Identification of spatial agglomerations in the German food processing industry

Journal Article

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Publication date:
2017-03

Permanent link:
https://doi.org/10.3929/ethz-b-000237623

Originally published in:
Papers in Regional Science 96(1), https://doi.org/10.1111/pirs.12171

Postprint

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Abstract: We identify spatial agglomerations in the German food industry, using the Cluster Index by Sternberg and Litzenberger (2004). Previous studies have analyzed this industry utilizing aggregated data with the result of a lack of agglomerations. Given its heterogeneous character, the present study analyzes subsectors of the German food industry at a disaggregated spatial and sectoral level. The results show spatial agglomerations in particular for the subsectors processing and preserving of meat, fish, fruit, wine, milk, mineral water as well as for breweries. This indicates that those subsectors are characterized by stronger cluster self-enforcing processes likely in combination with a favourable proximity to natural resources.

Keywords: Regional Clusters, Spatial Economics, German Food Processing Industry

JEL-classification: R11, R12, O14

1. Introduction

During the last few decades, regional clusters have attracted increasing attention in spatial economics as well as in politics. The popularity of the topic is demonstrated by a growing number of publications worldwide (for reviews of the literature see: van der Linde, 2003; Ketels, 2003; Lazzeretti et al., 2014) as well as by regional political initiatives (Preissl and Solimene, 2003). The increasing interest in this concept is based on insights that local factors such as knowledge creation, face-to-face contacts or trust-based relationships can provide. These are important to enhance regional as well as firm performance (Bathelt et al., 2004; Henkel, 2008; Stahlecker, 2008).

Several studies have analyzed whether agglomerations exist in different industrial sectors (e.g. Potter and Watts, 2014; McDonald et al., 2007; Cooke, 2002; Belso-Martínez, 2012) with the most famous examples being the Silicon Valley and the Detroit automobile cluster (Klepper, 2007, 2010).

Important studies analyzing the German industry, using qualitative as well as quantitative methods are amongst others: Sternberg and Litzenberger (2004), Rocha and Sternberg (2005), Brenner (2006), Alecke and Untiedt (2008), Titze et al. (2010), Brachert et al. (2011), Eigenhüller et al. (2013), Wrobel (2013). Sternberg and Litzenberger (2004) find that the formation of industrial clusters has a positive impact on the number of start-ups in Germany. Previous results for the food processing industry are mostly based on highly aggregated data and show a dispersed geographical distribution of firms without any cluster activities (Lagnevik et al. (2004) for the Swedish food industry; Steiner (2007) for Canadian food processing; Wandel (2010) for Kazakhstan's agro-food sector; Diez-Vial (2011) for the Spanish ham cluster). Steiner (2007) provides evidence for significant constraints in clustering processes in the food industries of Canada, Ireland, Belgium and Brazil and confirms these results based on a case study for Alberta's food processing industry. Several studies also focus on specific food industry subsectors such as the wine industry (Porter, 2000; Mytelka and Goertzen, 2004; Visser, 2004; Aylward and Glynn, 2006; Gwynne, 2008). Giuliani and Bell (2005) analyze knowledge transfer within the Chilean wine cluster with the result that knowledge is mainly exchanged by a core group of firms with superior receptive competencies. Giuliani and Arza (2009) as well as Giuliani et al. (2010) focus on university-industry linkages in the Chilean, Italian and South African wine cluster and show that the firms' knowledge as well as the researchers' individual characteristics are the main drivers of successful linkages.

Due to the heterogeneity of the German food processing industry, with about 651,560 employees working in 33 different subsectors (BVE, 2010), an analysis at an aggregated level does not appear adequate (Cluster Competitiveness Group, 2007).[1] While in earlier studies the food industry has either been analysed as a whole or has been disaggregated to only nine different subsectors (such as "manufacture of beverages", "processing and preserving of meat products")[2] this study aims to fill this gap in the literature by assessing whether spatial agglomerations exist at the most disaggregated level of subsectors of the German food processing industry (four-digit level of the WZ03). While the method applied in this article is suitable to identify spatial concentration of firms in different regions and subsectors, relationships between firms and sectors cannot be identified.

The article is further motivated by the economic importance of the German food industry, which becomes apparent when it is compared to the entire manufacturing sector. With a contribution of 16.2% to the total number of German manufacturing firms and 9.3% to total manufacturing turnover in 2008, the food industry is one of the most important sectors within German manufacturing. Also in a European

[1] Several case studies on spatial agglomerations in the food processing industry have also been realized at a more disaggregated level (e.g. Deimel et al., 2008).

