

## Mapping Local and Regional Potentials for Inter-sectoral Technology Flows in Industrial Clusters – Empirical Results for Germany

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Abstract:

The paper explores the potential for inter-sectoral technology flows in industrial clusters in Germany. With the help of a product-embodied R&D flow matrix, calculated using data on input–output tables and sectoral R&D employment, we construct industrial cluster based networks of technology provider and user relationships and examine the regional embeddedness of different sectors in the technological diffusion network of industrial clusters. As a result, the paper shows that simple graphical representations of relevant product-embodied R&D flows illustrate substantial differences in potentials for technological relations within industrial clusters.

Keywords:

Industrial clusters; Qualitative Input–Output Analysis; Embodied R&D flows; Germany

## 1 Introduction

*‘Localized clusters of similar and related firms form the basis of a local milieu that may facilitate knowledge spillovers and stimulate various forms of adaption, learning, and innovation.’* (Malmberg and Maskell 2002: 433)

This paper explores the potential for inter-sectoral technology flows in industrial clusters in Germany. With the help of a product-embodied R&D flow matrix, calculated using data on input–output tables and sectoral R&D employment, we construct industrial-cluster-based networks of technology provider and user relationships, and examine the regional embeddedness of different sectors in the technological diffusion network of industrial clusters. In line with Drejer (2000: 378) the paper shows that simple graphical representations of relevant product-embodied R&D flows illustrate substantial differences in potential for technological spillovers within industrial clusters.

The focus on product-embodied R&D flows is important, as R&D efforts made in one sector do not only affect that sector itself, but can also have repercussions on other sectors through ‘imported’ innovations via intermediary products or investment goods (Düring and Schnabl 2000: 363). This effect holds especially for industrial clusters. As firms within industrial clusters do not only differ in their R&D efforts but also with respect to their use of technology embodied in goods produced by other firms, upstream suppliers and downstream customers within industrial clusters can become essential sources of productivity gains (Porter 2000: 256). In addition, inter-sectoral linkages can act as important sources of technological learning. In the 1960s, Schmookler (1966) observed that one potential way for industries to innovate is through the improvement of the inputs it buys from other industries. In this way, the success of interactive learning is supported by close localised input–output relations (Lundvall 1988; Lundvall and Johnson 1994; Edquist 1997). To sum up, if the transfer of technological knowledge works best with spatial proximity, ‘then any spillover that might be gained from a strong core of manufacturing and R&D will be easiest to exploit if the receiver of such spillovers locates near this core’ (Baptista and Swann 1998: 526).

Based on this assumption, we offer a systematic illustration of German industrial cluster structures with a special focus on the potential for inter-sectoral technology flows. The analysis allows specific insights into these important functional linkages, which have a high impact on regional technological progress and growth. The paper is structured as follows. After a short review of cluster theory and empirical approaches in industrial cluster research, we present a multiple-step approach for mapping potentials for inter-sectoral technology flows within industrial clusters. We apply this framework to the Federal Republic of Germany, describe the spatial allocation of industrial cluster structures, and compare differences in the internal structure of sectoral technological interdependencies of industrial clusters as expressed by (1) simple input–output flows; and (2) embodied technological knowledge flows. The paper also presents a case study of Nuremberg with its first order neighbouring regions and concludes with a discussion of the advantages of this new methodological framework and the classical tools of cluster identification.

## 2 Industrial clusters

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

The term 'cluster' was first used by Czamanski and Ablas (1979), and contributions to this topic increased with the introduction of Porter's diamond model (Cruz and Teixeira 2009). Porter (1998: 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 advantages such as related and supporting industries, factor and demand conditions, and the context for firm strategy and rivalry (1998).

Another approach explaining the advantages of the geographic concentration of economic activity was presented by the knowledge-based theory of spatial clustering (Malmberg and Maskell 2002). Based on a multidimensional approach, Malmberg and Maskell (2002) highlight localised learning capabilities as sources of cluster-specific advantages (see also Gordon and McCann 2000; Bathelt 2004; Benneworth and Henry 2004; Maskell and Malmberg 2007; and Blum 2008 for multidimensional approaches). Regionally concentrated specialised firms linked by value chains benefit from complementary competencies and a greater level of trust between partners (Bathelt *et al.*, 2004). Within the same step of the value chain firms show similar or substitutive competencies, leading to cognitive proximities that enable mutual learning and motivation. Even if they do not have any direct exchange with their competitors they can benefit from the parallel performance of similar tasks (Malmberg and Maskell 2002).

However, 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 Focus: The potential for Inter-Sectoral Technology Flows in Industrial Clusters**

Thus cluster theory highlights the role of sectoral interdependencies along the value-adding production chain as the key carrier of embodied and disembodied technological knowledge. However, direct observation of inter-sectoral technology flows is not possible (Düring and Schnabl 2000: 363). Bearing in mind that technological knowledge becomes diffused through different channels and can be identified with different indicators such as patents (Scherer 1982; Jaffe *et al.* 1993), innovation flow matrices (DeBresson 1996), formal co-operation projects (Jorde and Teece 1990; Katz and Ordover 1990), bibliometric analysis (Abramo *et al.* 2008) and other, informal ways, we use embodied R&D flows as a first approximation of the potentials for intersectoral technology flows within industrial cluster structures.

Input-output-based measures of sectoral interdependence have a long-standing tradition in the analysis of industrial cluster structures. An elementary cluster analysis was introduced by Bijnen (1973), but this focused only on the strongest inter-industry linkages to indicate sectoral interdependence and thus excluded potentially important secondary linkages. Oosterhaven *et al.* (2001) applied intra-regional intermediate sales matrices. To identify relevant inter-industry linkages they used above-average absolute intermediate transaction size, relative importance of intermediate transactions and absolute size of flows as threshold values. Sonis *et al.* (2008) proposed structural Q analysis to identify sectoral forward and backward linkage clusters in input-output systems. Hill and Brennan (2000) used discriminant analysis to group industries according to common variances in input-output tables. In combination with additional indicators such as regional specialisation and export characteristics, they identified cluster-specific driver industries. However, because of the restriction that one industry can belong only to one cluster, this approach is of limited use when an industry serves different sectors at

the same time (vom Hofe and Chen 2006). The most common method applied in the input–output field has been principal component factor analysis (Roepke *et al.* 1974; Czamanski 1974, 1976; Ó hUallacháin 1984; Feser and Bergman 2000; Feser *et al.* 2005). Feser and Bergman (2000), for example, used principal components factor analysis 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 used the similarity of intermediate purchases and sales structure to group different industries into one cluster (Oosterhaven *et al.* 2001). Thus the highest-loading industries were treated as being members of an industrial cluster (see also vom Hofe and Dev Bhatta 2007; Kelton *et al.* 2008 for recent applications), and the identified industrial clusters were seen as templates and used as indicators of regional transactions.

