Methods for the Identification and Analysis of Clusters in Metropolitan Economies: Overview and Comparative Assessment

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1. Clusters in Metropolitan Economies

Economic activity is not randomly spread across space. It shows an increasing tendency to concentrate in cities and metropolitan regions, as evident from the global megatrend of urbanisation (UN 2019). Economists use the concept of agglomeration economies to summarise the benefits, but also drawbacks of spatial concentration. They distinguish between general effects of urban size (*urbanisation economies*) and spatially bound externalities emanating from the concentration of firms in the same, similar, or related industries, so-called *localisation economies* (Fujita/Thisse 2013; McCann 2008). Although the benefits of specialised knowledge, suppliers, and infrastructure in close geographical proximity have been studied since the 19th century (Marshall 1890; 1919), their resurgence in academic and policy circles is tied to the seminal publication by Porter (1990) showcasing the benefits of what he branded as *clusters* (for a critical review see Martin/Sunley 2003).

According to the most widely used definition, clusters are

> geographic *concentrations* of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (for example, universities, standards agencies, and trade associations) in particular fields that compete but also *cooperate*. (Porter 2008, 213f.; emphasis added)

Within clusters, spatial proximity facilitates cooperation, the sharing of resources and the exchange of knowledge in localised learning processes (Malmberg/Maskell 2006). There is ample evidence that clusters can increase innovation, productivity and profitability in firms, as well as new firm formation and survival (Kiese 2012, 58–65). However, this link is not universal, but depends on specific circumstances, such as a cluster's position in its life cycle (Menzel/Fornahl 2010). History has shown that mature and declining clusters can turn former economic powerhouses into old industrial regions (Hassink 1997; 2010).

Furthermore, clusters differ widely in their state of development (Enright 2003, 104). While *working clusters* contain a critical mass of local knowledge, expertise, personnel, and resources that support the competitiveness of firms, *latent clusters* have a critical mass of firms in related industries but no sufficient level of interaction and information flows for firms to exploit the benefits. *Potential clusters* display some elements of working clusters but are too narrow and/or shallow to reap full benefits. Finally, there are many policy-driven clusters chosen by governments for support but lacking a critical mass of firms or favourable conditions and 'wishful thinking' clusters without any critical mass or any particular source of advantage for organic development.

Clusters are predominantly, but not exclusively, an urban or metropolitan phenomenon. Although their spatial extent may vary, an early literature overview by van der Linde (2002; 2003) showed that out of 705 clusters, the majority was confined to either individual cities (41.8 percent) or metropolitan regions (18.9 percent). While most other clusters extend beyond their urban or metropolitan cores, there are also clusters outside larger urban agglomerations, primarily feeding on localisation economies. Metropolitan economies often contain portfolios of clusters that may be diversified, thus reducing the exposure to asymmetric shocks, but may also overlap, converge, and reinforce each other (Evans/Karecha 2014). The spatial concentration of diverse yet often related pools of knowledge make them nodes in the expanding knowledge economy (Simmie 2003).

Over the last three decades, clusters have become a popular tool for the promotion of local and regional, i.e. sub-national economic development all around the world (cf. Lindqvist et al. 2013) and on all spatial scales as shown by Kiese (2012) for the case of Germany. First and foremost, cluster policies require the proper identification and analysis of (potential) clusters, which can also serve as methods for their evaluation at the end of the policy cycle (Kiese 2019). While *cluster identification* refers to the discovery of hitherto unknown or only assumed cluster potential and structures, *cluster analysis* denotes the quantitative and qualitative measurement and assessment of known cluster potential and structures.[1] In general, these methods can serve three different yet complementary purposes (Sautter 2004, 68):

- the sectoral and geographical delineation of clusters: what industries does a cluster contain, and what is its spatial extent?;
- assessing the presence (quantity) and quality of elements of a regional value system;
- identifying and assessing transactions in a cluster, including input-output (supplier-buyer) linkages as well as communication (knowledge flows).

A generally recognised methodology for identifying (potential) clusters does not exist, nor does a universal cluster theory (Martin/Sunley 2003, 18–23). In the meantime, however, a broad spectrum of methods is available, which differ in their approach (top-down versus bottom-up) as well as in the time and cost required and consequently

1 Note that this contribution does not deal with cluster analysis as a statistical procedure, which aims at grouping objects into clusters based on measures of similarity (Kaufman/Rousseeuw 2005).

also in their practical dissemination.[2] The aim of this chapter is to provide a structured overview and comparative assessment of the most common/relevant methods of cluster identification and analysis, which can be broadly classified into quantitative top-down (macro) and qualitative bottom-up (meso and micro) approaches (see table 1). While the former draw on aggregate statistical data, the latter focus on individual stakeholders or organisations and their linkages, often requiring the gathering of primary data through surveys.