[2] That is, the two- or three-digit level of the German Classification of Economic Activities, Version 2003 (WZ03).

context the German food industry is of high economic importance, contributing 17.4% to total EU-27 food industry turnover in 2008 (Eurostat, 2014). Germany is also one of the globally leading exporters of food products with a volume of €51.2 bn. in 2012 (BVE, 2014). Furthermore, the food industry is confronted with specific structural difficulties such as increasing price volatility in upstream markets and high concentration and thus market power in the downstream sector. Retailers' market power is further increased by a growing share of private labels (Hirsch et al., 2014). Therefore, due to its high economic relevance and the given challenges in the up- and downstream sectors, it appears appropriate to further analyze the German food industry regarding cluster tendencies. Furthermore, given those challenges the results might serve as the basis for cluster initiatives to enhance the competitiveness of the German food industry (e.g. BMBF, 2014). This is important, as Germany is the EU's main initiator of cluster initiatives to support productivity and innovation of SME's (Hantsch et al., 2013). In addition, Porter (1998) notes the importance of clusters for Germany's international competitiveness.

The paper is structured as follows: First, to provide the general theoretical background, the concept of clusters within spatial agglomeration theory is discussed in the second section. In the third section different methods to identify clusters are presented, with a focus on the Cluster Index (CI), which will be used in the empirical analysis. This is followed by a description of the data used (section 4). The results are presented and discussed in the fifth section. Finally, the findings are elaborated upon and conclusions are drawn.

2. Spatial Agglomeration Theories

Theories on spatial agglomerations have gained increasing attention within economic geography in recent decades. They all trace back to Marshall's (1920) early work on industrial districts. Marshall (1920) focuses on a triad of agglomeration economies that occur as a consequence of concentration of an industry in a region: the availability of skilled labour, the growth of subsidiary trades in the vicinity and technological spill-over effects due to an increased flow of information and knowledge[3]. Those agglomeration economies are usually referred to as localization externalities. In contrast, Jacobs (1969) claims that knowledge spill-over is external to the industries in which firms operate. As the sources of

[3] Klepper (2005, 2010) shows that besides these agglomeration economies organizational reproduction in form of spin-offs can also be a main driver for the emergence of agglomerations.

knowledge are concentrated in cities, urban areas are seen as the main source of innovation within this approach. In addition, Jacobs (1969) argues that knowledge externalities increase with the diversity of industries in a region. Those effects of agglomeration are known as urbanization externalities. In the remainder of this paper we focus on localization externalities of agglomerations (Beaudry and Schiffauerova, 2009).

Particularly in the 1990s, several streams of spatial theories have evolved. Besides the concept of learning regions (e.g. Saxenian, 1994; Morgen, 1997; Hauser et al., 2007; Schiele and Ebner, 2013; Perry, 2014) and the innovative milieu (e.g. Camagni, 1991; Maillat, 1991; Ratti et al., 1997; Maennig and Ölschläger, 2011; Ortiz, 2012; Livi et al., 2014), the cluster approach became largely popular. While the former theories mainly concentrate on innovative activities and are therefore often applied in studies focusing on high-tech industries, the concept of clusters in a multidimensional way analyzes relationships along the supply chain, strongly focusing on competitiveness of the affected firms (Benneworth and Henry, 2004). Due to its relevance in regional sciences as well as in regional politics the cluster approach will also be used in the present analysis.

Although the term 'cluster' was first mentioned in Lasuén's (1973) work, later contributions on this concept mainly refer to Porter (1990) as its originator. Within his theory of international competitiveness, Porter has developed the well-known 'diamond model', in which the competitive advantage of industries within a nation is determined through four key factors: the proximity to related and supporting industries, competitors, a sophisticated demand as well as research institutions (Porter, 1990; 1998). In his early work, Porter has mainly focused on industrial phenomena. That is, competitive 'sectoral clusters' within a nation are determined by strong vertical and horizontal relationships. In his subsequent work Porter (2000a) shifts the focus to territorial dimensions in an analysis of 'regional clusters'. In addition to the sectoral element, Porter underlines the importance of geographical and network phenomena (Rocha, 2004).[4]

Due to the popularity that the concept of regional clusters has gained in recent years, the number of publications as well as the variety of definitions has increased greatly. Literature overviews are provided by Enright (1996), Martin and Sunley (2003) or Lazzeretti et al. (2014) who review the cluster literature

[4] In the literature, the distinction between 'sectoral' (or 'industrial') and 'regional clusters' is widely acknowledged (e.g. Litzenberger, 2007; OECD, 1999).

for the period 1989-2010 by means of bibliometric methods and social network analysis. Gordon and McCann (2000) state that one reason for the multi-perspective view of clusters is the adoption of this concept by several scientific disciplines. Due to the large number of definitions and a lack of drawing clear boundaries (geographical as well as sectoral), the concept has often been described as 'chaotic' (Martin and Sunley, 2003). Moreover, Cruz and Teixeira (2010) analysed the scientific cluster literature over the period 1962 to 2008 and demonstrated that there is only minor convergence between approaches.

We will base our understanding of clusters on Porter's view. We will, however, take into consideration the main problems of his concept. Consequently, in this study clusters are defined as "geographic concentrations of interconnected companies and institutions in a particular field" (Porter, 1998). Following this definition, clusters are based on vertically (buyer/supplier) and horizontally (use of common technologies, customers, etc.) linked firms which can be related through cooperation as well as through competition (Atherton and Johnston, 2008; Delgado et al., 2010). Another important factor of this definition which has been of no relevance in the industrial district concept is the relationship between firms and associated institutions such as universities, consultancies, associations or R&D-institutes (Porter, 1998; 2000). Such institutions within spatial agglomerations can strengthen regional as well as firm competitiveness.