However, all these approaches used basic input–output-based linkages to measure sectoral interdependence. As one key element of industrial cluster success is an increase in factor productivity and innovativeness, the importance of interdependence between cluster agents has to be viewed in relation to R&D efforts and technological knowledge (Drejer 2003: 9). This highlights the importance of the re-evaluation of input–output coefficients and the introduction of knowledge within the input–output concept to avoid an over-estimation of the role of some industries compared to others in the transfer of technological knowledge (see, for example, Schnabl 1995; Leoncini *et al.* 1996; Verspagen 1997; Düring and Schnabl 2000; Los and Verspagen 2000).

We now present a multiple-step approach for the systematic identification of industrial clusters' potential for inter-sectoral technology flows, based on a graph-theoretical model. By applying input–output matrices supplemented with information about the R&D activities of the sectors we answer the question of whether sectors within industrial clusters in Germany can expect to receive localised spillover through technological knowledge flows from other sectors or not.

## **4 Methodological Framework**

The graph theoretical model is based on the approach of Titze *et al.* (2009a) who identified industrial clusters with the help of a combination of a measure of spatial concentration (for the identification of basic cluster structures within a region) and Qualitative Input–Output Analysis (QIOA) (for the identification of the vertical sectoral interdependence of identified industrial cluster structures). In the following three subsections we first explain the identification of basic cluster structures within a region. Next, we present the QIOA. And finally, we describe the incorporation of information on intersectoral technology flows to identify technology provider and user relationships in this framework.

### **4.1 The identification of basic cluster structures using the Sternberg and Litzenger (2004) cluster index**

The empirical literature on the identification of industrial clusters provides a wide range of analytical tools to calculate concentration measures (for a short overview see, for example, Aiginger *et al.* 1999). Among these, the Sternberg and Litzenger (2004) cluster index offers a suitable measure for cluster identification. This index involves three components: the relative industrial density, the relative industrial stock, and the relative size of establishments. Equation (1) describes the calculation of the cluster index (CI) of a branch  $i$  for a region  $r$ :

$$CI_{ir} = \frac{\frac{e_{ir}}{\sum_r e_{ir}} \cdot \frac{b_{ir}}{\sum_r b_{ir}}}{\frac{z_r}{\sum_r z_r} \cdot \frac{a_r}{\sum_r a_r}} \quad (1)$$

The variable  $e$  represents the number of employees,  $b$  denotes the number establishments,  $z$  is the number of inhabitants and  $a$  shows the area size of the respective region. The advantage of the use of this index in comparison to other simple measures of concentration (the Gini index, Herfindahl index etc.) arises out of the control for the firm size distribution within the clusters. Sternberg and Litzenberger (2004) argue that the spatial concentration of firms should not be dominated by just one or two establishments; therefore this measure needs to be included alongside a high industrial density and a high relative industrial stock to identify industrial clusters. The integration of the firm size distribution in the cluster index eliminates the problem of the misinterpretation of concentration.

#### 4.2 The Identification of vertical sectoral interdependence using the QIOA

The principle of QIOA relies on the need for a reduction in the complexity of the input–output table to apply graph theoretical methods. This method differentiates between important and unimportant buyer–supplier relations using national input–output tables. In other words, this procedure transforms a quantitative input–output table into qualitative information. Mathematically, this transformation can be realised by a binarisation of the input–output table. An intermediate input flow  $s$  between sector  $i$  and sector  $j$  becomes 1 if it exceeds a filter rate  $F$ . Otherwise the flow becomes 0. The resulting matrix is denoted as adjacency matrix  $W$ :

$$w_{ij} = \begin{cases} 1 & \text{if } s_{ij} > F \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Equation (2) makes clear that the value of the filter rate  $F$  influences the number of important intermediate input flows. Schnabl (1994, 2000) developed a multi-stage iterative procedure to determine this filter value endogenously. The algorithm aims to minimise the loss of information through the binarisation – or, in other words, the procedure aims to maximise the information content of the binary input–output table (for recent applications see, for example, Titze *et al.* 2009a; 2009b). To determine the optimal filter rate, Titze *et al.* (2009a) applied two different measures: an entropy measure and the average value of an element of the resulting connectivity matrix. The optimal filter rate can be derived from the average of these two measures.

The input–output flows in the national input–output tables provided by the Federal Statistical Office of Germany represent individual buyer–supplier relations valued in currency units. This gives us information about the value of traded intermediates between two sectors. However, these flows do not contain information about the degree of technological knowledge being transferred by the products. This problem can be solved if we re-evaluate the input–output flows. Mathematically, we have to solve an assignment problem. The next subsection describes an approach that transforms input–output flows into product-embodied R&D flows.

### 4.3 Identification of product-embodied R&D flows within an input–output framework

The classical input–output model relies on Equation (3), where  $x$  is the vector of production values,  $C$  denotes the Leontief inverse and  $y$  represents the vector of total demand:

$$x = C \cdot y \quad (3)$$

The Leontief inverse can be written as Eulerian series, in which  $I$  denotes the unit matrix and  $A$  reflects the matrix of input coefficients:

$$C = (I - A)^{-1} = I + A + A^2 + A^3 + \dots \quad (4)$$

In the next step we can apply the basic assignment model, in which  $Z$  is the re-evaluated core matrix of the input–output model;  $B^D$  is the assignment matrix and  $\langle y \rangle$  is the diagonal matrix of the total demand vector (for details see, for example, Meyer-Krahmer and Wessels 1989; Schnabl 1995, 2000; Straßberger and Stäglin 1995):

$$Z = B^D \cdot (I - A)^{-1} \cdot \langle y \rangle \quad (5)$$

Equation (6) shows the replacement of the total demand vector by a synthetic vector  $I$ . This step allows the identification of the ‘technological’ structure of the core matrix. For our purposes, we use the standard vector. After the diagonalisation, this corresponds with the unit matrix  $I$ :

$$Z = B^D \cdot (I - A)^{-1} \cdot I = B^D \cdot (I - A)^{-1} \quad (6)$$

The assignment matrix  $B^D$  equals the diagonal matrix of the vector  $b^{R\&D}$  including the number of R&D employees multiplied by the diagonal matrix of the production value vector  $x$ . In addition there are other different approaches to integrate innovation or knowledge into interdependence studies (Drejer 2003: 9). The application of R&D employees is in line with Leoncini *et al.* (1996). In contrast, Verspagen (1997) and Los and Verspagen (2000) use patent data; Schnabl (1995) and Düring and Schnabl (2000) apply sectoral R&D expenditures; and Drejer (1999) relies on multiple indicator R&D expenditures supplemented by patent grants and the formal qualifications of employees.

$$B^D = \langle b^{R\&D} \rangle \cdot \langle x \rangle^{-1} \quad (7)$$

Re-evaluating the original input–output flows, we get information about the R&D intensity of these flows – the product-embodied R&D flows. Thus it is assumed that the product-embodied technology flows between sectors are proportional to the R&D employees of the industries. According to Equation (4), one can separate Equation (6) into the following layers:

$$\begin{aligned} Z_1 &= B^D \cdot A \\ Z_2 &= B^D \cdot A^2 \\ Z_3 &= B^D \cdot A^3 \quad \text{etc.} \end{aligned} \quad (8)$$

