8. Measuring specialisation and concentration in regional clusters – an empirical analysis for Eastern Bavaria

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8.1 INTRODUCTION

What is a cluster? Is it more than just a fashionable brand used for a strand of regional politics and economic development? A prerequisite of a brand is a definition and a clear shape. Clusters have not attained these sharp outlines yet. Despite a vast literature on the topic, an unequivocal definition that also includes a mode of operationalisation and falsification is still missing, as are methodical frameworks for cluster identification and empirical analysis.

Being such a soft concept, the term "cluster" is very broadly used and can be interpreted in nearly as many different ways as there are users. It is also a rather attractive concept: clusters are embraced in a vast spectrum of contexts from highly formalised models of regional economic theory (see Fujita et al. 1999, chapter 16) to practical training units for business development institutions. Undoubtedly, the concept is in vogue, thereby making it a ripe target for criticism. On the other hand it can be seen as a good example of new results of applied research quickly finding their way into practical economic policy.

Cluster phenomena are manifold and can be observed - be it in the geographic concentration of companies, in the functional specialisation of regions, in cooperation between companies and even competitors, as well as in strong networks linking research institutions and companies. The description of localisation economies - standing at the core of cluster theory - dates back to the work of Marshall (1890).

Nonetheless, empirical studies using sound scientific methods are scarce. It is still an open question if clusters really do have a positive effect on the "fitness" of companies and regions. Many results are either based on more or less anecdotal evidence

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or rely on statistical data with thin cluster-specific information. Considering the hefty sums – usually from public sources – invested in network development and support programmes, more reliable measures for gauging the effects and benefits of policies would constitute a valuable contribution.

An obstacle on the way to conduct sound empirical studies is the lack of suitable data. The official industry classifications are based on branches and can therefore only partially support value-chain-oriented studies. Input–output tables depicting trade links between industries could be applied to aspects of cluster analysis if they had a regional focus, a prerequisite for location-based studies. In addition, the analysis of cluster structures requires data at the company level. Cluster phenomena are observed by looking at the links between firms, suppliers, customers, their research and development partners, and other network connections.

Adding a company-based, cluster-oriented information system to the existing industry-level data would greatly contribute to our ability to study cluster structures. Of course, the systematic collection of this type of information requires a considerable amount of work, beginning with an identification of regional clusters. For many purposes such databases with company-specific information exist, but they are rarely systematic, lacking data on backward and forward linkages. They are also often not publicly accessible.

Thanks to a local initiative of public institutions and private companies, a cluster-oriented regional information system[1] was created in 2000 for Eastern Bavaria, consisting of the districts of Upper Palatinate and parts of Upper Franconia and Lower Bavaria. Further work is currently being carried out in the European Metropolitan Region Nuremberg and in the economic space along the Danube from Regensburg to Passau at the Austrian border.

The idea of this paper is to use the cluster-specific information collected in CORIS in order to contribute to the quantification and operationalisation of cluster phenomena, focusing on measurements of regional specialisation and spatial concentration of economic activities.

8.2 CLUSTERING PHENOMENA

According to Feser and Sweeney (2002, p. 111), "... industry clusters are typically defined as significant geographic concentrations of major end-market industries, their extended supply chains, other sectors that share close technological or human capital affinities, and various specialized supporting institutions". Alternatively, a cluster can be understood as "... a geographically proximate group of interconnected companies, suppliers, service providers and associated institutions in a particular field, linked by externalities of various types" (Porter 2003, p. 562). Examining these statements, it is clear that clusters can encompass a variety of things and that a precise definition is lacking. But there is overwhelming evidence for the existence of this phenomenon of clustering. Indeed the most powerful argument for such an approach to understanding regional economies is that clusters are simply there.

[1] Available under the brand CORIS at www.coris.eu.

New Economic Geography provides a justification why clusters – although differing largely in their phenotype and being so difficult to grasp by hard statistics – have become a dominant feature of our thinking about regional economic development. One theoretical backbone is the interrelationship between economies of scale, transport costs in the widest sense and externalities of market size. How can it be advantageous to locate where others are? New Economic Geography[2] discusses models based on monopolistic competition. They explain the phenomenon of clustering through the interactions of companies and consumers and the existence of scale economies and transport costs (Dixit and Stiglitz 1977, Ethier 1982). Krugman's core–periphery model (1991b) with its modifications and expansions[3] represents an important step in explaining the concentration and aggregation of production under certain parameter settings. The interaction of choice of location, production and consumption can lead to a self-reinforcing process of production centralisation. The focus here is on the vertical integration along a value chain. Companies are grouped not only by their industry affiliation, but by the industries they are connected with. These forward and backward linkages (Hirschman 1958) are externalities occurring through increasing demand or production in the market and are characteristic for the dynamics of clustering.

In the Dixit-Stiglitz world of New Economic Geography, a major benefit of agglomerating economic activity is the variety of inputs available in the vicinity at low transport costs. Finding accurate inputs spurs productivity. However, for increasing the probability of good matches, "blurred" and unspecific diversity is not helpful. The nature of the input diversity has to correspond to the companies' fields of activity, or their specialisations. In other words, what counts is variety focused on a specific value chain. This is closely related to the concept of functional specialisation at the regional level, a notion that has been coined to indicate the loosening of the traditional clear-cut borders of industrial branches, which are now often crossed by more and more complex customer–supplier relationships. Hence diversity meets specialisation.

Neglecting the borders of different industries along the lines of input-output linkages and between productive units on the one hand, and supporting services on the other appears to be quite typical for clustering. It can therefore be understood as a holistic form of regional specialisation combining the actions of different players along a – by integration of production and outsourcing possibly sliced (for example Ethier 1982, Feenstra 1998) – value chain including the cooperation of firms and research units and other supporting institutions. This new approach takes the edge out of the dichotomy between diversity and specialisation postulated in former studies (for example Glaeser et al. 1992).

Functional specialisation also plays a role in grasping major trends in structural development of the economy. Several empirical studies show for instance that the specialisation of regions measured by the spatial concentration of certain production activities using conventional industry classifications has been declining (Kim 1995 for the USA, Möller and Tassinopoulos 2001 and Haas and Südekum 2005 for Germany).

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[2] See, for example, Krugman 1991a, Ottaviano and Puga 1997, Fujita et al. 1999, Fujita and Thisse 2002, Head and Mayer 2004.

[3] See, for example, Krugman and Venables 1995, Helpman 1998, Puga 1999, Forslid and Ottaviano 2003.

Seen in isolation these results indicate a growing geographic spread of horizontally interlinked companies and could be used as an argument against clustering.