Although a wide range of cluster definitions exists, it is common sense that the different actors within these agglomerations have to be interconnected (e.g. Grabher, 1993; Porter, 1998; 2000). Nevertheless, what still remains unclear is the dimension of the relations (Bathelt and Glueckler, 2003; Martin and Sunley, 2003). While some authors focus solely on exchange relationships (Gordon and McCann, 2000), others highlight the importance of additionally being socially embedded in the cluster (e.g. Porter, 2000; Koschatzky and Lo, 2007).

Another problem of clarity (according to Porter's definition) is based on the emergence of cluster structures. Several authors state that clusters have to arise through a self-enforcing process (Sternberg and Litzenberger, 2004; Brenner, 2006). Thus, clusters close to natural resources or sophisticated clients are mostly ignored, although a direct relationship between these resources and the cluster emergence is not necessarily verified. In contrast, several of the studies about the wine industry provide evidence of typical cluster effects, despite natural conditions (e.g. Porter, 2000; Gwynne, 2008). Due to the difficulty of measuring the self-enforcing process and the proven existence of regional clusters close to natural resources, it is, in our view, justified to include the respective industries in the analysis.

The question remains why cluster structures should exist in the food industry. If it is assumed that consumers incorporate search and transportation costs into their purchase decision, it is likely that producers of expensive products – which entail high search costs – have a higher motivation for agglomeration than producers of fast moving consumer goods such as food products (Roos, 2002). However, the EU food industry is defined by several structural characteristics that might encourage cluster formation. Here, the highly concentrated downstream sector likely plays an important role as high retailer concentration, which is enforced by a significant share of private labels, exerts strong competitive pressure on firms in the processing industry (Hirsch and Hartmann, 2014). Therefore, agglomerations in the food industry might play an important role in increasing the countervailing power towards the retail sector. Furthermore, the EU food industry is characterized by high degrees of competition and market saturation (Hirsch and Gschwandtner, 2013). Hirsch and Hartmann (2014) show that in such markets innovations are an important measure for firms to remain competitive. According to Delgado et al. (2010), strong cluster environments enhance the capabilities of innovation, and therefore likely increase the competitiveness of food industry firms.

The EU food industry is characterized by a highly concentrated size structure with less than 1% of large firms[5], which account for more than 50% of total industry turnover. We therefore assume hub-and-spoke clusters according to Markusen (1996) where large hub-firms interact with smaller firms that are linked to the hubs like wheel spokes (He and Fallah, 2011).

Thus, contrary to the results of previous studies, we suppose that regional concentrations in the German food processing industry exist. However, due to the aforementioned diversity within this sector, we argue that clusters are particularly relevant at the level of specific food subsectors.

While the theoretical approaches described in this section highlight the importance of considering vertical relations along the supply chain, as well as relations with research institutions, those links cannot be captured by the Cluster-Index introduced in the following section. Thus, according to Sternberg and Litzenberger (2004) we aim to identify ‘regional clusters’, which are defined as ’a concentration of

[5] Large firms are defined as having more than 250 employees according to the SME definition of the European Commission (2005)

interdependent firms within the same or adjacent industrial sectors in a small geographical area' whereby buyer-supplier and supplier-buyer interrelations are not captured[6] (European Commission, 2002 p. 14).

3. Methodology

The problem of varying theoretical cluster definitions described above is also present for the empirical measurement of this phenomenon (for an overview see Bergman and Feser, 1999; Kiese, 2008; Hoffmann, 2014). Martin and Sunley (2003) state that "there is no agreed method for identifying and mapping clusters, either in terms of the key variables that should be measured or the procedures by which the geographical boundaries of clusters should be determined." Therefore, the number and size of identified clusters varies significantly among different studies due to the chosen boundary and measurement methods (Litzenberger and Sternberg, 2006; Lerch, 2009).

Generally, the methods to identify clusters can be differentiated into top-down (quantitative methods) and bottom-up (mostly qualitative case studies in a defined region) approaches (e.g. Bergman and Feser, 1999; Martin and Sunley, 2003). The analysis in this paper will focus on the former method as our aim is to identify nationwide clusters which cannot be detected through bottom-up approaches. Moreover, as signified by Martin and Sunley (2003), bottom-up approaches are usually based on loose means of identification, which leads to the identification of clusters that in many cases turn out to be insignificant and barely connected groups of related firms.