Tab. 1: Methods of cluster identification and analysis: overview

Level	***Methods***
Macro (top-down)	measures of spatial and sectoral concentration growth analyses, e.g. shift-share input-output analysis
Meso	expert opinion, stakeholder participation cluster mapping for case studies competitive methods
Micro	value chain analysis network analysis

Source: Adapted from Sautter (2004, 68).

2. Top-Down Approaches

2.1 Measures of Localisation and Specialisation

The absolute number of firms and employment[3] in a regional industry or their share of the national total[4] offers a first indication of the specialisation of a place or region or of the concentration of industries across space. In addition, empirical regional research offers various *relative concentration measures* to identify spatial-sectoral agglomerations (cf. Westerholt in this volume).[5] These include above all the location quotient (LQ), but

2 See Bergman/Feser 2020, ch. 3; Krätke/Scheuplein 2001, ch. 3; Sautter 2004; and Koschatzky/Lo 2007.

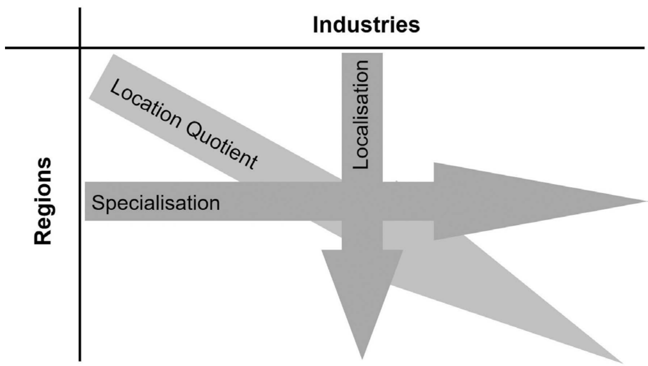
3 In the following, we will use *employment* (the number of employees) as the key measure for economic activity as it is most widely available in spatial and sectoral disaggregation. However, alternative indicators like value added (a net concept) or turnover (a gross concept including expenditures on inputs) might as well be used.

4 For simplicity's sake, we use the term *region* in this contribution to denote any sub-unit of a superordinate larger area, which we label as *nation*. In practice, this larger entity can also be subnational, e.g. a province or federal state, or a supranational entity like the European Union.

5 Spatial data analysis holds many generic measures of concentrations which are outside the scope of this review (Fischer/Wang 2011; Oyana 2021). Farhauer/Kröll (2014, ch. 14) provide an extensive introduction to various measures of spatial concentration and regional specialisation. Fornahl/Brenner (2009) apply the Ellison-Glaeser index, the Gini coefficient, the Herfindahl index, and Moran's *I* as a measure of spatial autocorrelation, to the spatial pattern of patenting activity across German regions. For spatial data analysis, cf. also Westerholt in this volume.

also coefficients of localisation (CL) and specialisation (CS; Schätzl 2000, 60–67). Fig. 1 illustrates their complementary relations: while the CL shows the degree of an industry's spatial concentration, the CS measures the degree of a region's sectoral specialisation. The LQ combines both the sectoral and the spatial perspective by indicating how strongly an industry is concentrated in a particular region, which may indicate the presence of a cluster.

Fig. 1: Measures of localisation and specialisation (Source: Author's illustration)



Measures of spatial and sectoral classification also comprise the coefficient of geographical association (CGA) that shows to what extent pairs of industries co-locate across regions (Schätzl 2000, 66). However, co-location does not necessarily imply a functional (e.g., input-output) linkage between industries. It may also be caused by drawing on the same locational endowments, or simply coincidental.