However, taking into account intersectoral specialisation changes the picture. A decline of industry-based specialisation might well be compatible with a growing importance of functional specialisation.[4]

The advantages of functional specialisation of a region (and thereby clustering) are based on three lines of arguments: input sharing, labour market pooling and knowledge spillovers.[5]

All in all, one can conclude that economic theory provides powerful theoretical arguments for the existence of clustering. For empirical analysis, however, the fuzziness of cluster concepts remains, a fact well recognised in the literature (for a critical view see for example, Martin and Sunley, 2003). As Enright (2003, p. 101), for instance, bemoans: "Despite all the research that has been done, the variety of regional clusters still poses a problem of definition. Similar terminology is used for clusters with widely different characteristics. 'Cluster' terminology seems so embedded that one despairs of redefining or sharply defining the term." He suggests a range of criteria to provide a useful and applicable classification for various types of clusters. Unfortunately, most of these criteria, or cluster dimensions as Enright puts it, remain fuzzy as well.

Enright (2003) offers some evidence of the variety of specific clusters along these dimensions on the basis of a questionnaire sent to 160 cluster experts worldwide. These dimensions cover aspects like geographic scope, density, breadth, depth and stage of development of the clusters. Moreover, characteristics of firms forming the clusters like geographic span of sales, technological activity, innovative capacity, and ownership structure all play a role in classification. It turns out that existing clusters vary widely with respect to all of these dimensions. Concerning geographical scope, for example, "... the cluster can spread across provincial or national borders, spread through a state or province, be located in city, or even highly localized within a city." (Enright 2001, p. 3)

The underlying problem is that economic spaces are byproducts of historical processes of business formation, growth and decline. They reflect economic and political history, regional circumstances like accessibility and market potential, availability of natural resources, artisan traditions, impacts of economic policy and so on. Additionally, the value-added chains in which regions typically specialise differ substantially in their complexity and in their requirements for technology, skills and logistics. The conglomeration of all these diverse forces makes the resulting structure of each economic space as idiosyncratic as any organic structure, or, as Guinet (2003, p. 154) puts it: "A cluster is always a singularity in the economic space. (...) Clusters are inherently different between countries (or regions), between technological areas, and

[4] A new variant of functional specification is described by Duranton and Puga (2005). They observe an important change in the division of labour between cities of different size. "Cities shift from specialising by sector – with integrated headquarters and plants – to specialising mainly by function – with headquarters and business services clustered in larger cities, and plants clustered in smaller cities" (Duranton and Puga 2005, p. 343). The authors find evidence for this hypothesis by investigating the spatial dispersion of occupations and skills.

[5] For details see, for example, Marshall 1890, Rosenthal and Strange 2003, Duranton and Puga 2003 or Baptista 2003.

ultimately between individual clusters themselves."

This variety hampers the operationalisation of clustering as a workable empirical concept. It seems that a passepartout is illusionary. However, the situation is not as bad as it seems at first glance. In the following section we argue that there are strategies for identification of clusters and that objective measurement concepts do exist at least for certain cluster dimensions. Instead of presenting a comprehensive strategy, we demonstrate how empirical methods can be applied if a suitable database for a regional economy is available. It is argued that the empirical analysis of cluster phenomena should be based not only on secondary statistical sources but also on data collected using a region-specific survey design.

8.3 IDENTIFICATION OF REGIONAL CLUSTERS AND BUILDING A DATABASE

For the analysis in this paper it is necessary to obtain a cluster-oriented regional database that does not structure a region according to the usual statistical industry classification, but along regional value chains or clusters. Inherent in this approach is the recourse to firm-specific data. For Eastern Bavaria, such information has been collected.

8.3.1 Methodology of cluster identification

To identify regional clusters we developed a methodology to systematically register the value-chain-oriented structures and functional specialisation in an economic space. The survey is conducted along the core competencies of individual companies and institutions and their interactions that can be observed. Firm-specific and cluster-relevant data are collected and backed by geographic information.

The methodology involves several interconnected elements. To gain initial insight into the economic structures and identify some leading companies in the region, in-depth interviews with experts from different institutions are conducted. In the following step, members of the managing board of the leading companies are interviewed as well, leading to information about further relevant firms and institutions in the region, which are then also considered for interviews. Since many different fields of interest have to be taken into account, a detailed manual for each type of interview has been developed.

After this stage, a rough outline of the region's main value chains is visible – including first indications about the segments covered by regional competencies – and a share of the relevant companies and institutions are identified. The geographic boundaries of the cluster-specific economic space also begin to shapen. These often span administrative borders and should if possible be defined by functional considerations.[6]

[6]Feser et al. (2001) also work on the conceptual problem of clusters neglecting administrative borders. As a basis for further quantitative and qualitative analyses they develop a methodology that combines a non-spatial technique revealing inter-industry links with an analysis of employment patterns in economic space.

cluster	criteria				
	concen-tration	pole companies	pool workforce	support. inst.	networks
AUT	++	+++	++	++	+++
EE	+	+++	+++	++	++
S-MAC	++	++	+++	++	++
PLA	+	++	++	+	o
P&C	++	+++	+++	+++	+
G	++	+++	+++	++	+
IT	++	o	+	++	++
LOG	+	++	+	+	+
BIO	+++	o	++	++	++
(FPT)	++	+	+	o	o

Table 8.1: The set of cluster criteria and their application to Eastern Bavarian data

We then develop a company survey on the basis of the information acquired in the interviews regarding cluster potential, inter-firm linkages, and the location's strengths and weaknesses. The questionnaire focuses on deepening the cluster-specific information. It contains sections inquiring about customer–supplier relationships and co-operations, joint projects, for example in the development of human capital or research, functional versus industry affiliation, products and services offered, core competencies, innovations, company size by turnover and number of employees, company structure and so on. The detailed firm-specific information is complemented by a focused analysis of secondary statistical data.

For the identification of cluster potential in a region we developed a set of five criteria to which the data apply. Table 8.1 gives an overview of these criteria and to what extent they are evidenced by different fields in our reference region, Eastern Bavaria. The nine value chains we identified in the Eastern Bavarian economic space as clusters operate in the Automotive Industry [AUT], Electronics & Electrical Engineering [EE], Specialised Automation [MAC], Plastics Industry [PLA], Biotechnology [BIO], Information Technology [IT], Glass & Glass Processing Industry [G], Porcelain & China [P&C] and Logistics & Specialised Trade [LOG]. After the first expert interviews some other industries, for instance food processing technology [FPT], were considered as well, but the data could not support their inclusion as clusters.

The first collection of data was carried out in 2000 and 2001. The information system is constantly updated, offering the opportunity to trace developments in the regional economic structure. Consequently, two new clusters – Sensors and Renewable Primary Products – will be included in the information system soon.

We used five criteria to identify clusters. In the next section we describe them with reference to examples from Eastern Bavaria.