Thus layer zero is excluded from the analysis because it contains only the diagonal matrix  $B^D$  of the vector  $b^{R\&D}$  divided by the vector  $x$  according to Equations (4) and (7). In the following step, we transform each layer matrix into a binary adjacency matrix  $W_k$ , where:

$$w_{ij}^k = \begin{cases} 1 & \text{if } z_{ij}^k > F \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

We continue the layer-wise calculation of adjacency matrices  $W_k$  until no element  $z_{ij}^k$  of the  $Z_k$  matrices exceeds the filter rate  $F$ . In addition, we calculate the product matrix  $W^k$  as follows:

$$W^k = W_k \cdot W^{k-1} \text{ for } k > 0 \quad (10)$$

The  $W^k$  matrix involves the sectoral interdependencies between the sectors via the varying layers. In the next step we calculate the dependence matrix  $D$  by adding the product matrices  $W^k$  layer-wise. We apply a Boolean addition (marked by '#') as it is important to know whether a connection exists between two sectors. Information on how many layers are needed to fulfil the filter criterion is not necessary here.

$$D = \#(W^1 + W^2 + W^3 + \dots) \quad (11)$$

Equation (11) determines the connectivity matrix  $H$ :

$$H = D + D' + D \quad (12)$$

The element  $h_{ij}$  of the connectivity matrix  $H$  gives us information about the type of intersectoral product-embodied R&D flows. A zero indicates that no sectoral interdependencies exist between  $i$  and  $j$ ; a value of one can be interpreted as a technology user; and a value of two reflects a technology supplier relationship. When  $H$  shows values of 3, a sector both provides and uses knowledge from other sectors. The procedure for the calculation of the optimal filter rate equals the indicators used in the basic approach. We apply the entropy measure and the average value of an element of the resulting connectivity matrix.

## 5 Empirical results

We now apply the proposed framework and compare the differences in the industrial cluster structures in Germany when applying solely input–output flows and product embodied R&D flows. The analysis is carried out for the year 2003 at the NUTS 3 level (districts and district-free cities). For the calculation of the cluster index we use data on the number of inhabitants for 2003 and the area size for 2004 as provided by the Federal Statistical Office of Germany (Regionaldatenbank Deutschland, codes 173-01-4 and 171-01-4). Data on the number of employees and the number of establishments stem from the Federal Employment Office of Germany. The QIOA is based on the input–output table from 2003 provided by the Federal Statistical Office of Germany (Fachserie 18, row 2, published on 20 April 2007, revised 7 May 2008). This table contains 71 industrial sectors. Information about the sector's number of R&D employees is calculated from the data of the German Mikrozensus survey (2004), provided by the Federal Statistical Office of Germany.

The first part of this section identifies industrial clusters in Germany. In the second subsection we compare the results of intersectoral interdependencies based on the application of input–output flows alone and on product-embodied R&D flows. In the third subsection we analyse the effect of differences on the internal structure of industrial clusters in Germany. Finally, we carry out a case study of Nuremberg and its first-order neighbours to illustrate a graphical model of the industrial cluster structures in this region.

## **5.1 The identification of industrial clusters in Germany**

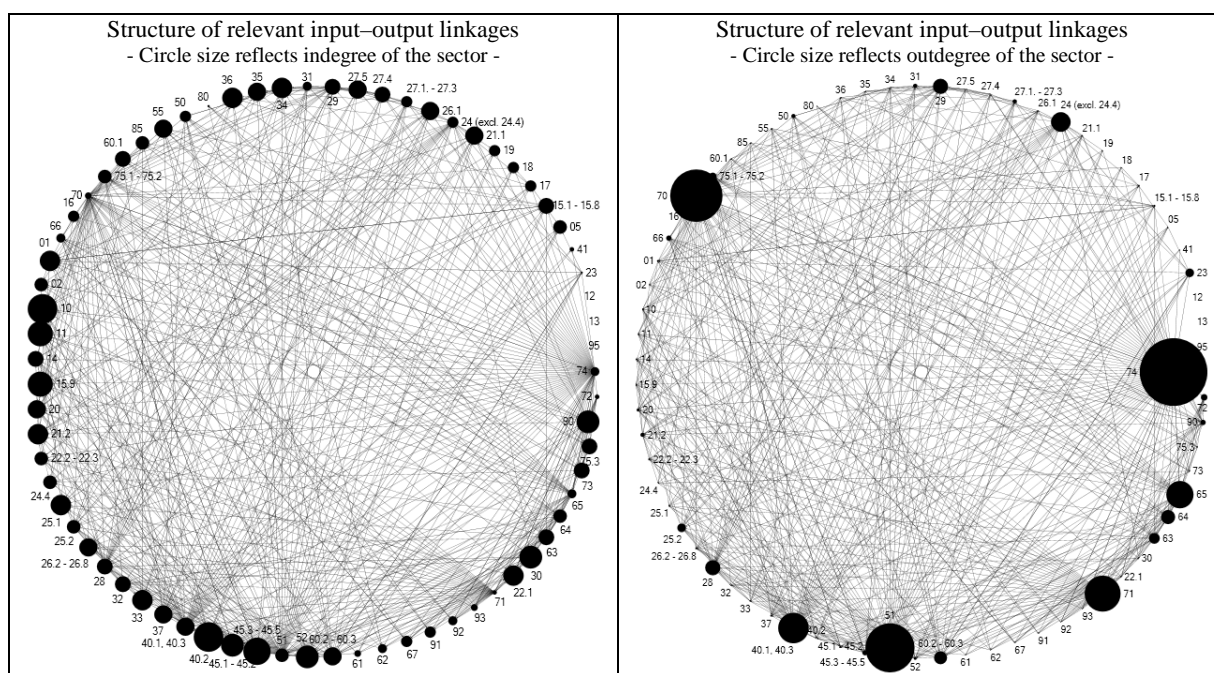
To identify industrial clusters in German regions (NUTS 3 level) we apply the Sternberg and Litzenger (2004) cluster index for the year 2003. The critical element in this analysis is the definition of a threshold value. Sternberg and Litzenger (2004) propose that a cluster index of 4 can be interpreted as the first sign of clustering. In line with other studies on cluster identification in Germany (for example, Brenner 2006) we chose a cluster index of 64, so the component values of the index are four times higher than average. By applying this threshold value we identify 347 industrial clusters in Germany allocated in 177 out of 439 regions (40.3 per cent). With respect to the sectoral structure 194 out of 347 industrial clusters (53.3 per cent) are related to the manufacturing sector. In total, 50 sectors out of 71 were involved in our analysis. A high number of industrial clusters are located in the West German agglomerations of Munich, Frankfurt am Main, Nuremberg, Stuttgart, Hamburg and Düsseldorf. Other important horizontal clusters can be identified in the regions of Würzburg, Kassel, Mainz and Darmstadt. With respect to East Germany, important locations of horizontal clusters can be found in the regions of Jena, Dresden, Zwickau, Stralsund and Rostock.