Location Quotient

The location quotient relates the employment share of an industry in a region to the share of this industry across all regions, i.e. in the nation:

$$LQ = \frac{\dfrac{Y_{ij}}{\sum_{j=1}^{m} Y_{ij}}}{\dfrac{\sum_{i=1}^{n} Y_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} Y_{ij}}} = \frac{\dfrac{\textit{industry j in region i}}{\textit{all industries in region i}}}{\dfrac{\textit{industry j overall}}{\textit{all industries overall}}}$$

The LQ can take values between zero and infinite. While LQ 1 indicates a less than proportional, LQ > 1 indicates a more than proportional presence of industry j in region i. LQ = 1 means that the industry's share in region i is exactly the same as overall. Comparing a region's LQ across all industries shows the region's industry profile, whereas comparing an industry's LQ across all regions shows the industry's geographic distribution (Krätke/Scheuplein 2001, 40). Changes of LQ values over time indicate increases or decreases in the level of concentration and specialisation.

Table 2 illustrates the calculation of the LQ, using employment in the furniture industry of North Rhine-Westphalia (NRW) as an example. While NRW's employment share in this traditional industry is already three times the national average (LQ = 3.26), further spatial disaggregation into counties shows the industry's strong concentration outside the metropolitan cores in the eastern part of NRW, Ostwestfalen-Lippe – Germany's largest furniture cluster with deep historic roots (Rafiqui et al. 2009; VDM 2019). This case shows that the highest LQ values can often be found in non-metropolitan regions due to their smaller and less diversified economic base. As another example, Lichtblau et al. (2018) employ the LQ extensively in a detailed analysis of spatial concentrations of the metal-processing and electrical industries across Germany.

Tab. 2: Location quotients for employment in the furniture industry in North Rhine-Westphalia, 2019

County	***Furniture Industry***	***Total Employment1***	***Regional Share***	***LQ2***
Herford	7,830	53,060	14.8 %	58.93
Gütersloh	6,632	111,577	5.9 %	23.74
Borken	2,252	88,326	2.5 %	10.18
Lippe	2,241	62,868	3.6 %	14.24
Minden-Lübbecke	1,940	70,512	2.8 %	10.99
Paderborn	1,600	68,589	2.3 %	9.32
Hochsauerlandkreis	1,260	60,633	2.1 %	8.30
Soest	941	62,292	1.5 %	6.03
Coesfeld	854	37,900	2.3 %	9.00
Steinfurt	685	91,642	0.7 %	2.99
Höxter	608	23,999	2.5 %	10.12
Oberbergischer Kreis	406	62,107	0.7 %	2.61
Bielefeld	303	84,369	0.4 %	1.43
North Rhine-Westphalia	31,568	3,865,016	0.8 %	3.26
Germany	101,779	40,645,000	0.3 %	1.00

1) Covered by social insurance
2) Location quotient (Germany = 1.00)
Data: IT.NRW (2021); Statista (2021); StBA (2021); own calculations

However, there is disagreement about the value of the LQ above which a significant regional industry agglomeration can be assumed (Martin/Sunley 2003, 20). In practice, very different thresholds are usually set arbitrarily: while, for example, the DTI (2001) identified clustered industries with an LQ of 1.25 or more for the UK, Isaksen (1996) set the bar much higher and still found 143 regional industry agglomerations for Norway, which together represented one fifth of the country's manufacturing workforce. In principle, however, the lower the threshold, the more potential clusters can be found, which makes the procedure very flexible but also somewhat arbitrary. O'Donoghue/Gleave (2004) contributed to the solution of the threshold problem by developing a standardisation procedure for the LQ and testing it for business services in the UK. For the standardised and logarithmised LQs, the significance level of five percent commonly used in the social sciences can be used as a threshold.

Further problems of the LQ, which also apply to other relative and absolute concentration measures, are:

- Employment data for industries at the regional level is often limited in order not to reveal information about individual establishments – a common obstacle to top-down cluster analysis especially in Germany.
- A cluster usually does not consist of a single industry alone, but a set of related industries that needs to be defined and assembled first with the help of complementary methods. These include input-output analysis, as well as alternative clustering algorithms like the one developed by Delgado et al. (2016) that systematically generates and assesses sets of cluster definitions, i.e., groups of closely related industries.
- The results depend on the level of aggregation chosen, as values increase with spatial and sectoral disaggregation.
- A high LQ says nothing about the absolute size of a sector agglomeration and must therefore be supplemented by absolute concentration measures.
- As a rule, clusters exceed the limits of statistical industry classifications; in particular, young fields such as biotechnology or nanotechnology and cross-sectional industries such as optical technologies or production technology are difficult to capture with concentration measures (Koschatzky/Lo 2007, 8f.).