First, we consider the economic activities in the region and see whether we can identify particular elements. Along with that comes a structuring of each value chain according to the main competencies covered by the regional players. Especially when using the database for economic policy guidelines and network management, it is useful to move beyond the simple categories of producer, supplier, and institution in order to further differentiate the various parts of the value chain. In some clusters it is possible to refer to the NACE codes for a description of the various functions, but for others it makes sense to depict them in more detail. Taking the automotive industry, for instance, the NACE codes DM.34.00 cover manufacture of motor vehicles (DM.34.10), manufacture of bodies (coachwork) for motor vehicles (DM.34.20) and manufacture of parts and accessories for motor vehicles and their engines (DM.34.30). In CORIS the automotive industry is divided up into ten categories: car manufacturers, first tier suppliers of plastics, electronics, metals and further systems, second tier suppliers of plastics, electronics and further components, further suppliers of services and machinery, supporting institutions and services. This is one strategy to shed some light on the hierarchical structures in a value chain and at the same time to further describe and analyse the region's economic competencies.

Second, we look for the existence of leading companies in the industries under consideration. We speak of a leading company if a local firm shows at least two of the three following characteristics: it is highly dynamic and leads in the development of technologies and manufacturing processes (technology leader); it has a leading market position in certain segments (market leader); its name is closely connected to a certain product or technology at a national and/or international level (image). For Eastern Bavaria, qualifying firms in the automotive industry include the producer BMW (including process and product optimisation, but no further R&D), leading first tier suppliers like Siemens VDO, Webasto, Grammer and Harman/Becker (all of them with either headquarter or R&D facilities) and further pole companies in other parts of the value chain.

Third, the phenomenon of labour market pooling is taken into account. Can the existence of a specialised workforce be observed? In some areas an obvious pooling of skills is found, for instance highly specialised craftsmen in glass and porcelain, or engineers in electronics and robotics. Interviews reveal that employers are aware of the improved possibilities for skill matching in a functionally specialised region (as observed as well by Andersson et al. 2004). Also, there is evidence of poaching incidents as described by Combes and Duranton (2001) and Fosfuri and Rønde (2003). Indications for a trade-off between pooling and poaching can be derived from a range of cooperation projects that include the intense cross-company exchange of employees.

Fourth, we examine supporting institutions and their sectoral importance. Vital contributors to cluster structures include universities and universities of applied sciences with cluster-relevant faculties and fields of research and the willingness to cooperate, research institutes, technical and vocational schools, technology transfer institutions, regional development agencies, working committees and network management organizations. All of these can be found in the economic space analysed: namely an internationally renowned vocational school for a broad range of glass applications, faculty chairs for special fields in biochemistry, in logistics, and in psychology for the development of man–machine interfaces, and network management agencies for biotechnology, sensors and information technology.

The last criterion is the evidence of cooperation between firms and between companies and institutions. Joint actions in the sense of coopetition, described by Brandenburger and Nalebuff (1996) as the cooperation between competitors, are also of some importance. In Eastern Bavaria the latter can be observed in joint R&D projects undertaken by porcelain manufacturers – usually fierce competitors in the end markets – and research institutions, as well as in a mutual purchase group and a cross-company trainee-programme. Many different kinds of cooperation occur in managed networks such as the "cluster initiative" in Security IT or the strategic partnership in sensor technology. Another example is the microsystems laboratory at the Regensburg University of Applied Sciences, which enables joint research projects with electronics companies. Lastly, there are also several instances of collaborative development projects between producers and suppliers, often involving exchange of personnel.

8.3.2 Database

We use data collected in the cluster-oriented regional information system CORIS[7] for Eastern Bavaria. Firm-level data stem from the implementation of the methodology described above, to which we append geographic information. A company survey conducted in the region in 2001 led to 315 questionnaires returned. The information obtained was added to the results of more than 100 in-depth interviews with experts of regional economic structures and company representatives. Further information was garnered from media reports and internet research. Also, companies and institutions are invited to submit their indications with an online questionnaire.

Roughly 1,400 online entries of firms and institutions are available and updated on a regular basis. For the following analysis we use only company information. Since some of them are affiliated with more than one cluster, the total number of observations is 1,433. All company database entries include an indication of size – either the exact number of employees at the location or the company's placement in employment size categories. In the latter cases we used the mean of the class as indicator for the size of the firm.

8.3.3 Evidence on functional specialisation

The company survey conducted in Eastern Bavaria included two questions aimed at highlighting divergences between a company's official industry classification and its functional affiliations in regional value chains. The outcomes are depicted in figures 8.1 and 8.2.

The answers to the question "Which industry is your company working in?" reveal that electrical engineering dominates with nearly one third of all employees in the region. The second largest industry is automobile construction with more than 20 per cent, followed by metals and mechanical engineering (see Figure 8.1).

[7]available under http://www.coris.eu

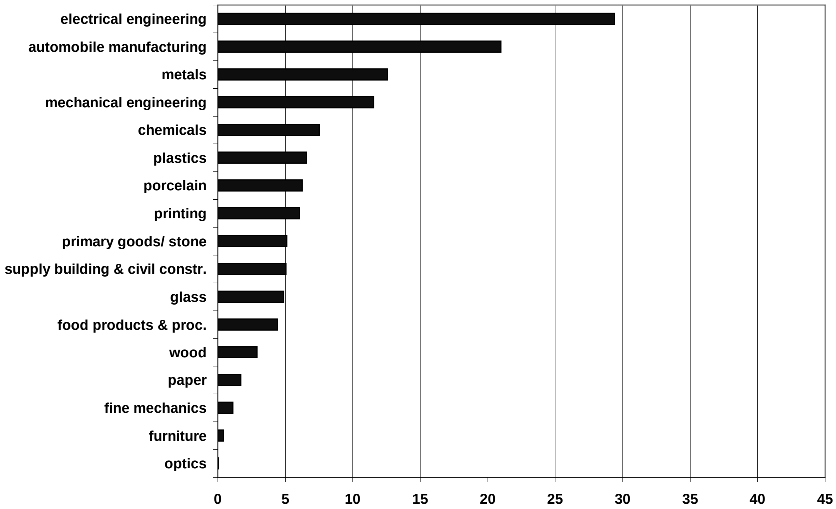

Figure 8.1: Industrial affiliation of companies (source: Eastern Bavarian company survey, companies weighted by number of employees)

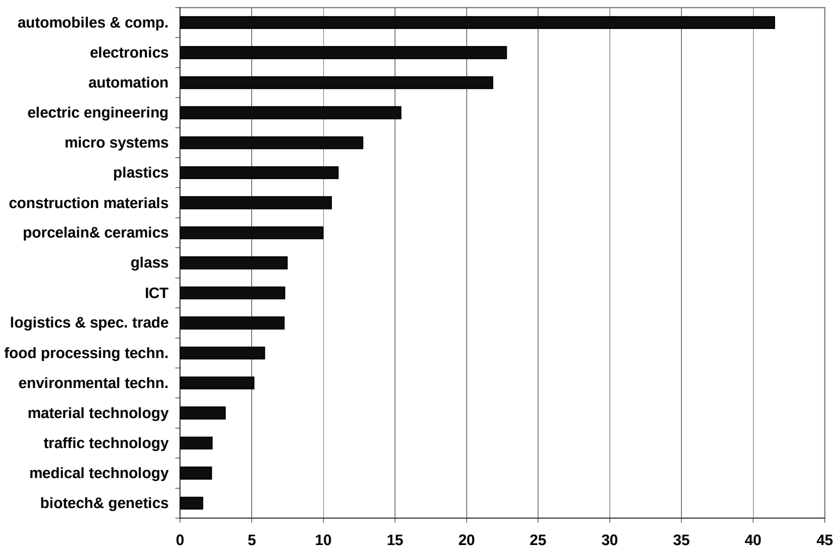

Figure 8.2: Industries and functional specialisations (source: Eastern Bavarian company survey, companies weighted by number of employees)

In order to capture the complexity of functional affiliations, the question "Which industry is your company working in, be it as a producer, a supplier or a service company?" offered firms the option of choosing more than one industry. The results of this question suggest the dominant industry is automobiles and components with more than 40 per cent of employees connected to it, followed by electronics and automation with roughly one fifth of employees (see Figure 8.2).