When using the top-down method, the spatial concentration of an industry in a specific district has to be analyzed in relation to the whole region. Most previous studies seeking to identify regional clusters were based on indicators that measure the spatial concentration of labour, such as the Gini coefficient or the Ellison-Glaeser-Index (for Germany see Helmstädter, 1996; Brenner, 2006; Alecke and Untiedt, 2008). The Ellison-Glaeser-Index is a top-down measure that has commonly been used in US studies (e.g. Braunerhjelm and Johansson, 2003; Holmes and Stevens, 2004). Ellison and Glaeser (1997) describe their index as the dartboard approach where the darts on the board represent firms on a map. An advantage of this index is that random spatial agglomerations of firms are not detected as clusters. However, the data needed for the implementation of this index is usually hardly available, which makes this index

[6] This is according to the European Commission (2002) the hierarchically lowest degree of cluster concepts.

unsuitable in many cases (Alecke and Untiedt, 2008). Furthermore, without taking into account the dimension of the analyzed unit -in the present case the districts-, industrial specialization instead of concentration is measured.

We therefore employ the Cluster-Index (CI) suggested by Sternberg and Litzenberger (2004). The CI is composed of the following three components: the relative industrial stock (IS), the relative industrial density (ID), and the relative plant size (PS). In order to identify spatial industrial clusters, those components are related in a multiplicative way, leading to the CI for district *i* and sector *j*:

$$CI_{ij} = IS_{ij} * ID_{ij} * \frac{1}{PS_{ij}} = \frac{e_{ij}}{b_i} \Bigg/ \frac{\sum_{i=1}^{n} e_{ij}}{\sum_{i=1}^{n} b_i} * \frac{e_{ij}}{a_i} \Bigg/ \frac{\sum_{i=1}^{n} e_{ij}}{\sum_{i=1}^{n} a_i} * \frac{\sum_{i=1}^{n} e_{ij}}{\sum_{i=1}^{n} p_{ij}} \Bigg/ \frac{e_{ij}}{p_{ij}} \quad (1)$$

with:

e_{ij} number of employees in district *i* and sector *j*

b_i number of inhabitants in district *i*

a_i size of the district *i* measured in sq. km

p_{ij} number of plants in district *i* and sector *j*

$\sum_{i=1}^{n} e_{ij}$ no. of employees of sector *j* in the whole region

$\sum_{i=1}^{n} b_i$ number of inhabitants in the whole region

$\sum_{i=1}^{n} a_i$ size of the whole region measured in sq. km

$\sum_{i=1}^{n} p_{ij}$ no. of plants of sector *j* in the whole region

The IS is calculated on the basis of the location quotient (LQ), with the difference that the IS is based on the number of inhabitants as the reference value instead of total employment[7]. The ID is included as otherwise scarcely populated regions, in which most of the inhabitants work in the same sector, are considered to be a cluster without being spatially concentrated in relation to the overall region, while the PS is included to eliminate an overestimation of the IS or the ID caused by one large company.

[7] The LQ might therefore lead to extremely high values in sectors where only a small fraction of the population is employed.

All three components of the CI are defined between zero and infinity, implying that the whole index also has the potential range from zero to infinity.[8] Values below one indicate below average economic activity of sector *j* in district *i,* while values in excess of one point towards an overrepresentation.[9] The multiplicative connection of the CI components implies that extreme values of single components have a higher influence than e.g. in additive connections (Gallus, 2006). An underrepresentation of a component could possibly be compensated by higher positive values of the other two elements. Hence, even in cities with a high number of inhabitants (and therefore possibly a lower IS) a cluster can be detected due to a higher ID. In contrast, also in a very specialized and scarcely populated huge rural district, clusters will be identified through a possibly high IS, although the ID can be below one (Sternberg and Litzenberger, 2004).

To identify potential clusters, all three components of the CI have to be overrepresented or compensated by at least one other element of the index. Generally, there is no exact threshold value for the definition of a cluster, implying that this threshold has to be determined individually in each cluster study applying the CI (e.g. Titze et al., 2010; Koschatzky and Lo, 2007; Litzenberger and Sternberg, 2006). When determining the interpretation categories we distinguish between the single, the double, the quadruple and the octuple value of each component, with the quadruple value (CI=64) being the threshold for relevant clusters (see Table 1).

Insert Table 1 around here

The main advantage of the CI is that a value for each analyzed district/sector can be derived. Therefore, comparison between districts/sectors is easier than with other measures such as the Gini coefficient, which does not consider the size of the statistical units (i.e. the districts). This makes comparisons of values for districts of different size unreliable (Litzenberger and Sternberg, 2006). Martin and Sunley (2003) highlight the importance of the type of industry/district classification when implementing top-down approaches such as the CI. This is the case because clusters usually exceed standard industry classifications and given administrative geographical units. Martin and Sunley (2003)

[8] If there is no firm of the analysed sector operating in a district (i.e. e_{ij} and $p_{ij} = 0$), 1/PS is not defined. Due to interpretative reasons, the CI is then set to zero, indicating that there is no economic activity and an underrepresented distribution in this district.