Cluster Index

A high LQ could indicate an agglomeration of firms in an industry, but could also be caused by a single large firm. This is where the cluster index of Sternberg/Litzenberger (2004, 779) comes in, which expands the LQ by relating the number of employees in a sector in a region to the area, the number of inhabitants and the number of companies in that region.

$$CI_{ij} = ID_{ij} \times IS_{ij} \times \frac{1}{SB_{ij}} = \frac{\frac{e_{ij}}{\sum_{i=1}^{n} e_{ij}}}{\frac{i_i}{\sum_{i=1}^{n} i_i}} \times \frac{\frac{b_{ij}}{\sum_{i=1}^{n} b_{ij}}}{\frac{a_i}{\sum_{i=1}^{n} a_i}}$$

with

i = region
j = industry
ID_{ij} = relative industrial density of industry j in region i

IS_{ij} = relative industrial stock of industry j in region i
SB_{ij} = relative firm size of industry j in region i
e_{ij} = employment of industry j in region i
b_{ij} = number of firms (businesses) of industry j in region i
a_i = area of region i
i_i = population (inhabitants) of region i

As the formula shows, the cluster index consists of three components (Litzenberger/Sternberg 2006, 211–214):

1. The spatial concentration of industries in a region – in relation to the region as a whole – can be measured with the *relative industrial density* (ID_{ij}). To calculate ID, the value of the absolute industrial density of a region is divided by the absolute industrial density at the national level. The absolute industrial density in turn relates the employment of an industry or a group of industries to the area of the corresponding spatial unit.
2. This is combined with the *relative industrial stock* (IS_{ij}), which is calculated from the absolute industrial ratio of the region divided by the absolute industrial ratio at the national level. The absolute industrial stock relates the economic activity indicator – in this case employment – to the number of inhabitants or the total number of employees.
3. The relative firm size (SB_{ij}) is the ratio of the average establishment size of the industry in the region to the average establishment size of the industry at the national level.

Like the LQ, the cluster index assumes values from zero to infinite, while the average across all regions is always 1. It refines the LQ approach, but also requires more data that may not always be available. Apart from the inclusion of additional regional characteristics (number of firms, area, and population of the region), the drawbacks listed above for the LQ also apply to the cluster index.

Absolute and relative concentration measures are relatively easy to calculate when spatially and sectorally disaggregated data are available, but they can basically only provide indications of spatial-sectoral concentrations. The *cluster mappings* carried out top-down for Germany by Brenner (2004; 2006) and Sternberg/Litzenberger (2004) can only identify industry agglomerations and thus establish cluster assumptions. In order to draw conclusions about interdependencies or even institutional or socio-cultural cluster characteristics, a combination with bottom-up methods is necessary.

2.2 Growth Analyses

In economic development practice, expectations about the future growth of an industry on a national or supranational scale are often transferred to regional concentrations of that industry, without considering the existence of specific regional contexts. Instead, however, the development dynamics of an industry in a specific region can be determined by the absolute and/or relative change in the number of companies, turnover, or employees or with the help of *shift-share analysis (SSA)* introduced by Dunn (1960; for a more extensive introduction see Farhauer/Kröll 2014, ch. 15).

The latter decomposes a region's growth differential vis-à-vis the national total into a structural effect and a regional effect, which is the residual left after accounting for the impact of industry structure on regional growth (Krätke/Scheuplein 2001, 45–47). In essence, for a given period t_0 to t_1, regional employment or value-added growth is compared to national employment or value-added growth in the same period. This may basically be achieved through subtraction or division (table 3). In any case, a hypothetical value for the region in t_1 is computed under the assumption that all industries in the region grew with the respective industry growth rates at the national level, yielding the *structural effect* on regional growth. The residual between this hypothetical and the actual t_1 value is the *location effect* that can be attributed to anything but the region's industry structure.

Tab. 3: Shift-share analysis based on subtraction vs. division

Operation	***Method***	***Procedure***
subtraction	difference method	total net shift = net proportionality shift + net differential shift
division	index method	regional factor = structural factor + location factor

Source: Author's illustration based on Schätzl 2000, 77–84

The results of an SSA point at possible reasons for growth differentials across regions. Positive structural effects indicate agglomerations of dynamic industries, which could be high-tech clusters. Positive location effects, on the other hand, show that industries are more successful in a particular region than elsewhere. In contrast to global trend studies, SSA accounts for specific regional assets and may thus be used as a complement. The significance of SSA results, however, depends on the period examined as well as on the level of sectoral and spatial disaggregation of the initial data. It is often criticised as a descriptive tool and therefore complemented with shift-share regressions (Farhauer/Kröll 2009). Consequently, the suitability of SSA as a forecasting instrument is also doubted (Schätzl 2000, 84).