## **5.2 Identifying sectoral interdependence based on input–output flows alone and product-embodied R&D flows**

To characterise the sectoral interdependencies of the identified industrial clusters, we first apply QIAO to input–output flows alone. The optimum filter rate is 0.0097 in terms of input coefficients. Applying this filter rate to the input–output table, 521 out of 4,790 ( $71 \times 71 - 71$  main diagonal) elements remain as important sectoral interdependencies. Figure 1 shows the structural characteristics of the relevant input–output linkages. The figures are differentiated by the indegree (the number of important vertical linkages where a sector receives inputs from others) and outdegree (the number of important vertical linkages where a sector provides inputs to others) of the 71 sectors of the national input–output table. Thus the indegree of relevant input–output linkages is more evenly distributed between the sectors, with a maximum number of 14 ingoing relations in sectors 10 (Mining of coal) and 40.2 (Distribution of gas). Three sectors remain isolated in this framework (sectors 12 - Mining of uranium and thorium ores, 13 - Mining of metal ores and 95 - Private households' services). In contrast, the outdegree of the sectors is distributed more unevenly and dominated by the service sectors 74 (Business activities), 71 (Renting), 70 (Real estate activities) and 65 (Financial intermediation). These sectors serve a wide set of other sectors. Regarding the manufacturing sector, sectors 24 (Chemicals), 28 (Fabricated metal products) and 29 (Machinery) in particular provide substantial relevant input–output linkages for the economy.



Figure 1: Structural characteristics of important input–output linkages



01 – Agriculture; 02 – Forestry; 05 – Fishing; 10 – Mining of coal; 11 – Extraction of crude petroleum; 12 – Mining of uranium; 13 – Mining of metal ores; 14 – Other mining and quarrying; 15.1–15.8 – Food products; 15.9 – Beverages; 16 – Tobacco products; 17 – Textiles; 18 – Wearing apparel; 19 – Tanning; 20 – Products of wood and cork; 21.1 – Pulp, paper; 21.2 – Articles of paper and paperboard; 22.1 – Publishing; 22.2–22.3 – Printing; 23 – Coke, refined petroleum products; 24.4 – Pharmaceuticals; 24 (excluding 24.4) – Chemicals (excluding pharmaceuticals); 25.1 – Rubber; 25.2 – Plastic; 26.1 – Glass; 26.2–26.8 – Ceramic; 27.1–27.3 – Basic iron; 27.4 – Basic precious and non-ferrous metals; 27.5 – Casting of metals; 28 – Fabricated metal products; 29 – Machinery; 30 – Manufacture of computers; 31 – Electrical machinery; 32 – Communication equipment; 33 – Precision instruments; 34 – Motor vehicles; 35 – Other transport equipment; 36 – Furniture; 37 – Recycling; 40.1, 40.3 – Electricity; 40.2 – Gas; 41 – Water; 45.1–45.2 – Civil engineering; 45.3–45.5 – Building installation; 50 – Sale; 51 – Wholesale trade; 52 – Retail trade; 55 – Hotels and restaurants; 60.1 – Transport via railways; 60.2–60.3 – Other land transport; 61 – Water transport; 62 – Air transport; 63 – Supporting transport activities; 64 – Post and telecommunications; 65 – Financial intermediation; 66 – Insurance and pension funding; 67 – Financial intermediation; 70 – Real estate activities; 71 – Renting of machinery; 72 – Computer and related activities; 73 – Research and development; 74 – Other business activities; 75.1–75.2 – Administration of the state; 75.3 – Compulsory social security activities; 80 – Education; 85 – Health and social work; 90 – Sewage and refuse; 91 – Membership organisations; 92 – Culture and sport; 93 – Other service activities; 95 – Private households.

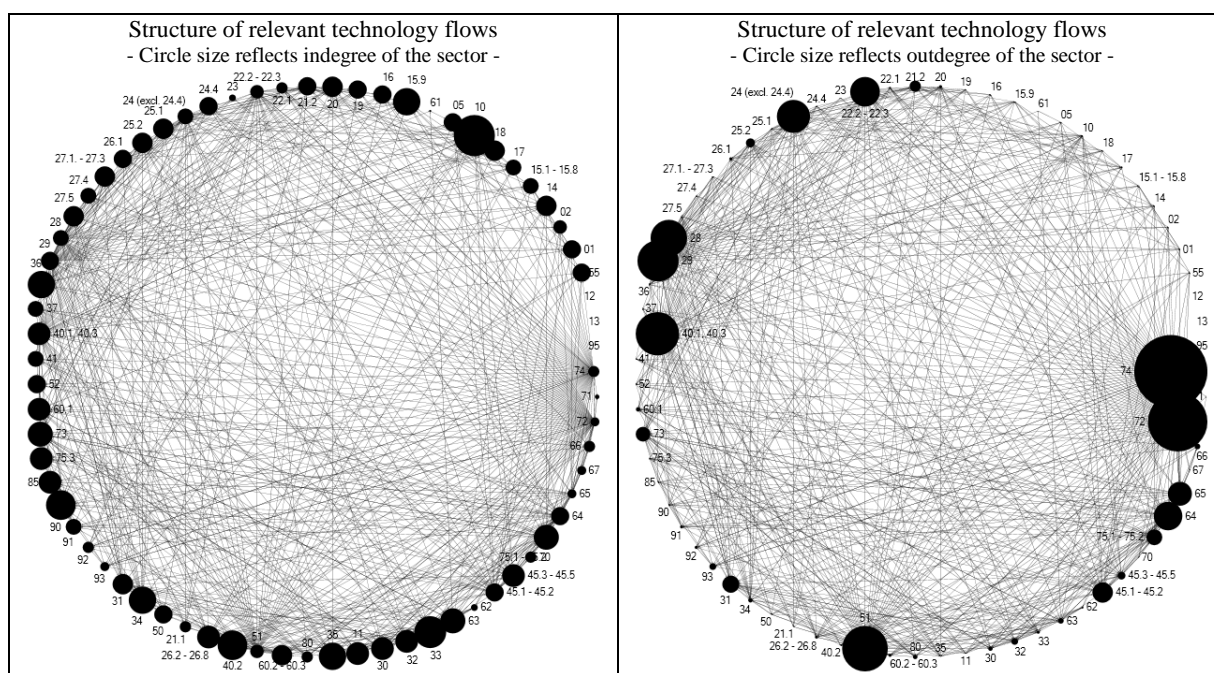
Rank	Sector	In-Degree	Sector	Out-Degree	Sector	Betweenness Centrality
1.	40.2	14	74	64	74	1008.3
2.	10	14	70	50	51	550.6
3.	45.3–45.5	13	51	47	70	471.3
4.	15.9	12	71	35	71	287.9
5.	11	12	40.1, 40.3	30	40.1, 40.3	252.5
6.	90	11	64	27	65	103.8
7.	30	11	24 (excl. 24.4)	20	24 (excl. 24.4)	92.3
8.	52	11	28	16	60.2–60.3	66.4
9.	45.1–45.2	11	29	16	28	62.6
10.	22.1	10	64	15	29	54.3
11.	33	10	60.2–60.3	14	63	52.4
12.	25.1	10	63	12	64	49.4
13.	21.1	10	25.2	10	45.3–45.5	38.7
14.	01	10	23	10	90	35.9
15.	36	10	75.1–75.2	9	52	30.0

Source: Authors' own illustration.