[9] Due to the asymmetry of the CI's value range comparisons between values above and below one are not possible. Furthermore, using the CI for further econometric analysis is difficult (Dalum et al., 1998). However, as we do not intend to conduct further econometric analyses with our results and since our focus will mainly be on positive CI values a standardization e.g. in the form of (CI-1)/(CI+1) which leads to values between -1 and 1 does not appear necessary. Furthermore, not standardizing the CI simplifies comparison to previous literature.

also argue that a high disaggregation of the data with respect to districts and sectors might lead to an exaggeration of the number of identified clusters. We therefore test the robustness of the results with regard to district size and assess the validity of the industry classification system used. The solid availability of data for the German food processing industry further justifies the implementation of the CI.

Nevertheless, the following drawbacks of the CI need to be pointed out: the inclusion of the ID in the calculation can lead to a greater difficulty to detect clusters in larger districts than in smaller ones. However, without this element biases with unidentified clusters in highly populated districts (e.g. cities) might occur. Additionally, the correcting with the PS could obscure clusters mainly consisting of large firms. However, this problem has not been verified in previous empirical studies (Titze et al., 2010; Litzenberger and Sternberg, 2006). More important is the fact that functional relations between firms and industries cannot be identified with the CI (Titze et al., 2010; Koschatzky and Lo, 2007) and information about the sectoral or spatial interdependence of industrial clusters cannot be derived (Brachert et al., 2011). Hill and Brennan (2000) apply a combination of spatial concentration measures and input-output methods to identify clusters both from a horizontal and a vertical perspective. Input-output methods are usually based on discriminat, cluster or factor analyses that group industries according to similarities in their input-output relationships (e.g. Hill and Brennan, 2000; Feser et al. 2005; Yang and Stough, 2005). The advantage of this method is that it is not based on a priori information regarding the location of clusters, and that agglomerations in industrial geography can be detected that might not be revealed if a default industry classification system, which is based on a similarity-of-product scheme, is used (Feser et al., 2005). Feser et al. (2005) further advance the methodology by applying input-output methods to identify value chains, and afterwards utilizing the *G*-statistic introduced by Getis and Ord (1992) to detect regions where comparatively high levels of employment for a given value chain are clustered. The *G*-statistic is a measure of spatial association that identifies 'hot-spots' in the geographic distribution of value chains (Ord and Getis, 1995; Feser et al., 2005). However, due to the high data requirements of input-output analyses, inter-industry trade data is hardly available for individual districts/industries, this method cannot be implemented in the case of the German food industry (Martin and Sunley, 2003).

Another drawback of the CI is that inter-cluster knowledge spillovers, intra-cluster innovativeness or linkages to research institutions are not considered (e.g. Bode, 2004; Alecke et al., 2006; Brenner and Broekel, 2011; Broekel, 2012). In previous studies, those issues have either been analysed by means of data referring to corporation in R&D projects (e.g. Brenner et al., 2011; Broekel, 2013) or patent statistics (Maggioni et al., 2011). For example, Paier and Scherngell (2011) find that inter-firm R&D cooperation within the 'European Framework Programmes for Research and Technological Development' is significantly influenced by geographical proximity of participants. Based on patent statistics Maggioni et al. (2011) provide evidence for relations between 'innovation-creating' and 'innovation-adapting' regions while Eisingerich et al. (2012) identify university linkages as a driving force of innovation in firm clusters. Regarding the food sector, the results of Kühne et al. (2014) indicate that vertical interrelations improve innovative performance of member firms. This is of particular importance for the food sector, which is a rather low-tech/low-innovation industry, where innovation is not solely based on firm-level R&D but rather on learning processes which in turn are improved by interrelations (e.g. Weaver, 2008).

4. Data

For the calculation of the CI, data of firms and their employees in each food industry subsector as well as of the inhabitants and the size of the analyzed districts is required at a disaggregated level. For the German food processing industry, this data is provided by the German Federal Employment Services (Bundesagentur für Arbeit, 2008). The sample comprises the number of establishments employing at least one person as well as the total number of employees. Establishments are defined as regionally and economically bounded units that provide employment liable to social security. Data is available at the four-digit industry classification level for any of the 429[10] German districts. We focus on the year 2008, as this is the last period for which complete data for all districts and four-digit food industry subsectors is available. Due to the possibility of having less than three establishments operating in one district, publication of the data would violate the restrictions of data protection by German law. Therefore, the data had to be particularly requested for the present analysis and is not freely available.

The given industry classification system is the German Classification of Economic Activities, Version 2003 (WZ03) of the Federal Statistical Office. The WZ03[11] corresponds to the Statistical Classification

[10] The data is based on 429 districts, although after the reform of districts in Saxony in 2008 the number decreased to 413.

[11] In 2008 a revision of the classification system has been introduced (WZ08). Advantages of the WZ08 are a better consideration of vertical integration and outsourcing (Gutberlet, 2009). In addition, WZ08 reports the two large subsectors of the

of Economic Activities in the European Union (NACE Rev. 1.1), which is an EU directive for all member states and is closely related to the International Classification of Economic Activities of the United Nations (ISIC). Although most analyses have been realized on a three-digit level, not only food processing specialists have claimed that functional relations can be better detected at the four- or even five-digit level, as firms in disaggregated industry classes are more likely related via common procurement markets, labour pools, or research institutions than in aggregated sectors (Krätke and Scheuplein, 2001; Dannenberg and Kinder, 2004). The 4-digit level of the WZ03 comprises 33 divisions for the chapter "DA food processing industry" e.g. "production of meat products", "manufacture of wine" or "manufacture of beer". If establishments are active in several 4-digit subsectors, they are assigned to the subsector with their main activity, measured by value added (Greulich, 2001).