2.3 Input-Output Analysis

As a supplement to national accounts, input-output (IO) tables provide detailed insights into the flows of goods and production interdependencies in the national economy and with the rest of the world (Bleses 2007). It is a mandatory element in the European System of National Accounts, hence IO tables are available for all European countries. At the regional level, they would be an ideal instrument for identifying value-chain linkages as key elements of clusters, but domestic flows of goods are not captured in national accounts. National tables can therefore only be regionalised by means of very complex data collection or with the help of derivative methods in which the regional specifics that are particularly important for clusters can only be estimated (Krätke/Scheuplein 2001, 49). For instance, a textbook example provided by Farhauer/Kröll (2014, 402ff.) assumes no difference in technology and the age of the capital stock between the region and the nation in which it is embedded.

Feser/Bergman (2000) identified 28 cluster templates from national input-output tables for the U.S., which they applied to data for the state of North Carolina to map regional transactions. Their results deviated substantially from conventional industry-level analysis and provided an approximation of intra-firm linkages within the state. Here too, however, national patterns were broken down without considering regional specifics. The main problem with estimates of regional IO tables is the simultaneous export and import of goods from the same group of goods, so-called cross-hauling (Kronenberg 2009). Többen/Kronenberg (2015) developed a method to include this effect in estimates of multi-regional input-output tables. Vogt (2011) shows how this method was tested and further developed to estimate exports and imports according to the IO concept for Baden-Württemberg.

According to Farhauer/Kröll (2014, 424), IO analysis is mostly used to estimate the impact of one industry's demand on regional output, income, and employment. Its occasional application to the identification of clusters is limited to those based on value-chain linkages (vertical clusters). Its proper application would require data on three- or even four-digit industry classification levels, which is rarely available in IO tables. They conclude that IO analysis may complement other methods, but one should not rely on it as the sole method when looking for clusters.

3. Bottom-Up Approaches

3.1 Expert Opinion and Stakeholder Participation

Individual interviews or moderated workshops with representatives of business, science, the public sector, chambers and associations, etc. not only provide information on strengths and weaknesses as well as development trends of the regional economic structure, but can also mobilise regional actors for the subsequent implementation of a cluster strategy. According to Bergman/Feser (2020), this is the most common method of cluster identification. Taking into account existing sector analyses, expert, and media reports, it is possible to draw conclusions about existing input-output relations or other cluster potential in the region. The disadvantages of this method are generally to be seen in the limited reproducibility and comparability of the results, as well as in possible distortions due to the self-interest of the experts involved and other vested interests (Kiese/Wrobel 2011).

Brun/Jolley (2011) review a case study of a collaborative approach involving *stakeholders* in cluster identification in North Carolina and assess the costs and benefits of this method. They find that increased stakeholder participation in cluster identification improves the quality of the analysis, as well as community and political acceptance of the results. Stakeholders also challenged the authors to define a renewable energy cluster and analyse their county's competitive position in this sector. The main costs were the time and money required to organise stakeholder participation.

This basic approach can be extended to possible future trajectories in the *regional foresight* method (Koschatzky 2005; Stratigea/Papadopoulou 2013; Bassani et al. 2016). This is a participative and moderated procedure to forecast regional technological development. Regional actors with different technological and social backgrounds are brought together to exchange views on possible future development paths. This process condenses their assessments and expectations into a common vision of regional development, which enables regional specifics (traditions, established strengths) to be linked with global trends (Hospers 2004). This is very much in the spirit of the entrepreneurial discovery process that the European Union demands as part of smart specialisation strategies underlying their cohesion policy since 2014 (Foray 2018).

3.2 Value Chain Analysis

The ultimate goal of the analysis of regional clusters is to map inter-firm linkages in value chains and their degree of localisation. As a starting point, a value chain at the lowest possible aggregation level (bottom-up) can be chosen, whose links can be assigned to individual companies. It is advisable to first identify one or more cluster cores (e.g. end manufacturers as focal companies or important suppliers or distributors) and from there a cluster environment with subordinate chain links (Krätke/Scheuplein 2001, 52).