The introduction of innovation and knowledge in the input–output framework leads to substantial changes in the internal structure of sectoral interdependencies. Here, the optimal filter rate is 0.00172. Based on this filter rate, 616 inter-industry linkages can be identified as important product-embodied R&D flows between the 71 sectors of the input–output table. Figure 2 presents the structural

characteristics of these. While the indegree of the sectors is more evenly distributed than the outdegree, we can identify the increasing importance of the manufacturing sector as the provider of technological spillover via product-embodied technology flows. In particular, sectors 29 (Machinery), 28 (Fabricated metal products), 22.2–22.3 (Printing), 24 - excl. 24.4 (Chemicals), 73 (Research and development) and 31 (Electrical machinery) experienced sharp increases in important sectoral interdependencies and played a more pronounced role as technology providers in the analytical framework.

Figure 2: Structural characteristics of important product embodied R&D flows



01 – Agriculture; 02 – Forestry; 05 – Fishing; 10 – Mining of coal; 11 – Extraction of crude petroleum; 12 – Mining of uranium; 13 – Mining of metal ores; 14 – Other mining and quarrying; 15.1–15.8 – Food products; 15.9 – Beverages; 16 – Tobacco products; 17 – Textiles; 18 – Wearing apparel; 19 – Tanning; 20 – Products of wood and cork; 21.1 – Pulp, paper; 21.2 – Articles of paper and paperboard; 22.1 – Publishing; 22.2–22.3 – Printing; 23 – Coke, refined petroleum products; 24.4 – Pharmaceuticals; 24 (excluding 24.4) – Chemicals (excluding pharmaceuticals); 25.1 – Rubber; 25.2 – Plastic; 26.1 – Glass; 26.2–26.8 – Ceramic; 27.1–27.3 – Basic iron; 27.4 – Basic precious and non-ferrous metals; 27.5 – Casting of metals; 28 – Fabricated metal products; 29 – Machinery; 30 – Manufacture of computers; 31 – Electrical machinery; 32 – Communication equipment; 33 – Precision instruments; 34 – Motor vehicles; 35 – Other transport equipment; 36 – Furniture; 37 – Recycling; 40.1, 40.3 – Electricity; 40.2 – Gas; 41 – Water; 45.1–45.2 – Civil engineering; 45.3–45.5 – Building installation; 50 – Sale; 51 – Wholesale trade; 52 – Retail trade; 55 – Hotels and restaurants; 60.1 – Transport via railways; 60.2–60.3 – Other land transport; 61 – Water transport; 62 – Air transport; 63 – Supporting transport activities; 64 – Post and telecommunications; 65 – Financial intermediation; 66 – Insurance and pension funding; 67 – Financial intermediation; 70 – Real estate activities; 71 – Renting of machinery; 72 – Computer and related activities; 73 – Research and development; 74 – Other business activities; 75.1–75.2 – Administration of the state; 75.3 – Compulsory social security activities; 80 – Education; 85 – Health and social work; 90 – Sewage and refuse; 91 – Membership organisations; 92 – Culture and sport; 93 – Other service activities; 95 – Private households.

Rank	Sector	In-Degree	Sector	Out-Degree	Sector	Betweenness Centrality
1.	10	19	74	66	74	848.4
2.	33	15	72	54	72	502.3
3.	40.2	14	51	42	40.1, 40.3	317.0
4.	90	14	40.1, 40.3	40	51	284.0
5.	35	13	29	38	29	261.0
6.	34	13	28	34	28	157.5
7.	36	13	24 (excl. 24.4)	31	22.2–22.3	130.4
8.	15.9	13	22.2–22.3	28	64	106.7
9.	75.1–75.2	12	64	27	24 (excl. 24.4)	104.5
10.	63	12	65	23	45.1	82.9
11.	73	12	45.1–45.2	20	65	79.6
12.	45.3–45.5	11	31	17	75.1–75.2	70.8
13.	32	11	75.1–75.2	16	63	49.7
14.	30	11	73	15	73	38.4
15.	11	11	21.2	12	31	34.1

Source: Authors own illustration.

Another important question is: do important intermediate goods flows alone match important product-embodied R&D flows? Table 1 answers this question. In total, 4,198 relations are neither important intermediate goods flows nor important product-embodied R&D flows. With respect to important

product-embodied R&D flows, 365 (59.3 per cent) out of 616 match important intermediate goods flows, while 251 (40.7 per cent) do not. If we focus on important intermediate goods flows alone, 365 out of 521 (70.1 per cent) match important product-embodied R&D flows, while 156 (29.9 per cent) do not. These differences in the structure of inter-industry relations have led to changes in the structural characteristics of the industrial cluster structures under analysis.

Table 1: Matching of different kinds of intermediate input flows

Number of elements in the binary input–output table	Original intermediate input flows		Total
	0	1	
Intermediate input flows valued at employment in R&D	0	1	
	4198	156	4354
	251	365	616
Total	4449	521	4970 <sup>a</sup>

<sup>a</sup> The input–output table provided by the Federal Statistical Office of Germany shows the intermediate goods flows of 71 sectors. Because we disregard intra-sectoral relations, we have  $71 \times 71 - 71$  (main diagonal elements) = 4,970 elements of the binary input–output table.

Source: Authors' own calculations and illustration.

### 5.3 Sectoral interdependencies of industrial clusters in Germany – an application at the regional level

To specify the industrial cluster structures in the German regions we rely on a classification scheme that allows the assignment of each region to a specified class of industrial clusters (see Titze *et al.* 2009: 9). The classification scheme is based on two elements: first, the number of industrial clusters in the region; and second, the number of important sectoral interdependencies between those industrial clusters. The specifications of the two elements result in five classes (see Table 2). In class 1, no concentrated economic activity can be identified. Regions with only one industrial cluster form class 2. A minimum condition for the existence of vertical sectoral interdependencies is the localisation of more than one industrial cluster in the region. Regions which possess more than one horizontal cluster can be divided into three further classes. Regions with no potential for sectoral interdependencies are grouped in class 3, class 4 hosts regions showing the potential for one vertical relation, while regions with the potential for more than one vertical relation are allocated to class 5.

Table 2: A classification scheme for industrial cluster structures

Number of linkages	Number of horizontal clusters		
	Zero	One	More than one
No linkages	Class 1	Class 2	Class 3
One linkage			Class 4
More than one linkage			Class 5

Source: Titze *et al.* 2009a: 9.

Applying the classification scheme, we identified 262 regions with no concentrated economic activity (class 1; see Table 3), and 103 regions possess only one industrial cluster (class 2). If regions host more than one horizontal cluster they show potential for vertical sectoral interdependencies. Thus we can distinguish three different kinds of buyer–supplier relations. With regard to important intermediate goods flows, 17 regions can be grouped into class 4. Only 14 (3.2 per cent) of the 439 regions fulfil the criteria of class 5.