8.4 SPECIALISATION OF REGIONS AND SPATIAL CONCENTRATION OF VALUE CHAINS

The phenomenon of clustering stands in close relation to two classic concepts in regional analysis, the specialisation of regions and the spatial concentration of economic activities. Regional specialisation is understood as the fact that a region has comparative advantages in the production of certain goods and services and uses – relative to other regions – a high share of its productive capacities in these fields. Concentration of an activity in space implies that production of a certain kind is not distributed "evenly" in space, that is, according to population density, for instance. Although the two concepts differ, they are interrelated to some extent. Specialisation typically entails concentration and concentration brings about specialisation.

Having collected data based on the concept of clustering we can apply indicators previously developed to measure specialisation and concentration in space. The results are compared to corresponding indicators using traditional industry classification in the region (source: Federal Labour Office). For this purpose we employ the 79 2-digit industries, as well as the nine biggest industries in the region out of all industries. In the following sub-sections we briefly describe the indicators we use for measurement (Krugman and Herfindahl indices as well as locational Gini coefficients).

8.4.1 Specialisation of regions

Measurement concepts

Let x_{ir} be the number of firms for measuring economic activity i in sub-region r, where the latter is taken as a spatial unit at NUTS3 level – typically counties – in the current context. Furthermore, let $x_{i.}$ denote activity i in all regions, $x_{.r}$ denote total activity in sub-region r and $x_{..}$ overall activity. Moreover define a_{ir} as the total share of activity i in region r and A_{ir} as the share of the region involved in activity i in the aggregate:

$$a_{ir} = \frac{x_{ir}}{x_{.r}} \quad \text{and} \quad A_{ir} = \frac{x_{ir}}{x_{i.}}. \tag{8.1}$$

In addition we use the share of region r across all activities and the share of activity i in total aggregate activity across all regions:

$$a_r = \frac{x_{.r}}{x_{..}} \quad \text{and} \quad A_i = \frac{x_{i.}}{x_{..}}. \tag{8.2}$$

We can then define measures of specialisation of a region according to the Krugman and Herfindahl indices as

$$\text{SPEC}_r^K = \sum_i |a_{ir} - A_i| \quad \text{and} \quad \text{SPEC}_r^H = \sum_i a_{ir}^2. \tag{8.3}$$

A third possibility for measuring regional specialisation is offered by the modified Gini coefficient. Calculate the Balassa index

$$B_{ir} = \frac{A_{ir}}{a_r} = \frac{a_{ir}}{A_i}, \tag{8.4}$$

then form pairs composed of the share of an activity in total economic activity of a region, a_{ir}, and the share of the corresponding activity in total economic activity, A_i. Sort these pairs in ascending order and denote the resulting sequences by a tilde. The cumulated ordered shares are given as

$$\tilde{s}_{jr} = \sum_{i=1}^{j} \tilde{a}_{ir} \quad \text{and} \quad \tilde{S}_{jr} = \sum_{i=1}^{j} \tilde{A}_i \quad \text{for} \quad j = 1, \ldots, I. \tag{8.5}$$

Plotting $\tilde{S}_{jr}$ on the horizontal and $\tilde{s}_{jr}$ on the vertical axis yields a quasi Lorenz curve. The modified Gini coefficient as a measure of regional specialisation can then be calculated as

$$\text{SPEC}_r^G = 1 - \sum_{i=1}^{I} (\tilde{s}_{i-1,r} - \tilde{s}_{ir}) \tilde{A}_i \quad \text{with} \quad \tilde{s}_{0r} = 0. \tag{8.6}$$

A Gini coefficient value of zero indicates no specialisation, while a value of one indicates perfect specialisation.

Specialisation by firms

We measure economic activity by the number of firms weighted by the number of employees.[8] Figure 8.3 depicts the results for the Lorenz curves for regional specialisation using conventional industry statistics for the nine biggest industries in the region, whereas Figure 8.4 gives the results using data from CORIS, which is based in the concept of functional specialisation.

In order to obtain more quantitative information on the degree of specialisation, we calculated the Gini coefficients, the Herfindahl and the Krugman indices. Again, we compared the results for specialisation indicators obtained by the cluster-based data with an indicator of specialisation using official statistics for the nine biggest industries in the region. The results are depicted in Figures 8.5, 8.6 and 8.7.

Three main conclusions can be drawn. First, the Lorenz curves clearly indicate differences in specialisation between the sub-regions in our sample. Both graphs in

[8] For some of the firms only employment categories are available. In these cases we used the mean of the class as indicator for the size of the firm.

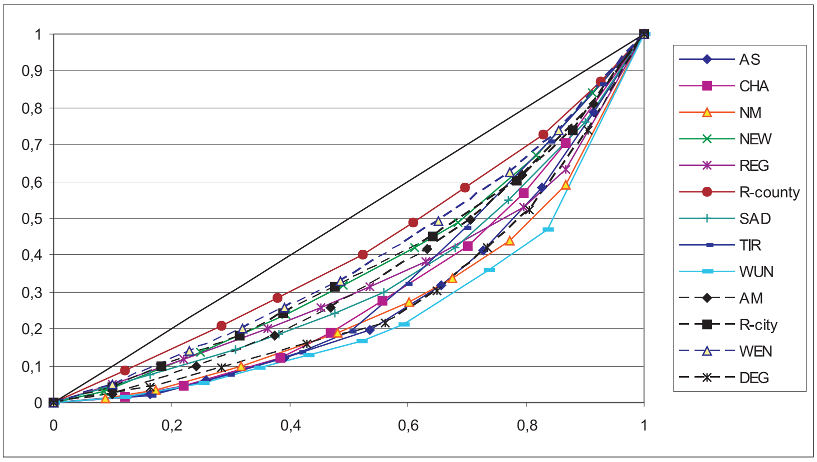

Figure 8.3: Lorenz curves of regional specialisation for 13 counties in Eastern Bavaria using the nine biggest industries (source: Federal Labour Office, industry size by number of employees)