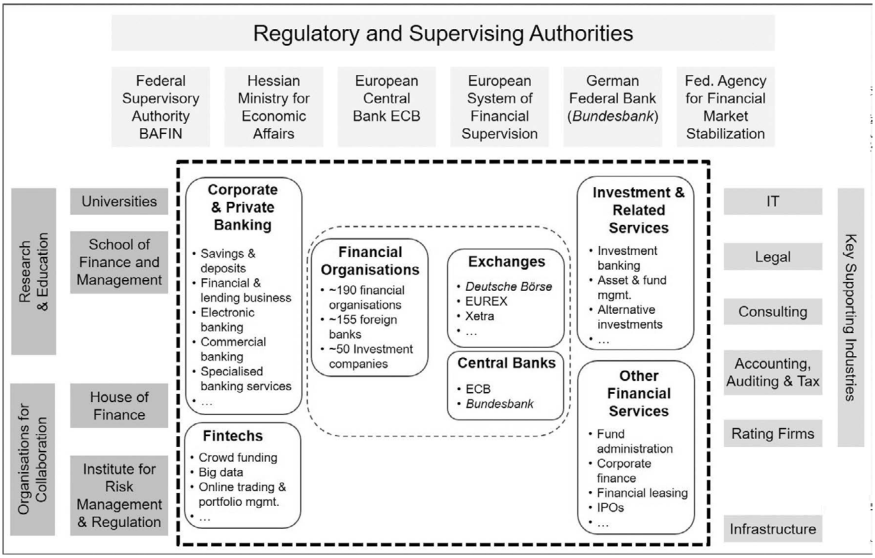
If the value chain is sufficiently mapped as a vertical cluster dimension, it should be expanded into a value creation system with horizontal and diagonal links to other companies and supporting organisations (Kiese 2012, 39). The functional analysis provides important information on the development status of the cluster and, if necessary, elements and links that are still missing for a functioning cluster. Due to the amount of research needed, however, the method can only be carried out on the basis of the value chain(s) relevant for regional specialisation.

3.3 Cluster Mapping for Case Studies

A cluster map is not a geographical map, but a visual schematic describing the different elements of a cluster and their relations. In a generalised overview, it illustrates the structure of industries and supporting organisations within a cluster. A cluster map can guide economic development strategies that account for the synergies between the cluster's components. It is not a primary method of cluster identification and analysis, as it merely structures information obtained from other methods, such as expert opinion and reports.

The example in fig. 2 shows that cluster maps are usually developed from the inside out. Some organisations may perform different functions, as can be seen from the double appearance of central banks as market players with some supervisory functions. Austrian (2000) points out that once accepted, a cluster map shapes the way in which a cluster is perceived both inside and outside the cluster. After reviewing different types of cluster maps, the author recommends an improved version that combines elements from several of the maps. Note that the term cluster mapping is also used for

Fig. 2: Schematic cluster diagram: Frankfurt's Financial Services Cluster (Source: Behrens et al. 2016, 17; slightly modified)



top-down quantitative approaches like the U.S. Cluster Mapping Project[6], the Italian cluster mapping project[7], and more heterogeneous data collections like the European Cluster Observatory[8].

3.4 Competitive Methods

Competitive procedures for identifying networks as important components of regional clusters have become popular since the mid-1990s. This is evidenced by the BioRegio, InnoRegio and leading-edge cluster competition of the German Federal Government, the cluster competitions of the NRW state government (Kiese 2012) or the initiative "Regional Competence and Innovation Centres" of the Stuttgart regional economic development corporation (Sautter 2004, 71f.). Although the efficient use of scarce funding and the mobilisation of regional potential can be singled out as the primary goals of these competitions, the origin of the applicants and award winners provides important indications of the existence and development status of (potential) regional clusters as a secondary effect. However, while the institutionalisation of networks is in the foreground, other characteristics of potential or functioning clusters are not considered in this method. As a consequence, significant cluster potential failing to mobilise collective action to apply for the contest may be overlooked.

6 www.clustermapping.us.

7 https://italiacompete.it.

8 http://www.clusterobservatory.eu.

3.5 Network Analysis

Developed for the analysis of social networks (Jansen 2014), network analysis is one of the more recent methods of cluster identification (Bergman/Feser 2020). In contrast to input-output analysis, the focus here is not on the supplier linkages of industries, but on the networking structure of actors which includes not only material supplier and buyer relationships, but also their communication networks for the exchange of knowledge. In addition to the exchange of goods, companies are surveyed about their respective contacts with other companies and other organisations in and outside the region. If the companies themselves are asked to name their most important business and communication partners, indications of other companies relevant to the clusters and supporting organisations will emerge. The information gained from a company represents the "ego network" of the firm. In summary, the information of all actors is aggregated into matrix representations of the cluster, whereby the actors are represented as nodes and their interactions as lines (Jansen 2014).