Table 3 allows us to distinguish the effects of different measures of sectoral interdependencies on industrial cluster structures. If we compare the results for the application of important intermediate goods flows with those for product-embodied R&D flows we can show that more regions were able to attract potential vertical relations, but this increase is very small (17 versus 18 in class 4, and 14 versus 18 in class 5).

Table 3: Description of the structural characteristics of industrial clusters

Class	Description	Number of regions			
		Intra-regional flows		Intra- and inter-regional <sup>a</sup> flows	
		Important intermediate goods flows	Product embodied R&D flows	Important intermediate goods flows	Product embodied R&D flows
1	Regions with no concentrated economic activity	262			
2	Regions with one industrial cluster	103		25	
3	Regions with more than one industrial cluster	43	38	78	79
4	Regions with one sectoral interdependency of industrial clusters	17	18	29	27
5	Regions with more than one sectoral interdependency of industrial clusters	14	18	45	46
Total number of regions		439			

<sup>a</sup> Including the region's flows with its first order neighbours under the condition that the region under analysis possesses at least one cluster.

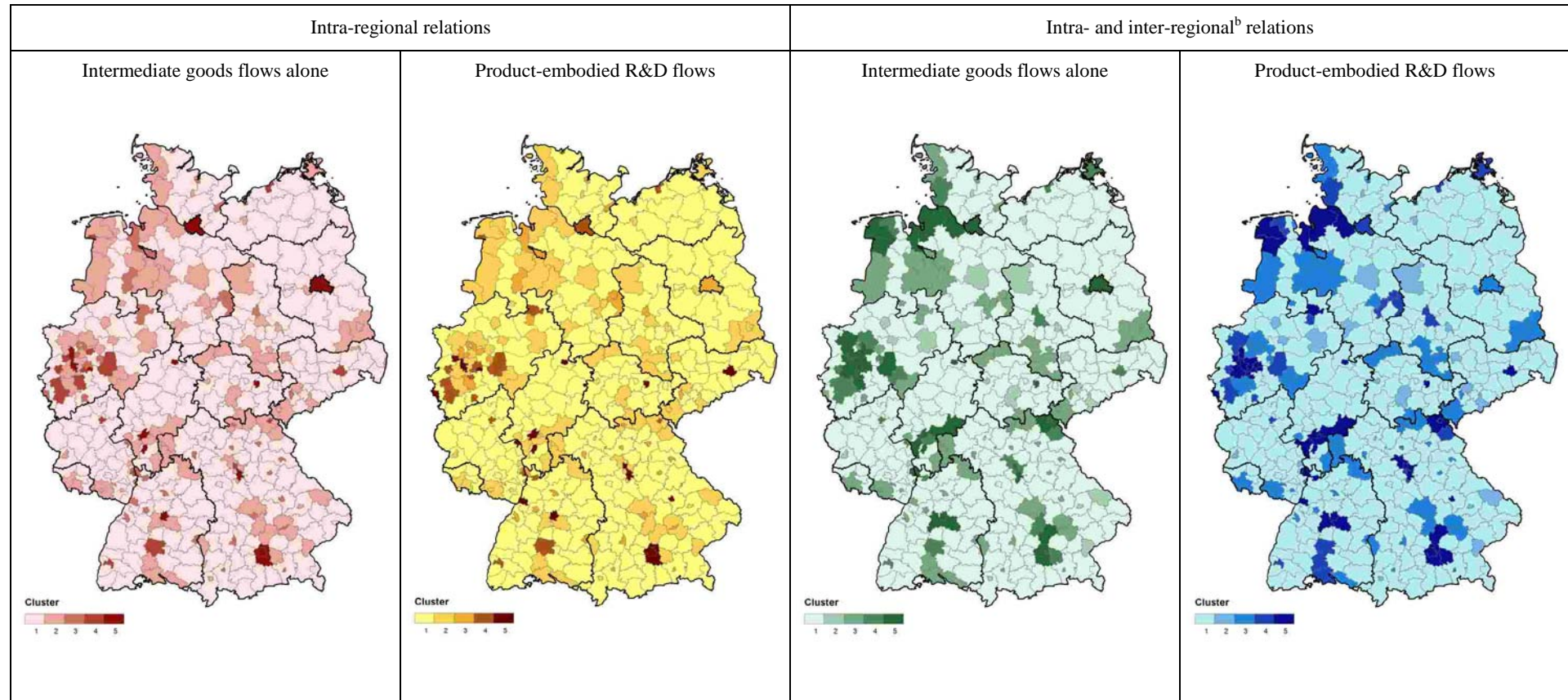
Source: Authors' own calculations based on Titze *et al.* 2009a:10.

We extend the regional focus of our analysis from the local to the regional level, and we may expect that the intensity of sectoral interdependencies will increase. We analyse the regional dimension of industrial clusters by integrating first-order neighbouring regions in the analysis. If the region under analysis possesses at least one industrial cluster, we search in a second step for any relations this local cluster may have with industrial clusters in neighbouring regions. We interpret these additional relations as the extended range of local industrial clusters. With respect to Table 3, we can determine that 25 out of 103 regions (class 1) are not able to widen their industrial base if we consider the neighbouring regions too. On the other hand, 78 out of 103 regions with one industrial cluster have neighbouring regions that possess at least one cluster. Here, the minimum condition exists for the formation of vertical linkages between clusters located in neighbouring regions. Against this background there is the not unexpected result that the number of regions showing cluster

characteristics increases. Furthermore, there appear to be no strong differences between important intermediate goods flow linkages and product-embodied R&D flows with respect to the number of regions having cluster structures. Figure 3 illustrates the spatial allocation of the industrial cluster structures in Germany.

With our approach, strong local vertical industrial clusters can be seen in the large urban areas of Hamburg, Berlin, Munich, Frankfurt am Main and Cologne. The south-west of Germany (Baden-Württemberg) and the Ruhr area in particular show spatially concentrated economic sectors which are rather linked intermediate goods flows alone and product-embodied R&D flows. East Germany as a whole lacks concentrated economic activity. Only a couple of regions hosted important production sites: Rostock, Stralsund and Wismar as maritime clusters; Dresden and Jena as high-tech clusters; Zwickau as an automotive cluster; and Magdeburg as a recycling cluster.

Figure 3: The spatial allocation of German cluster structures<sup>a</sup>



<sup>a</sup> According to the classification scheme cluster classes are denoted as follows: 1 Regions with no concentrated economic activity, 2 Regions with one industrial cluster, 3 Regions with more than one industrial cluster, 4 Regions with one sectoral interdependency of industrial clusters, 5 Regions with more than one sectoral interdependency of industrial clusters.

<sup>b</sup> Including the region's flows with its first-order neighbours, with the condition that the region under analysis possesses at least one cluster.

Source: Authors' own calculations and illustrations.

If we widen the geographical scope from local to regional clusters we expect an increasing degree of clustering. Indeed, if we examine important production sites (horizontal clusters) in (first-order) neighbouring regions we can identify a higher number of regions possessing sectoral interdependencies according to the input–output framework. Furthermore, we can determine differences between intermediate goods flows alone and product-embodied R&D flows. Cluster literature highlights this phenomenon as being important for the development of sustainable regional growth. In line with this idea we shall deal in detail with the differences mentioned.

