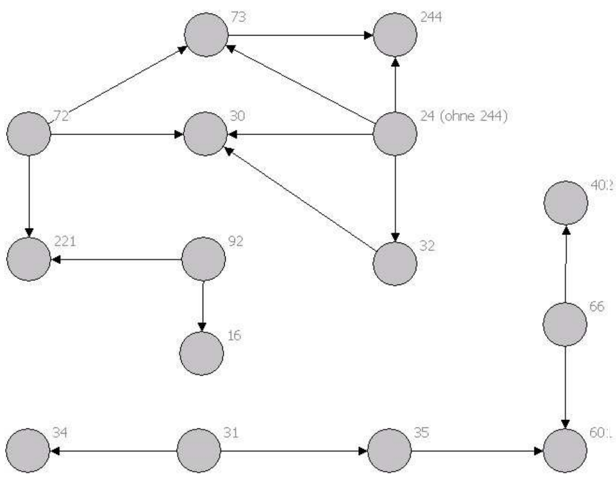
WZ[a]	Description	Gini	Herfindahl index	Number of districts
5	Fishing, fish farming and related service activities	0.84	0.023	15
10	Mining of coal and lignite, extraction of peat	0.96	0.058	6
11	Extraction of crude petroleum and natural gas	0.98	0.098	3
16	Manufacture of tobacco products	0.98	0.110	3
19	Manufacture of leather and leather products	0.84	0.024	16
21.1	Manufacture of pulp, paper and paperboard	0.82	0.015	23
22.1	Publishing	0.76	0.022	20
23	Manufacture of coke, refined petroleum products and nuclear fuel	0.96	0.076	4
24.4	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	0.87	0.026	14
24	Manufacture of chemicals and chemical products	0.77	0.026	22
25.1	Manufacture of rubber products	0.85	0.026	14
26.1	Manufacture of glass and glass products	0.82	0.018	23
27.1–27.3	Manufacture of basic iron and steel and of ferro- alloys, tubes and other first processing of iron and steel	0.82	0.025	17
27.4	Manufacture of basic precious and non-ferrous metal	0.89	0.031	11
30	Manufacture of office machinery and computers	0.90	0.049	7
31	Manufacture of electrical machinery and apparatus	0.73	0.016	25
32	Manufacture of radio, television and communication equipment and apparatus	0.79	0.016	22
34	Manufacture of motor vehicles, trailers and semi-trailers	0.85	0.027	12
35	Manufacture of other transport equipment	0.86	0.035	13
40.2	Manufacture of gas, distribution of gaseous fuels through mains	0.85	0.027	13
60.1	Transport via railways	0.79	0.022	17
61	Water transport	0.92	0.082	5
62	Air transport	0.98	0.098	3
66	Insurance and pension funding	0.92	0.048	7
72	Computer and related service activities	0.78	0.020	18
73	Research and development services	0.85	0.026	13
92	Recreational, cultural and sporting activities	0.71	0.024	18

Note: [a] German classification of economic activities, 2003 edition.

Source: Data use from German Employment Agency, reference date: 30.06.2003; calculations IWH.

The exclusion of forty-four sectors leads to a reduction of relevant inter-industry linkages from 524 to 38. Subsequently, we assign this structure to the NUTS-3 level. As an example, the results are presented for the NUTS-3 region of Munich (see Figure 2).

Figure 2
Structural graph for the NUTS-3 region of Munich



Legend:

16	Manufacture of tobacco products
22.1	Publishing
24	Manufacture of chemicals and chemical products
24.4	Manufacture of pharmaceuticals, medicinal chemicals and botanical products
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus
32	Manufacture of radio, television and communication equipment and apparatus
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
40.2	Manufacture of gas, distribution of gaseous fuels through mains
60.1	Transport via railways
66	Insurance and pension funding
72	Computer and related service activities
73	Research and development services
92	Recreational, cultural and sporting activities

Source: Illustration by IWH.

Munich shows strong concentrations specifically in the high-tech manufacturing sectors (WZ 24, 24.4, 30, 31, 34, 35) with substantial inter-industry linkages. These concentrations go along with complementary service sectors, especially research and development IT-services and media, which are strongly interrelated with the manufacturing sectors. Table 4 provides further insights into the Munich industry cluster.

The number of establishments with more than 500 employees gives an indication of the regional firm structure. Concentrations of several sectors are appearing, as a result of large establishments realizing mainly internal economies of scale (WZ 34, 35) with spatial proximate suppliers of vertical linked industry (WZ 31). We can also identify sectors with horizontal and vertical cluster structures marked by a mixture of small, medium and larger enterprises (WZ 22.1, 24, 24.4, 30, 32, 73) building up spatial proximate productions networks.