Since traditional approaches like the snowball method fail to identify isolated actors in networks, they have given way to the so-called roster-recall method (ter Wal/Boschma 2009). This method provides each respondent with a list of actors – the roster – that should ideally include the complete population to prevent a bias against those other actors not listed. In practice, however, this is often not feasible as the list would become too extensive. For each of the actors in the roster, the respondent is asked to indicate if she/he has a relationship of one or several predefined types.

Network analysis is more suitable than any other method for determining the quality of the interconnectedness, which is emphasised in theory as an essential determinant of cluster dynamics. It can be used to determine the density, cohesion, and centrality of the network as measures of the quality of the interconnections. As further indicators for a qualitative comparison of regional clusters, Krätke/Scheuplein (2001, 71) add the extent of functional differentiation, the supraregional transaction relations, the spatial concentration of cluster companies within the region, and the quality of the institutional infrastructure.

However, this approach comes at a high cost, since mapping a region's network structures in a reliable manner requires a high response rate, namely, a near-complete coverage of the relevant actors.[9] Even if this is achieved, however, a respondent's knowledge about the transaction and communication linkages of her/his organisation still introduces a considerable source of error that should always be remembered when interpreting fractional differences in network parameters (ter Wal/Boschma 2009, 748). Likewise, researchers depend on respondents' judgements when it comes to the intensity and quality of linkages of cooperation.

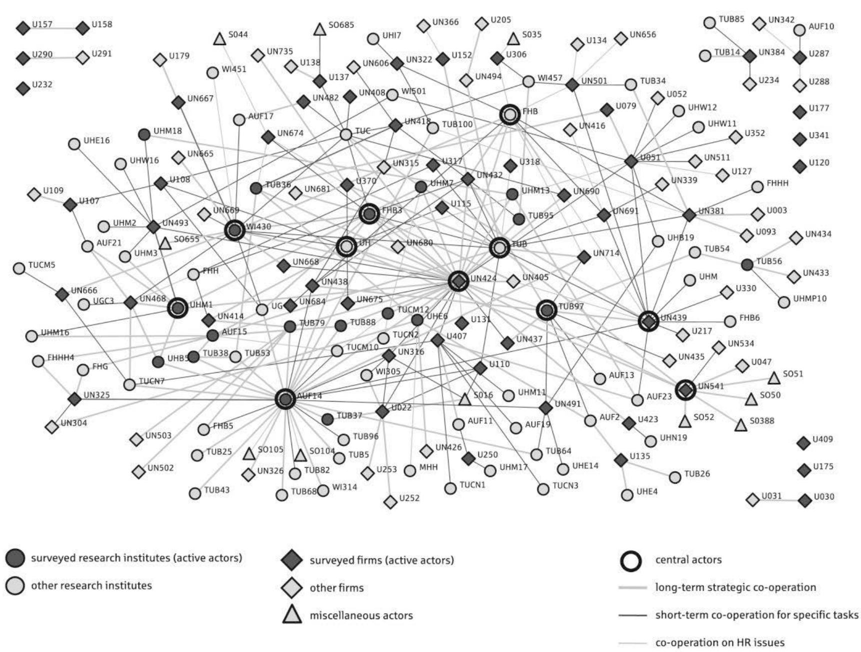
Due to the high costs of surveying entire cluster populations, the application of network analysis is usually constrained to smaller clusters with a limited number of firms and other organisations, such as the film industry in Potsdam/Babelsberg (Krätke

9 Some non-response is commonly considered tolerable since each link should ideally be mentioned by both of the partners involved (reciprocation; ter Wal/Boschma 2009, 747).

2002), logistics in Bremen and Hamburg (Wrobel 2004), the emerging IT security cluster in the Ruhr (Scheideler 2009), or nanobiotechnology in Münster (Ammermann 2011). A notable exception of an extensive regional network analysis covering the entire metropolitan region of Hannover-Braunschweig-Göttingen-Wolfsburg was conducted by Brandt/Hahn/Krätke/Kiese (2009) and updated to trace changes over time by Brandt et al. (2021). The population for the initial survey comprised 496 economically relevant university and non-university research organisations and 670 innovation-oriented firms, from which a sufficient response rate of 81 percent was obtained.