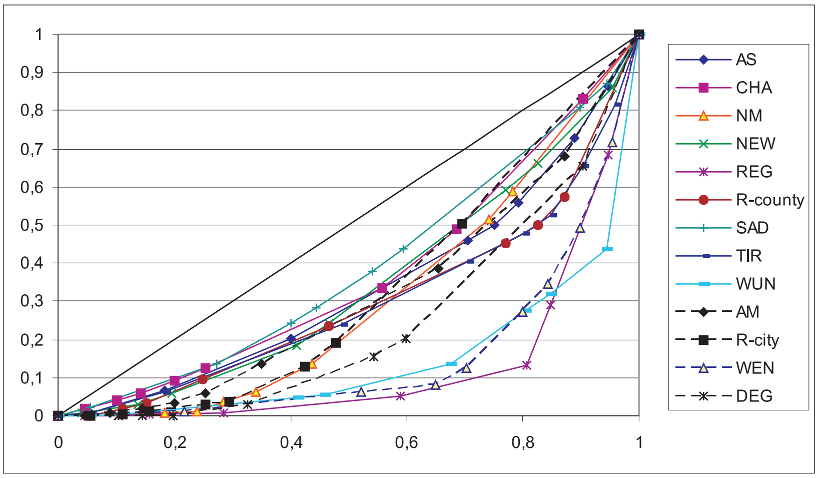

Figure 8.4: Lorenz curves of regional specialisation for 13 counties in Eastern Bavaria using the nine value chains (source: CORIS data, firms weighted by number of employees)

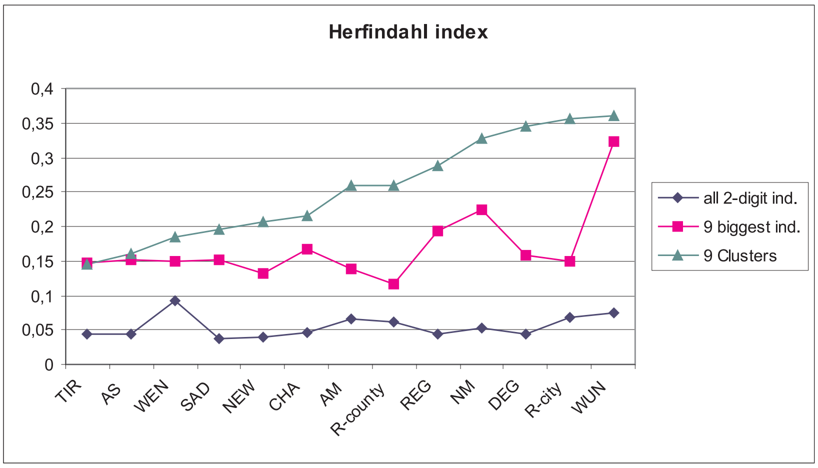

Figure 8.5: The Herfindahl indices of regional specialisation, using official statistics (all 2-digit industries and the nine biggest industries in the region) and the cluster-based CORIS data.

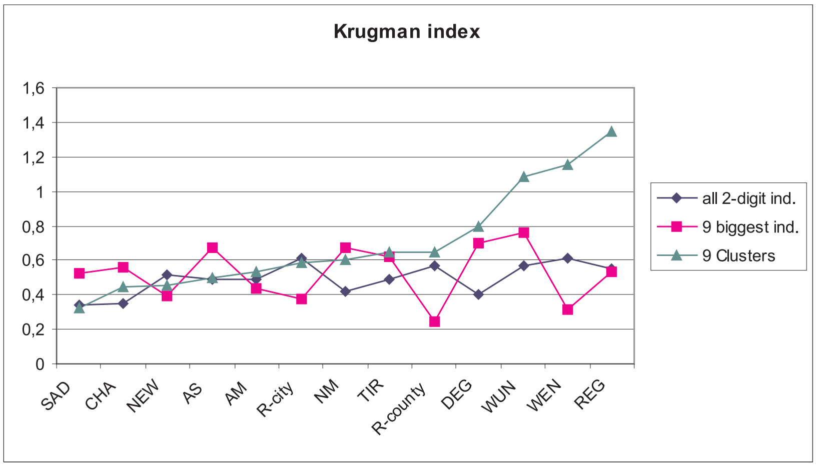

Figure 8.6: The Krugman indices of regional specialisation, using official statistics (all 2-digit industries and the nine biggest industries in the region) and the cluster-based CORIS data.

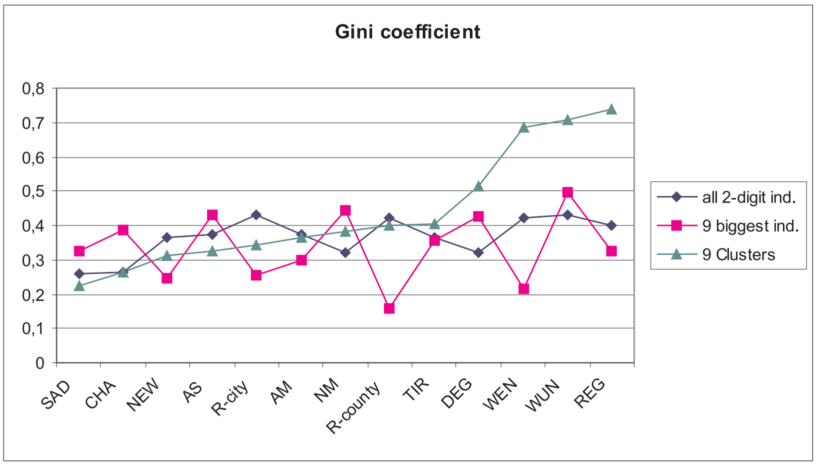

Figure 8.7: The Gini coefficients of regional specialisation, using official statistics (all 2-digit industries and the nine biggest industries in the region) and the cluster-based CORIS data.

Figures 8.3 and 8.4 show that the Lorenz curves for regional specialisation vary considerably between the NUTS3 regions in Eastern Bavaria. Independent of firm size we observe a high level of specialisation for example in the Regen county, a small region in the Bavarian Forest heavily specialised in glass industry. Other regions, like Cham or Schwandorf, are much more diversified across value chains or clusters.

Second, the degree of observed specialisation differs markedly between the concepts of official industry and cluster affiliation.

Third, the variance in regional specialisation is much higher for the cluster-based concept. Three regions (REG, WUN and WEN) show a considerably higher degree of specialisation than the others. The results indicate that these regions exhibit an industrial structure dominated by few value chains or forms of functional specialisation.

A systematic overview of the results for the three different indicators of specialisation is given in Table 8.2, whereas Figures 8.5–8.7 depict the patterns of the individual indices. For the Herfindahl index the cluster-based approach nets higher values than the conventional industry measurement in all counties but one. In the case of the Krugman index this is true for seven out of 13 counties. The Gini coefficient is higher using the cluster-based approach in only five of the thirteen counties. In all three cases the cluster-based approach yields a larger range of values between counties.