Besides industry data, numbers on inhabitants per district and district size are needed to calculate the CI. This data was obtained from the German Federal Statistical Office (Statistisches Bundesamt, 2009) and contains the size measures in square kilometres as well as the number of inhabitants for each of the 429 German districts.

Table 2 shows the descriptive statistics. The German food industry consists of 33,441 establishments providing employment for 651,560 people. On average, 1013 firms operate in each 3-digit sector[12]. The largest 3-digit sectors regarding the number of employees and establishments are the "manufacture of other food products (DA 158)" and the "production and processing of meat (DA 151)", followed by the beverage industry (DA 159). An average German district has a size of 832.4 sq km and comprises 191,650 inhabitants. The rather large standard deviation of district size shows that districts vary significantly in size. The mean value of establishments and employees in each district is 78 and 1,519 respectively. Each of the 33,441 establishments provides on average employment for 41 people.

Several authors (e.g. Hoffmann, 2014) have shown that a small number of establishments with a dispersed distribution in a district can lead to an overestimation of the CI. By means of random data analysis, Hoffmann (2014) finds that given 429 districts biases in the estimation of the CI can occur if the number of establishments in a subsector falls below 100. Therefore, only divisions that comprise more

miscellaneous sector DA 158 "Manufacture of bread and fresh pastry goods and cakes (DA 1581)" as well as "Manufacture of rusks, biscuits, preserved pastry goods and cakes (DA 1582)" as three subsectors within a separate superordinate category. However, due to data availability the present study is based on WZ03.

[12] For reasons of clarity and comprehensibility the descriptive statistics is based on the 3-digit level while the statistical analysis in chapter 5 is based on the 4-digit level.

than one hundred establishments are analyzed. This implies that 10 of the 33 4-digit subsectors had to be excluded from the analysis. However, these subsectors together only contain 636 establishments, meaning that only 1.9% of the establishments are dropped from the sample.

Insert Table 2 around here

5. Results

In addition to those 23 4-digit subsectors of the German food processing industry with at least one-hundred active establishments superordinate 3-digit categories were analyzed, for some sectors with a high economic importance. Due to the criticism that smaller sectors might lead to an upward bias in the CI, we checked the reliability of the results by analyzing on the basis of count data analysis if subsectors with a small number of establishments or employees showed a generally higher number of relevant clusters (CI > 64). The results of the respective regression showed no significant impact of sector size on the CI.[13] In addition, the correlation coefficient between district size and average CI per district was close to zero (-0.079)[14]. Moreover, despite its high level of disaggregation the 4-digit WZ03 was characterized by a rather high heterogeneity[15] in a variety of its subsectors such as the "production of meat products (DA 1513)" and the "processing and preserving of fruit and vegetables n.e.c. (DA 1533)". Therefore, the CI appears to be suitable to identify the existence as well as the geographical location of clusters in a reliable way (Martin and Sunley, 2003).

Insert Table 3 around here

Table 3 indicates that (with around 80%) the majority of the 213 relevant clusters (with CI>64) can be found in densely populated and city districts. Figure 1 illustrates the overall distribution of clusters on districts. A large number of clusters can be identified in particular for several districts in the south-eastern part of the federal state Bavaria and for the border region of North-Rhine-Westphalia and Lower Saxony.

Insert Figure 1 around here

Insert Table 4 around here

To get a more detailed picture, Table 4 presents the number of districts in each CI-category for the different subsectors as well as some superordinate 3-digit sectors. The results indicate that relevant

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[13] A detailed description of the count data analysis and of the regression analysis can be found in Hoffmann (2014), p. 62ff. or is available upon request.

[14] Correlation between district size and the number of identified clusters is also small (-0.283).

[15] E.g. the 6-digit NAICS system used in the U.S. contains 49 rather homogeneous subsectors as compared to the 33 4-digit WZ03 subsectors

clusters can be identified for nearly all subsectors of food processing at the 4-digit level (see the last two columns of Table 4). Only the “production of meat products (DA 1513)” and the “manufacture of bread, fresh pastry and cakes (DA 1581)” are not characterized by relevant cluster tendencies. These two subsectors demonstrate a strongly dispersed distribution: nearly every district contains at least one establishment and the majority of CI values lie around one. The subsector for which the highest number of districts can be defined as a relevant cluster (19) is the “manufacture of wine (DA 1593)”. This aspect is mainly determined by the thirteen defined regions for quality wine in Germany in which the identified 19 districts are located. For the remaining subsectors between 3 and 15 relevant clusters can be identified with the majority of these sectors showing around 10 districts with a CI>64.