The results show clear differences between seven fields of competence across all network parameters, which are also expressed in network diagrams. The example for the competence field of mobility (i.e., automotive industry and research) represents a high degree of density and centralisation (fig. 3), in contrast to the much looser networks of the heterogeneous ICT field. The visualisation allows to identify focal organisations, but also peripheral actors with no or only weak ties into the network. Note that as for the cluster map, a network diagram is not a geographical map. Organisations, which are anonymised with codes in this example, are arranged according to their centrality in the network by the software.

Fig. 3: Network diagram for the mobility field of competence in the metropolitan region of Hannover-Braunschweig-Göttingen-Wolfsburg (Source: Brandt et al. 2009, 244)



As a consequence of survey costs, the application of network analysis to the identification and analysis of clusters has shifted to secondary data, such as co-patenting as 'paper trails' indicating knowledge flows. Ter Wal/Boschma (2009) provide a review of such studies. A more recent example is the analysis of cluster policy effects on local patent co-application and co-invention networks in 17 German regions that participated in the BioRegio contest by Graf/Broekel (2020). However, this data only captures one particular form of interaction, whilst surveying can basically cover any kind of linkage, which in turn increases the danger of mixing apples with oranges.

4. Comparative Assessment and Conclusion

All methods portrayed in this chapter have characteristic strengths and weaknesses, which is why a mix of complementary methods (see Terfrüchte/Frank in this volume) – such as top-down and bottom-up approaches – is generally recommended (Komorowski 2020). Industry agglomerations identified through top-down approaches can lead to the formulation of assumptions about potential clusters, thus serving as a starting point for the targeted use of bottom-up approaches. However, clusters are moving targets that require continuous monitoring. A one-off analysis can only provide a snapshot that may soon become obsolete as technologies and demand shift.

Tab. 4: Comparative assessment of methods (Source: Author's compilation)

Level	***Method***	***Strengths***	***Weaknesses***
macro	measures of localisation and specialisation	draws on secondary data, no surveying needed	captures agglomeration, but no linkages results depend on level of aggregation
	growth analysis (shift-share analysis)	dynamic approach (decomposing growth differentials) no surveying needed	descriptive and coarse (location effect as residual) results depend on level of aggregation
	input-output analysis	approximates interaction in clusters no surveying needed	only data on national patterns regional IO linkages can only be estimated
meso	expert opinion and stakeholder participation	relatively easy to organise	self-interest, vested interests
	cluster mapping		secondary method drawing on other approaches
	competitive methods		only captures organised clusters
micro	value chain analysis	provides detailed insights	costly
	network analysis	concrete measurement of interaction in clusters	

Due to the resources required by many methods, the spectrum summarised in table 4 is usually not fully exploited to inform the design and implementation of *cluster policies*. A survey of economic development agencies in 94 large cities across Germany by Hollbach-Grömig/Floeting (2008, 11) found that internal knowledge was most widely used to identify clusters: 71.3 percent of respondents already knew which clusters they had. Expert opinion was second, with 58.5 percent stating commissioned reports and 45.7 percent moderated processes. The latter share also came out for growth analyses, although this was not specified as SSA in this standardised survey. This methodology may also help to explain the responses for network analysis (29.8 percent), concentration measures (28.7 percent), and value chain analysis (25.5 percent), as respondents' understanding of these terms could not be verified. Interview research for multiple prominent regional cluster policy case studies suggests that only expert opinion and concentration measures are widespread in practice, while the political selection of clusters for promotion often precedes the analysis (Kiese 2012, 311).

In practice, the above-mentioned methods for identifying (potential) clusters are often supplemented by indicators for the measured or potential growth of sectors and technologies in order to identify growth clusters and to filter out stagnating or even shrinking clusters at the end of their life cycle (Menzel/Fornahl 2010). In addition to the analysis of the past employment trends, global trend studies are often very popular. However, this not only entails the risk of incorrect forecasts, but also infuses herd behaviour into cluster policy, as reflected in the high degree of congruence of regional cluster portfolios (cf. Kiese 2012). Region-specific development paths too often fade into the background. Sloppy cluster identification and analysis may save money short-term but increases the risk of misallocating public funds in the longer run. It thus appears advisable to exploit the available methods more fully – not just in reports commissioned by policy-makers, as more independent research is also needed.

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