The Krugman index and the Gini coefficient tend to move together and produce a similar ordering of the regions. The results of the Herfindahl index, however, differ markedly from the other two measures. This can be verified by the correlation coefficients between the three different indices shown in Table 8.3. The Krugman index and Gini coefficients for the same underlying data sets are highly correlated with correla-

region	all 2-digit industries			nine biggest industries			nine value chains (Clusters)		
	Herf.	Krugm.	Gini	Herf.	Krugm.	Gini	Herf.	Krugm.	Gini
AS	0.044	0.487	0.373	0.151	0.677	0.432	0.160	0.502	0.327
CHA	0.046	0.347	0.262	0.167	0.562	0.386	0.216	0.449	0.262
DEG	0.044	0.404	0.319	0.158	0.696	0.426	0.344	0.797	0.515
NM	0.052	0.419	0.321	0.225	0.675	0.445	0.327	0.605	0.383
NEW	0.039	0.515	0.366	0.131	0.390	0.247	0.207	0.457	0.311
REG	0.043	0.547	0.402	0.192	0.532	0.325	0.287	1.347	0.738
R-county	0.061	0.570	0.420	0.117	0.244	0.160	0.259	0.647	0.399
SAD	0.037	0.337	0.257	0.152	0.522	0.326	0.196	0.322	0.225
TIR	0.044	0.493	0.365	0.148	0.620	0.358	0.145	0.643	0.405
WUN	0.075	0.572	0.431	0.322	0.764	0.496	0.360	1.085	0.708
AM	0.065	0.489	0.372	0.138	0.433	0.299	0.259	0.535	0.366
R-city	0.068	0.614	0.429	0.150	0.379	0.253	0.356	0.589	0.345
WEN	0.092	0.608	0.422	0.149	0.317	0.216	0.184	1.155	0.687

Table 8.2: Specialisation indices for 13 counties in Eastern Bavaria

tion coefficients exceeding 0.98 in all cases. The Herfindahl index is correlated with the other two indices in the case of the two industry data sets, but not for cluster-based data. Cross correlation between the nine biggest industries data and the other two data measurements is not significant. However, cross-correlation between the 2-digit industry measurement and the cluster measurement is statistically significant in both the Krugman and the Gini indices. Nonetheless the correlation coefficient does not exceed 0.6. We conclude that there are certain – but far from perfect – correspondences between information in a comprehensive industry data set and information based on the cluster approach.

The highest degree of specialisation is found for the regions WEN, WUN and REG. All these counties contain extensive shares of glass and porcelain industries, both forming traditional clusters.

Specialisation by occupations

Further evidence of specialisation can be obtained by analysing information on occupations. For this purpose we use a social security microdata set (IABS). IABS is a 2 per cent random sample of all employees obliged to pay contributions to the German social security system. The scientific use file includes detailed information on 130 occupations and gives regional information. Due to data security conventions, however, some of the counties in the economic space selected for our analysis were aggregated. As a result, the number of regions for our empirical investigation is reduced to ten. The dataset includes observations on 7159 persons employed as of 30 June in 2001, the most recent year for which data are available.

We went through the 130 occupations and ordered them into two groups. The first contains 32 occupations that have an affinity to at least one of the nine clusters identified in the region, while the other 98 occupations are classified as being not cluster-specific. For example, glass makers, porcelain painters, electric engineers

		all 2-digit industries			nine biggest industries			nine clusters		
		Herf.	Krugm.	Gini	Herf.	Krugm.	Gini	Herf.	Krugm.	Gini
all 2-digit industries	Herfindahl	1.000								
	Krugman	***0.670***	1.000							
	Gini	***0.649***	**0.984**	1.000						
nine biggest industries	Herfindahl	0.230	0.065	0.139	1.000					
	Krugman	-0.338	-0.438	-0.332	***0.660***	1.000				
	Gini	-0.261	-0.446	-0.342	**0.704**	**0.985**	1.000			
nine clusters	Herfindahl	0.245	0.186	0.242	0.537	0.206	0.253	1.000		
	Krugman	0.465	***0.558***	***0.583***	0.453	0.067	0.043	0.312	1.000	
	Gini	0.505	***0.557***	***0.597***	0.517	0.127	0.106	0.339	**0.986**	1.000

Note: Bold (bold italic) figures are significant at the 1 per cent (5 per cent) level.

Table 8.3: Correlation coefficients for industry-based specialisation indices of 10 counties in Eastern Bavaria

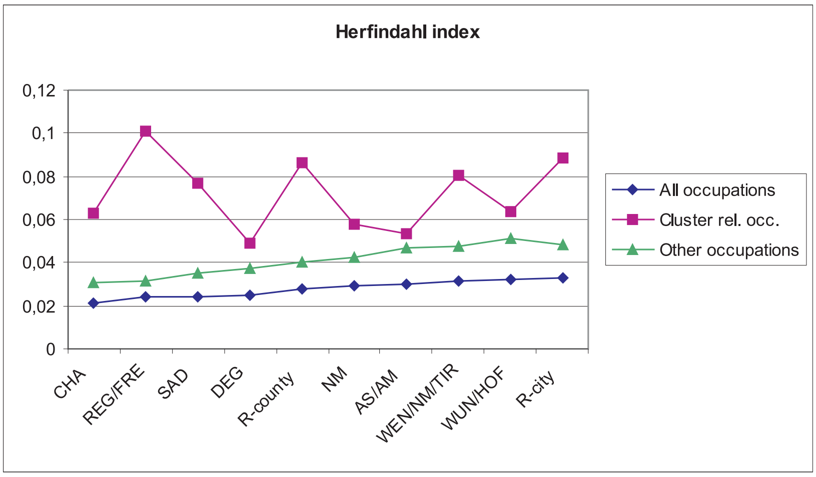

Figure 8.8: Herfindahl indices of regional specialisation by occupation ordered by results for all occupations

and IT experts belong to the first group, secretaries, accountants and salesmen to the second.

Specialisation measures were calculated for the ten regions using all occupations and dividing them by cluster-specific and other occupations. Again, the results in Figures 8.8–8.10 show a high degree of correlation between the Krugman and Gini indices, while the Herfindahl index follows a somewhat different pattern. For the former, the region with the highest number of employees (the city of Regensburg) exhibits the highest degree of specialisation, while smaller regions in northern Upper Palatinate and parts of Upper Franconia show the lowest. It is remarkable that the specialisation rankings for both the Krugman and Gini indices are more or less invariant against changes in the underlying sample of occupations. The correlation matrix in Table 8.4 reveals a high correlation between the Krugman and Gini indices for the same underlying data, but also a high correlation of the results for all occupations and the sub-sample of cluster-specific ones.

It should be stressed that for all cases the indices based on cluster-relevant occupations show the highest values. We conclude that regional specialisation – at least to some extent – is driven by cluster-specific occupations.