Comparing the findings at the 4-digit level with the respective superordinated 3-digit categories for the most important subsectors of the food processing industry based on turnover and the number of establishments, “Production and processing of meat (DA 151)”, “Manufacture of other food products (DA 158)” and “Manufacture of beverages (DA 159)”[16] it can be seen that the number of clusters at the 3-digit level is generally much lower (light grey fields at the bottom of the Table 4). At the 3-digit level, a large number of relevant clusters (11) can only be identified for the category “production and preserving of fish (DA 1520)”[17] in several districts adjacent to the sea. These results mainly correspond to those of previous studies at the 2- or 3-digit level for German industries where solely the fish industry has been identified as clustered (e.g. Alecke and Untiedt, 2008; Sternberg and Litzenberger, 2004; Brenner, 2006). In the following sections (5.1 and 5.2) the three most important subsectors of the food processing industry based on turnover and establishments will be analyzed in a more detailed manner, and reasons for the diverging results at the different levels of analysis (3 vs. 4-digit) will be derived. Section 5.3 provides some empirical examples regarding the role of natural resources and tacit knowledge for the formation of clusters.

5.1 The impact of subsectors with different size at the example of DA 151

[16] According to Bundesagentur für Arbeit (2008) and Eurostat (2014) “DA 158” is the largest 3-digit food processing sector with a contribution of 49.3% to the total number of firms and 28.6% to total food industry turnover. This is followed by “DA 151” (36.8% and 23.0%, respectively) and “DA 159” (6.2% and 12.1%, respectively).

[17] The category “manufacture of fish (DA 1520)” is the only one not being subdivided at the four-digit-level. Therefore, data are the same at the 3 and 4-digit level.

For the “processing and preserving of meat” (DA 1511), eight districts are identified as relevant clusters (see Figure 2). These include Cloppenburg (CI = 237.45) and the adjacent district Vechta (CI = 107.95), both located in the federal state of Lower Saxony in north-western Germany. Those two districts are highly concentrated regarding the keeping of farm animals and represent the centre of German livestock breeding and meat processing (Freisinger and Windhorst, 2005; Teller, 2007). The meat processors Heidemark as well as the PHW-Group, two of the largest German food manufacturers, operate in those two districts (von Laer, 2002; Bauer et al., 2010). Furthermore, according to slaughtering statistics, Cloppenburg is the German district with the largest quantity (665,280 tons) of processed meat (LkClp, 2014). Besides these two districts, several of the districts in western Lower Saxony and in the north of the federal state North Rhine-Westphalia have a CI above eight and are therefore overrepresented. Another important district with a surprisingly high CI for the meat processing sector is the city district of Hof (CI = 813.2) which is rather renowned for its textile industry than for meat processing. However, Hof and its adjacent area are characterized by an extremely high industrial density (IHK, 2014). In addition, compared to Vechta, Hof is thirteen times smaller and has three times fewer inhabitants, with only half as many establishments and employees being active in the district. Those issues lead to the extremely high CI for the meat processing sector in Hof. On the other hand, in 140 out of the 429 districts there is no establishment of the analyzed subsector located, while an additional 170 districts with at least one establishment operating in DA 1511 show an underrepresented CI. Thus, for this subsector three-quarter of all the districts have a CI which is below the German average of one.

Insert Figure 2 around here

Similar results can also be found for the smaller but closely related subsector “processing and preserving of poultry meat”, (DA 1512) where the district of Vechta (with a CI of 5,734.94) and the neighbouring district of Cloppenburg (CI = 529.69) again show the highest values. Considering the results for the two subsectors (DA 1511 and DA 1512) jointly, it is evident that there is a very high cluster tendency for “DA 151 processing and preserving of meat and poultry meat” in north-western Germany. Further analysis of the “manufacture of prepared animal feeds (DA 1571)” underlines these results. For this sector, Vechta again shows the strongest value (CI = 699.34), followed by Cloppenburg (CI = 129.5). This correlation of CI values across different but related branches of production in these two districts is a good indicator for existing “related and supporting industries” as an element for a competitive cluster.

The question remains as to how these results fit together with the lack of cluster tendencies in the main category “production, processing and preserving of meat and poultry meat products (DA 151)”. Besides the two described subsectors (DA 1511 and DA 1512) the main category “processing and preserving of meat” also comprises the subsector “production of meat products (DA 1513)”, which contains a much higher number of establishments and employees (more than 93% of all establishments) in relation to the other two 4-digit subsectors. In total, this sector has fourteen times as many establishments and five times as many employees than the other two subsectors put together.

Due to the structure of primarily very small plants which are often located near local demand, this is a highly dispersed sector. For this reason no relevant cluster can be detected by the analysis. Additionally, there are just three districts which do not have any establishments operating in the analyzed sector. Thus, considering the size of the subsector “production of meat products (DA 1513)” in relation to the other two subsectors, it is evident that possible cluster structures cannot be detected at the 3-digit level.

This distortion is one of the reasons why previous studies (e.g. Sternberg and Litzenberger, 2004; Deimel et al., 2008; Porter, 2000) as well as cluster specialists use case studies at a sub-category level of food processing (Cluster Competitiveness Group, 2007).