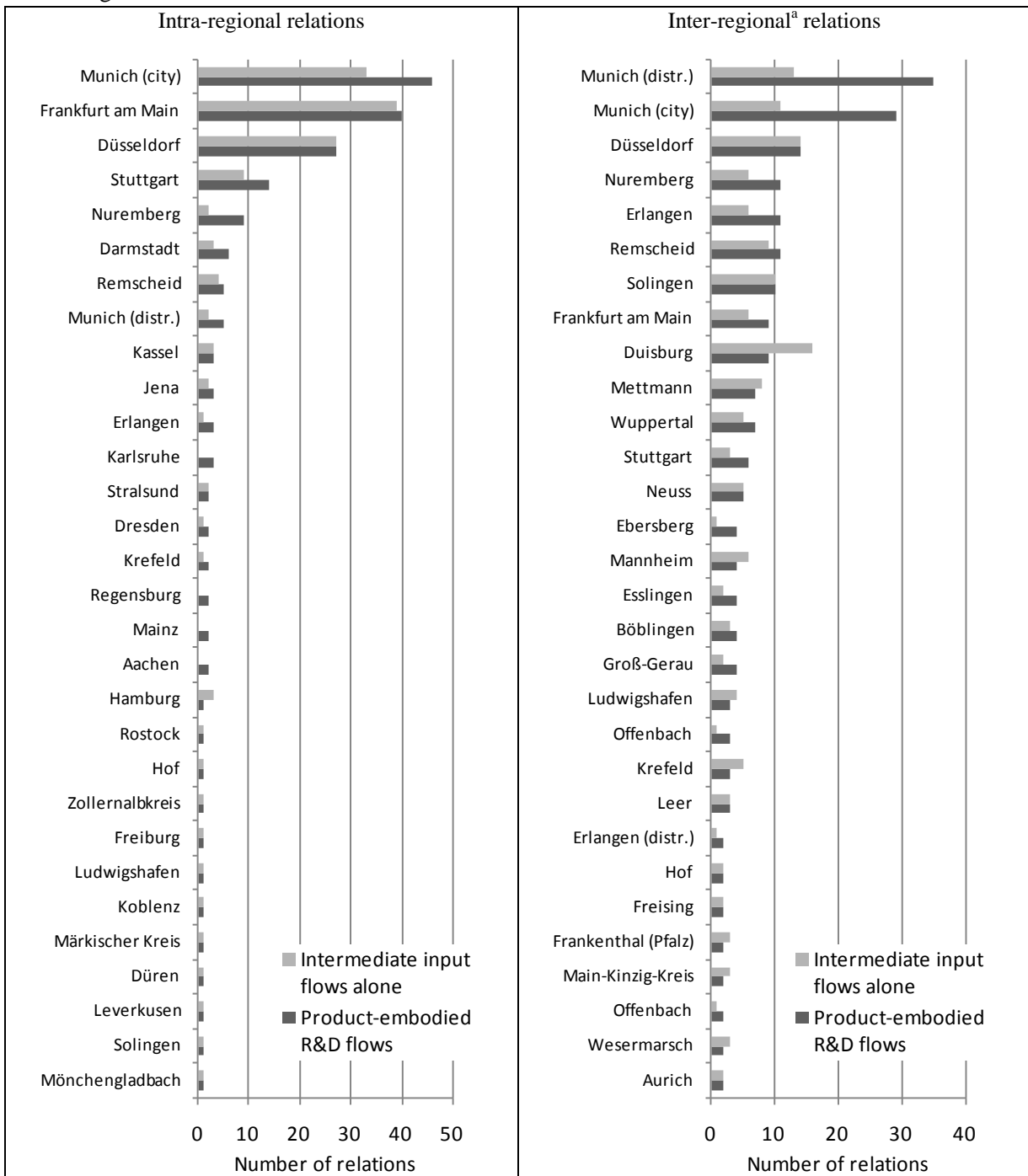
At this point we must pay attention to the fact that changes in cluster structures can only occur in regions possessing one or two important production site(s) at least. If a region lacks concentrated economic activities it becomes irrelevant for analyses of differentiated kinds of intermediate flows. So we describe in detail those regions that are capable of attracting important connected production locations according to the presented approach. In Figure 4 we distinguish first between intra- and inter-regional flows, and second between intermediate input alone and product-embodied R&D flows in the 30 most important regional clusters.

The left-hand side of Figure 4 displays regions possessing important production sites which show a higher degree of interaction in terms of product-embodied R&D flows than in intermediate input flows alone. Munich is a remarkable example of this phenomenon, as it hosts 13 horizontal clusters. With the sole focus on intermediate input flows alone one can detect 33 inter-industry relations. The number of connections increases to 46 if we consider product-embodied R&D flows rather than intermediate input flows alone. Obviously, these regions possess important production sites that are related predominantly in terms R&D linkages. Jena and Dresden are examples of that phenomenon in East Germany. On the other hand, there are regions showing an equal or higher degree of connectivity in terms of pure intermediate goods flows (Düsseldorf, Kassel, Hamburg, etc.). Obviously, these regions are dominated by important production locations that are linked in particular by original intermediate input flows.

The right-hand side of Figure 4 illustrates the changes if we take the first-order neighbouring regions into account. Here, we can also distinguish between the patterns discussed above. The district of Munich hosts only 3 important production locations (sector 72: Computer and related activities; and sector 73: Research and development). The degree of interaction between these two sectors and others situated in neighbouring regions is extremely high in terms of product-embodied R&D flows. In total, we can detect 35 direct linkages to production sites in neighbouring regions. In contrast to that, a couple of regions show strong direct linkages in terms of intermediate input flows alone (Duisburg, Mannheim, Mettmann, etc.). To sum up, the outlined approach gives us insights into the nature of different industrial clusters: pure value chains versus R&D intensive inter-industry relations, and local versus regional connections.



Figure 4: Changes in the structural characteristics of selected industrial clusters: the 30 most important cluster regions



<sup>a</sup> Including the region's direct flows with its first-order neighbours under the condition that the region under analysis possesses at least one cluster.

Source: Authors' own calculations and illustration.