Table 4
Characterization of concentrated economics sectors in Munich

WZ[a]	Description	Overall		Establishments with more than 500 employees (percentage)		Herfindahl index of employment
		Establishments	Employment	Share of establishments	Share of employment	
16	Manufacture of tobacco products	-	-	100	100	1,000
22.1	Publishing	425	10,206	0	0	0.297
24	Manufacture of chemicals and chemical products	43	3,239	2.3	55.4	0.421
24.4	Manufacture of pharmaceuticals, medicinal	22	1,846	4.5	46.4	0.356
30	Manufacture of office machinery and computers	19	1,427	5.3	87.5	0.770
31	Manufacture of electrical machinery and apparatus	57	23,233	5.3	89.1	0.798
32	Manufacture of radio, television and communication	76	11,611	3.9	91.2	0.834
34	Manufacture of motor vehicles, trailers and semi-trailers	29	38,786	10.3	97.0	0.941
35	Manufacture of other transport equipment	9	5,265	11.1	92.0	0.853
40.2	Manufacture of gas, distribution of gaseous fuels	5	264	0	0	0.845
60.1	Transport via railways	24	5,748	20.8	70.9	0.553
66	Insurance and pension funding	142	24,500	9.2	63.6	0.482
72	Computer and related service activities	1,117	25,362	0.5	35.5	0.224
73	Research and development services	174	5,031	0	0	0.435
92	Recreational, cultural and sporting activities	1,093	17,430	0.5	39.2	0.243
	Total	3,236	175,181			

Note: [a] German classification of economic activities, 2003 edition.

Source: Data use from German Employment Agency, reference date: 30.06.2005; calculations IWH.

As this first example is limited to the administrative boundaries of the respective region, the concept indicates potential inter-regional transaction flows and the distance between inter-industry linkages. If we extend the regional focus from a small area region (NUTS-3) to the functional area perspective, the industrial network enlarges. Figure 3 shows the industrial structure in the functional area of Stuttgart. At district level we find only weak intra-regional interaction, but by increasing the spatial scale the number of inter-industry linkages rises. As the region of Stuttgart is an important production location for the automotive sector (NACE 34), suppliers of electrical machinery and apparatus sector (NACE 32) show concentrations in near-by regions. Furthermore, the IT sector (NACE

30, and especially the service part in NACE 72) was able to establish regional concentrated value chains (see Figure 3).

Figure 3:
Structural graph for the functional area of Stuttgart

Legend:

19	Tanning and dressing of leather
21.1	Paper and paperboard
22.1	Publishing
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus
32	Manufacture of radio, television and communication equipment and apparatus
34	Manufacture of motor vehicles, trailers and semi-trailers
66	Insurance and pension funding
72	Computer and related service activities
92	Recreational, cultural and sporting activities

Source: Illustration IWH.

Subsumed results for Germany's NUTS-3 level show that, out of 439 regions, 257 (58.5 per cent) do not have any concentrated economic activities according to our selection, while 182 accommodate at least one concentrated sector. To typify these concentrations we developed a characterization scheme, which allows each region to be attached to a specified cluster type. This scheme is presented in Table 5.

Table 5:
Characterization scheme for concentrated economic activity

Number of linkages	Number of concentrated economic sectors 0	1	>1
No linkages	Class 1	Class 2	Class 3
1–5 linkages			Class 4
> 5 linkages			Class 5

Source: Illustration IWH.

In 110 regions, we identified, first, signs of horizontal clusters with a single concentrated economic sector. In 45 regions we could detect strong horizontal clusters in the sense of hosting more than one non-related sector. Overall, only 27 regions (6.2 per cent) showed the first signs (21) or strong vertical clusters (6) according to the German input-output table, indicating that, at this spatial scale, only small number of regions are able to organize production networks (compare Table 6).