8.4.2 Concentration of industries

Measurement concepts

As with indices of regional specialisation, one can also define indices for the measurement of spatial concentration of industries. There is no concentration if the share of an industry in total regional activity is the same across regions. By contrast, the highest

		All occupations			Cluster relevant occupations			Other occupations		
		Herf.	Krugm.	Gini	Herf.	Krugm.	Gini	Herf.	Krugm.	Gini
All	Herfindahl	1.000								
occupations	Krugman	0.035	1.000							
	Gini	-0.005	**0.994**	1.000						
Cluster	Herfindahl	0.040	0.420	0.388	1.000					
relevant	Krugman	-0.010	**0.975**	**0.984**	0.492	1.000				
occupations	Gini	-0.025	**0.960**	**0.975**	0.516	**0.992**	1.000			
Other	Herfindahl	**0.971**	-0.115	-0.157	-0.148	-0.186	-0.201	1.000		
occupations	Krugman	0.078	**0.983**	**0.968**	0.312	**0.921**	**0.901**	-0.045	1.000	
	Gini	0.021	**0.978**	**0.979**	0.235	**0.933**	**0.912**	-0.103	**0.984**	1.000

Note: Bold (bold italic) figures are significant at the 1 per cent (5 per cent) level.

Table 8.4: Correlation coefficients for occupation-based specialisation indices of 10 counties in Eastern Bavaria

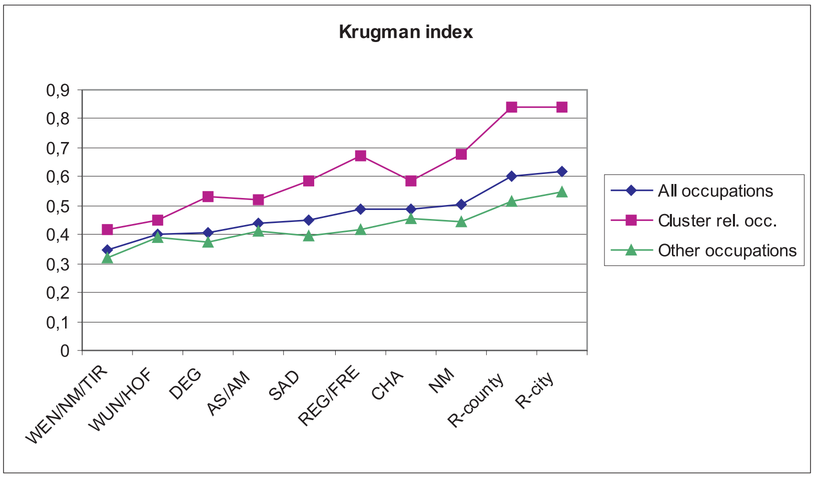

Figure 8.9: Krugman indices of regional specialisation by occupation ordered by results for all occupations

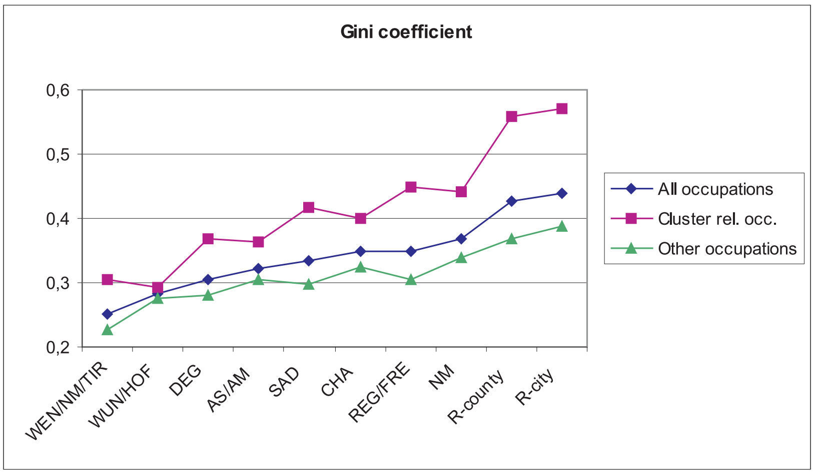

Figure 8.10: Gini coefficients of regional specialisation by occupation ordered by results for all occupations

clusters	Herf.	Krugm.	Gini
EE	0.215	0.490	0.287
AUT	0.247	0.453	0.290
MAC	0.146	0.611	0.419
IT	0.204	0.667	0.473
PLA	0.120	0.707	0.481
BIO	0.159	0.924	0.585
GLA	0.183	0.970	0.647
LOG	0.196	1.001	0.647
P&C	0.261	1.276	0.769

Table 8.5: Concentration indices for nine clusters in Eastern Bavaria

possible concentration is given if an industry is present in one region only.

The Krugman index as a measure of spatial concentration of industry i is defined as

$$\text{CONC}_i^K = \sum_r |A_{ir} - a_r|, \tag{8.7}$$

while the corresponding Herfindahl measure is

$$\text{CONC}_i^H = \sum_r A_{ir}^2. \tag{8.8}$$

Using the definitions from above, the Gini coefficient as a measure of spatial concentration can be calculated as follows. Starting point is a region's share of total aggregate activity in a given industry A_{ir}. Regions are sorted according to the Balassa index in ascending order. Again, denote the sequence of variables obtained in this way by a tilde. In addition to $\tilde{A}_{ir}$ the corresponding values of $\tilde{a}_r$ are also required, that is, the shares of total regional activity in total aggregate activity. Define cumulated values as

$$\tilde{Z}_{ij} = \sum_{r=1}^{j} \tilde{A}_{ir} \quad \text{and} \quad \tilde{z}_{ij} = \sum_{r=1}^{j} \tilde{a}_r \quad \forall \quad j = 1, \ldots, R. \tag{8.9}$$

The Lorenz curves are obtained if the $\tilde{z}_{ij}$ and $\tilde{Z}_{ij}$ are depicted on the horizontal and vertical axes, respectively. The Gini coefficient can be calculated as:

$$\text{CONC}_i^G = 1 - \sum_{r=1}^{R} (\tilde{Z}_{i,r-1} + \tilde{Z}_{i,r})\tilde{a}_i \quad \text{with} \quad \tilde{Z}_{0,i} = 0. \tag{8.10}$$

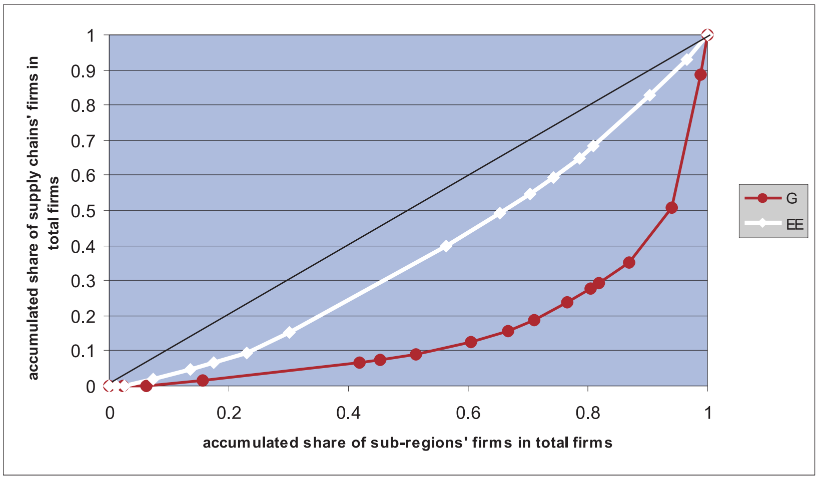

Figure 8.11: Lorenz-curves of glass and electronics industries (source: CORIS)