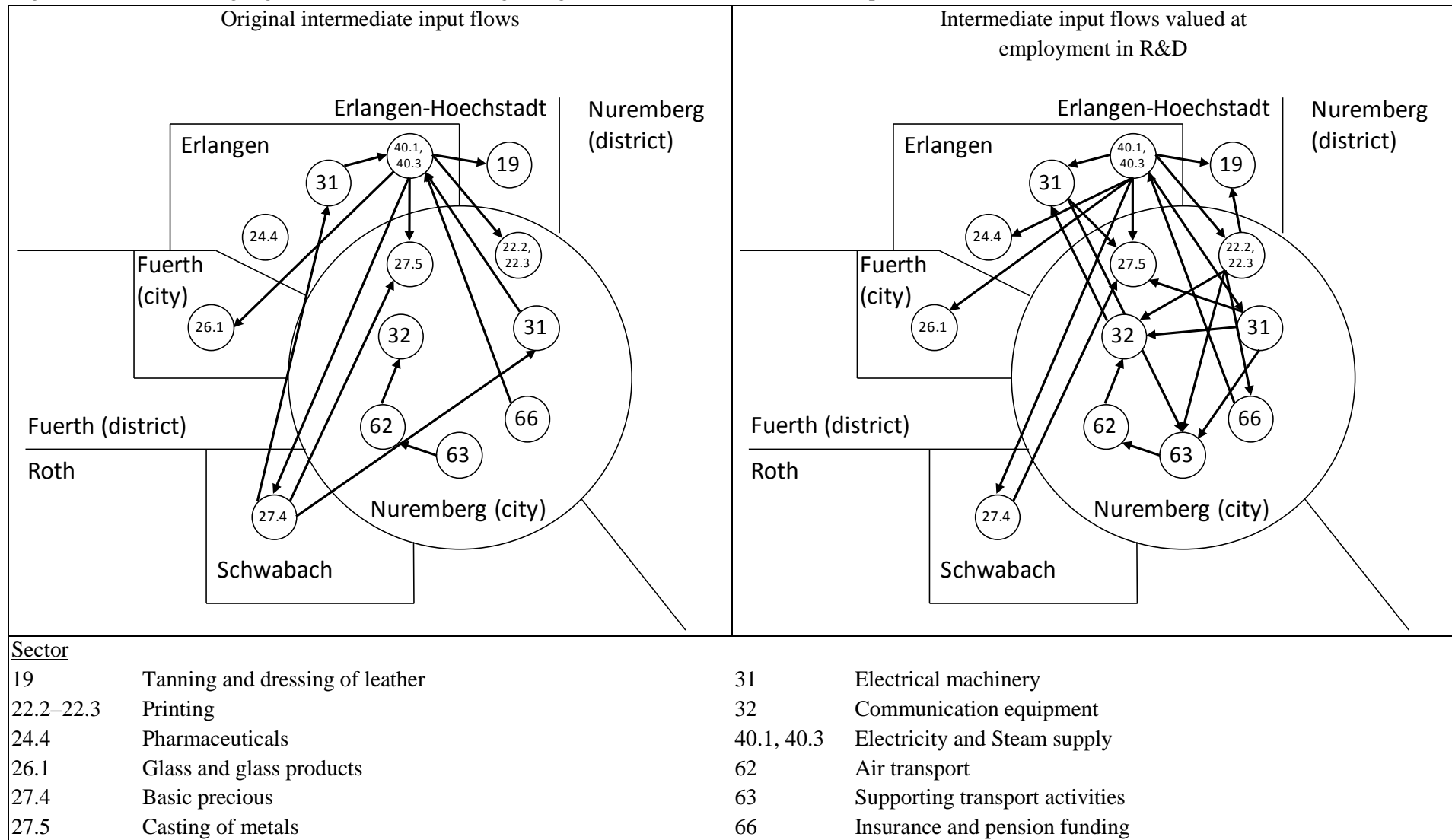
#### 5.4 Case study: Nuremberg

Using the example of Nuremberg and its neighbouring regions we illustrate the potential of the applied methodology. The greater Nuremberg region shows strong concentrations specifically in the

manufacturing sectors (19, 22.2–22.3, 24.4, 26.1, 27.4, 27.5, 31 and 32; see Figure 5). With respect to Nuremberg city, one can identify that only a small number of industrial clusters show vertical sectoral interdependencies in terms of important intermediate goods flows, indicating only a weak intra-regional potential to benefit from interaction. By increasing the spatial focus, the number of potential sectoral interdependencies rises. One can detect clusters in the neighbouring regions that are linked with industrial clusters in the city of Nuremberg. Here, the cluster Electricity and Steam supply (40.1, 40.3) plays a dominant role because it is strongly linked to other energy-intensive sectors, such as Glass production (26.1) and Casting of metals (27.5), in Nuremberg and surrounding regions. The region of Schwabach hosts another strongly interdependent cluster: the sector Basic precious and non-ferrous metals (27.4). To sum up, if we take Nuremberg's neighbouring regions into account, the structural graph becomes more complex and industrial cluster structures are described more comprehensively.

If we examine R&D intensive buyer–supplier relations, however, we get a different picture. First, we can see that the intra-regional interactions are more complex. Here, the sectors Printing (22.2–22.3), Electrical machinery (31) and Communication equipment (32) act as key players. Second, clusters in Nuremberg's neighbouring regions complete the structural graph. If we compare the two structural graphs we can determine that a number of linkages become apparent if the framework is extended from intermediate goods flows and product-embodied R&D flows. So, the sole focus on intermediate goods flows would identify only incompletely the potential for technological knowledge spillover in these industrial cluster structures, and the same applies to the regional focus of industrial cluster structures.

Figure 5: The Nuremberg region's cluster structures regarding different kinds of intermediate inputs



Source: Authors' own calculations and illustration.

## 6 Conclusions

This paper has dealt with the extent to which differences in the structure of potential inter-sectoral technology flows can be analysed with the help of a product-embodied R&D flow matrix. The claim was that a relatively simple graphical representation of relevant product-embodied R&D flows could illustrate substantial differences in potential for technological spillovers within industrial clusters. The potential for inter-sectoral technology flows studied was only local and regional. This, of course, does not imply that external linkages (for example, global pipelines in the sense of Bathelt *et al.* 2004) are not crucial in understanding and explaining technological knowledge spillovers within industrial clusters. Furthermore, the identified sectoral interdependencies do not show real linkages but only the potential for them. These linkages occur from the production-engineering point of view. Even though we have not detected real linkages, this analysis may help regional policy-makers to understand the structure and nature of potential inter-industry linkages at the local and regional level.

The approach used is based on four assumptions. First, we assume that the classification scheme of input–output statistics (CPA: classification of products by activity) is nearly equivalent to the NACE code. The second assumption applies to the technical production structure in the regions under analysis. We suppose that the industry templates derived from the input–output table at the national level are also applicable to the regional level, assuming that important industrial relations are (nearly) identical between different sectors at the national level to those of the regional level. Third, it is assumed that the sector’s productivity is equal in all the regions under analysis. Fourth, it is assumed that the product-embodied knowledge flows are proportional to the number of R&D employees in the sector, as well as the quantitative extent of the flows of intermediate goods between the user and producer industries (Drejer 2000: 381). We need this assumption to apportion intermediate inputs to the regional level according to the regional share of employment in the relevant sector. With these rigid assumptions in mind, the approach is able to illustrate systematically the potential for local and regional technological knowledge spillover within industrial clusters in Germany.

The approach shows that these potentials occur predominantly in the West German agglomerations like Munich, Frankfurt am Main, Nuremberg, Stuttgart, Düsseldorf und their first-order neighboring regions. East Germany is showing structural weaknesses regarding these potentials. Only a few regions like Dresden, Jena, Rostock and Stralsund possess industrial cluster structures offering potentials for inter-industry linkages. Even more apparent is the strong localized nature of these potentials in Eastern Germany. While West German regions often show related industrial cluster structure in their first order neighboring regions East German regions fall short of this phenomenon.

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