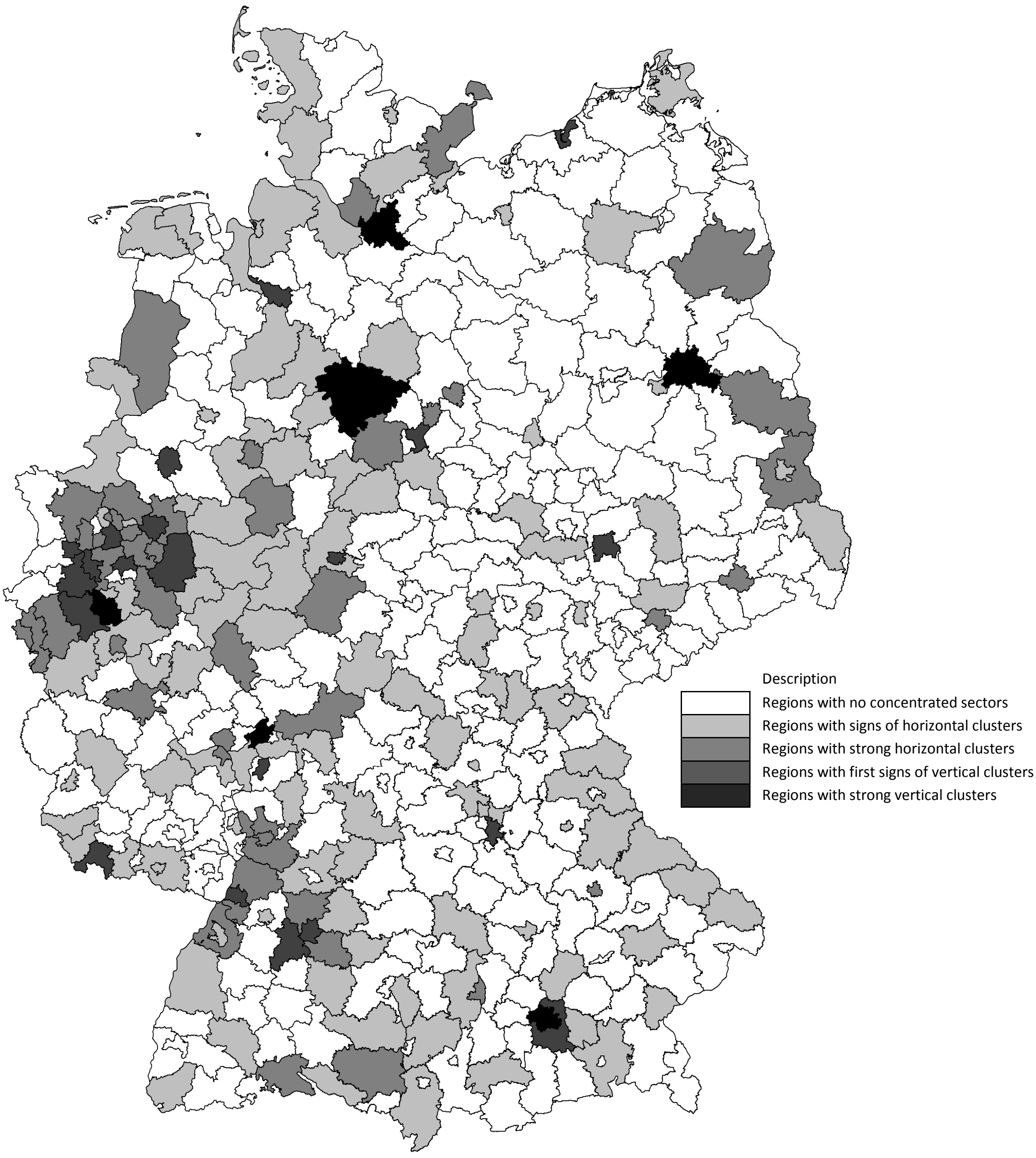
Table 6:
Description of cluster classes

Class	Description	Number of regions
1	Regions with no concentrated economic activity	257
2	Regions with signs of horizontal clusters	110
3	Regions with strong horizontal clusters	45
4	Regions with first signs of vertical clusters	21
5	Regions with strong vertical clusters	6

Source: Illustration IWH.

Figure 4 shows the regional allocation of the five classes in Germany. Strong vertical clusters can be seen in the large urban areas of Munich, Berlin, Hamburg, Cologne and Frankfurt, while, in particular, the south-west of Germany (Baden-Württemberg) and the Ruhr area display many spatial proximate concentrated economic sectors. Areas in the east of Germany fall short in this discussion. Only a couple of regions (Leipzig, Dresden, and Rostock as a maritime cluster) have successfully attracted concentrated economic activities, but most of the regions do not show any concentrations according to our classification scheme.

Figure 4
The spatial allocation of horizontal and vertical clusters at NUTS-3 level in Germany (2003)



Source: Illustration IWH.

Conclusion and Outlook

In this paper we have presented a method that is suitable for the identification of regional industrial clusters. It is generally acknowledged that these clusters influence regional economic development. Storper and Walker (1989) characterized this phenomenon as 'How Industries Produce Regions', meaning spatial dynamics of industry growth and their effects on regional development. However, a standard concept is still required to identify these industrial structures. In the economics literature we can find two ways of analysing cluster structures: input-output analysis, and concentration measures. We suggest combining these two methods. In our analysis we used, first, the minimal flow analysis of Schnabl (1994) for the detection of intermediate relations between certain branches. Then we transformed this structure to the regional level. In Germany, we found only 6 out of 439 NUTS-3 regions that were characterized by strong vertical clusters. All of these clusters are formed in German agglomerations. Notably, at this spatial scale, only a few regions are able to attract or build proximate production networks. Of course, clusters are not restricted to these administrative boundaries, but the results offer insights about the geographical extent of inter-industry linkages and regional specialization patterns. In further research we have to explore the effect of distance on the completion of these benchmark value chains; and we have to identify dynamic changes in cluster structures (the relevance of linkages and regional concentrations of economic sectors). It is self-evident that cluster structures, as well as the whole economy, are subject to structural change. Following this, we have to include cluster life cycles in our analysis and focus on their effects on regional cluster building and regional growth when adding long-term changes in regional intermediate production and inter-industry relations. Up to now, the results have been used as starting points for regional development policies attempting to encourage regional production networks. With the help of the identification of vertical linkages, missing parts of the regional value chain may be highlighted, which can help regional development agencies to understand the relative importance of complementary or related.

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