Concentration by industries

The patterns of supply chains in special fields do not necessarily correlate with population density. For example, the Glass & Glass Processing Industry (G) – one of the traditional specialised industries of the area under consideration – is strongly concentrated in the less populated rural areas of Northern Upper Palatinate and in the Bavarian Forest. Other supply chains – otherwise exhibiting typical attributes of regional specialisation – are either more uniformly distributed in space or are concentrated in urban areas, thereby more or less reflecting the distribution of population.

Applying the measurement concepts defined above to the G and EE data for Eastern Bavaria results in the Lorenz Curves shown in Figure 8.11. The glass supply chain (G) appears to be heavily concentrated, while electronics (EE) is more in line with a uniform distribution. In the glass industry about 50 per cent of firms are located in two sub-regions, representing roughly 6 per cent of total economic activity (as measured by the number of firms). For the EE supply chain we find half of the firms located in sub-regions, representing about one third of total activity.

The three different concentration indices for all clusters are given in Table 8.5 and are visualised in Figure 8.12. The level of concentration varies widely across clusters. The Gini coefficient ranges from 0.287 for EE to 0.769 for P&C. Beside these extreme cases, Automotive Industry (AUT) and Specialised Automation (MAC) tend to show lower concentration than Biotechnology (BIO), Glass Industry (G) and Logistics and Specialised Trade (LOG). These results also suggest that clusters do not occur only in "high tech" value chains, for example information technology, electronics or biotechnology, but are sometimes even more spatially concentrated in so-called "traditional" industries.

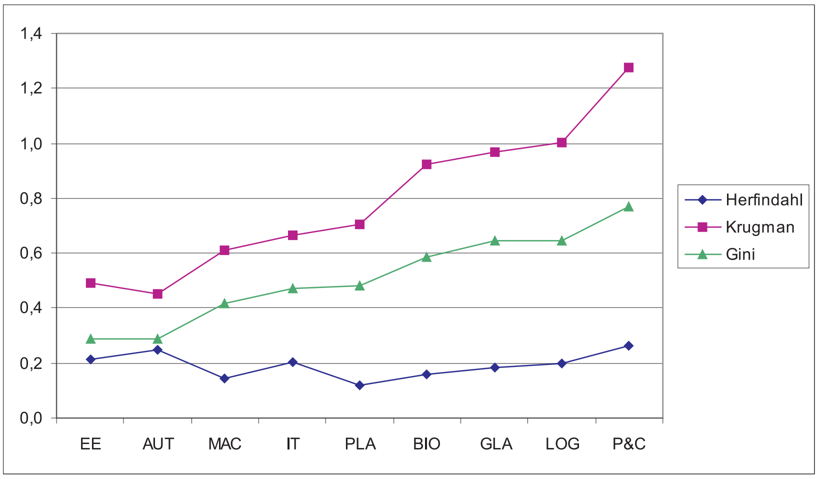

Figure 8.12: Concentration measures for nine clusters

	Herfindahl	Krugman	Gini
Herfindahl	1		
Krugman	0.158	1	
Gini	0.055	**0.986**	1

Note: Bold (bold italic) figures are significant at the 1 per cent (5 per cent) level.

Table 8.6: Correlation coefficients between concentration indices for nine counties in Eastern Bavaria

Again, the correlation between the Krugman and Gini coefficients is striking, while the Herfindahl index gives different information than the other two indices. This is corroborated by the correlation coefficients given in Table 8.6. The correlation coefficient between the Krugman and Gini index exceeds 0.98 and is significant at the 1 per cent level, while both cross-correlations between the Herfindahl and the two other measures are statistically insignificant.

Concentration by occupations

We also considered concentration by occupations using the same methodology as before. The concentration levels of the 130 observations vary widely. Figure 8.13 shows the Gini and Krugman indices of concentration differentiating between cluster-relevant and other occupations. At first glance, the concentration of the 32 cluster-relevant occupations does not deviate markedly from other occupations. Comparing the employment weighted mean of the indices shows that the concentration of cluster-

	N	Herfindahl		Krugman		Gini	
cluster relevant occupations	32	0.187	(0.071)	0.600	(0.215)	0.393	(0.128)
other occupations	98	0.157	(0.071)	0.425	(0.258)	0.275	(0.157)

Table 8.7: Mean and standard errors of concentration indices by industries (employment weights)

relevant occupations is higher for all three measures. The differences, however, are not statistically significant (see Table 8.7).

8.5 CONCLUSIONS

The term “cluster” is widely used and is especially popular in regional economic policy, despite the fact that the concept lacks clear definition. But the existence of clusters is supported by overwhelming and not just anecdotal evidence. A range of typical phenomena for clustering – some of them being very well founded in economic theory - can be observed. For empirical analysis, however, the fuzziness of the concept remains.

The popularity of clusters combined with blurry definitions has led to efforts to track the concept down – among them an urge to dimensionalise clusters and disentangle their various aspects. For some of these dimensions objective measurements exist or can be adapted. The approach in this paper is to look at the differing results of applying traditional industry-based administrative data and data relying on the concept of functional specialisation or clustering.

For obtaining a regional, cluster-oriented, firm-specific database we developed a methodology - so far implemented in Eastern Bavaria – to identify clusters by systematically registering value-chain-oriented structures and functional specialisation in an economic space. In this paper we highlight the two well-known measurement concepts of regional specialisation and spatial concentration of economic activities.

For the number of employees the results show marked differences in the specialisation pattern of the sub-regions and also between the concepts of official industry and cluster affiliation (indications of differences in levels of regional specialisation are much higher when using cluster data). Concerning the indices based on occupations, the cluster-relevant share again yields the highest values.

Also the spatial concentration of value chains varies widely. It is interesting to note that these patterns do not necessarily correlate with population density and are independent of the often invoked distinction between “high tech” and “traditional” industry.

Our results show that economic spaces appear considerably different when examined with cluster-oriented data as opposed to traditional industry classifications.

Figure 8.13: Gini and Krugman concentration indices of cluster relevant and other occupations

Profound knowledge about clusters and functional specialisation in a region leads to a new view of regional economic structures and focal points of economic activity. To enable a more systematic approach to cluster-related questions it would be very helpful to create or have access to adequate firm-based and supra-regional information on forward and backward linkages. Then it might be possible to move a step closer to a quantification and operationalisation of some cluster dimensions based on established and sound empirical methods.

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