Besides the meat industry, the two other important sectors for which cluster structures could be detected at the 4-digit level are the “manufacturing of other food products (DA 158)” and the “manufacturing of beverages (DA 159)”. These are defined by specific structural characteristics that limit the detection of clusters at a highly aggregated sectoral level. These aspects will be discussed in the following section.

5.2 The impact of heterogeneous subcategories at the example of DA 158 and DA 159

While for the meat industry the subsectors can be characterized as rather homogenous, one can find several examples in which the 3-digit categories contain a number of very heterogeneous 4-digit subsectors. This is particularly true for the three-digit categories “manufacturing of other food products (DA 158)” and “manufacturing of beverages (DA 159)”, which contain nine and eight very heterogeneous subsectors, respectively. Nevertheless, these sectors have often been analyzed at the three-digit level with the result that cluster tendencies could not be identified (see Alecke and Untiedt, 2008; Sternberg and Litzenberger, 2004 and Table 4).

In the case of "manufacture of beverages (DA 159)" there are only two districts with a relevant CI (Bamberg = 101.79 and Passau = 64.57) (see Figure 3). After careful consideration of those districts, it becomes apparent that more than 70% of the establishments operate in the beer manufacturing sector.

Insert Figure 3 around here

This aspect is underlined by the fact that the CI for Bamberg increases significantly if the "manufacture of beer (DA 1596)" is analyzed separately. Similar results can also be found for districts with a high number of establishments operating in the manufacture of spirits (e.g. Cochem-Zell with a CI of 27.56). These findings as well as the results at the four-digit level, in which each subcategory of beverages shows more than seven clusters, indicate the necessity to analyze the data on a more disaggregated level, especially in cases where 3-digit industry categories contain a rather heterogeneous group of 4-digit subsectors.

As described in the theoretical part of this paper, several studies of the wine industry -and thus at the 4-digit level- have been conducted in different regions of the world. Due to the thirteen defined regions for quality wine in Germany, an analysis of this industry might not be as interesting as, for example California, Chile, South Africa or Australia. For this reason we will focus our analysis on other important beverage subsectors in Germany, such as the manufacture of beer. While in the main 3-digit beverage category only two district with a relevant CI could be identified, the subcategory "manufacture of beer (DA 1596)" shows ten districts with a CI exceeding 64, which are all located in the German federal state of Bavaria (see Figure 4). As described above, especially the city district of Bamberg (CI = 397.71) can be considered as strongly clustered in this subsector. Additionally, the surrounding rural district of Bamberg is also characterized by a high CI value (CI = 45.35). Furthermore, several other adjacent areas such as Bayreuth (CI = 148.98), Lichtenfels (CI = 87.99), and Kulmbach (CI = 48.72) in Upper Franconia show relevant CI's. Due to the close proximity of these districts, the whole region can be considered as a relevant cluster.

Insert Figure 4 around here

Besides the "manufacturing of beer", cluster tendencies for subsectors of the beverage sector can be found for the "manufacture of spirits (DA 1591)", the "manufacture of wine (DA 1593)" and the "manufacture of soft drinks and mineral water (DA 1598)". The latter subsector, for instance, shows relevant cluster tendencies in seven districts of Germany. The three districts Vulkaneifel (CI = 171.98), Ahrweiler (CI = 82.4) and Mayen-Koblenz (CI = 38.07)[18] in the north of the German federal state of Rhineland-Palatinate are additionally in close proximity to each other.

The insights presented for the manufacture of beverages also hold for several other subsectors of the food processing industry, such as the "manufacture of other food products (DA 158)", in which the heterogeneity of subsectors is naturally high due to its broad definition. Like the beverage sector, no relevant clusters can be detected for this sector at the 3-digit level. The highest CI value in this sector can be found for Heilbronn with 28.77. However, results at the four-digit level only show a broadly dispersed distribution for one subsector out of nine ("manufacturing of bread, fresh pastry and cakes (DA 1581)"). According to Table 4 for this subsector, no relevant cluster can be detected. Based on the insights presented in this section, an aggregated analysis in the case of very heterogeneous subsectors seems to be inadequate.

5.3 The role of natural resources and tacit knowledge for cluster formation

Iammarino and McCann (2006) propose a cluster classification scheme that distinguishes between the relevance of explicit and tacit knowledge[19] for cluster formation. Apriori it could be assumed that most clusters identified for the German food industry are what Iammarino and McCann (2006) refer to as *pure agglomeration*. Such clusters are characterized by the exchange of explicit knowledge among its members and might simply be driven by natural resource endowments. An example might be the "production and preserving of fish (DA 1520)" where a large number of relevant clusters were identified in several districts close to the sea. However, in the following we provide two examples of sectors with a high cluster tendency to illustrate that this is not solely the case in the German food industry.

For the fruit and vegetable sector Hoffmann (2011) compares two districts, which have also been identified as relevant clusters in the present study, with two non-clustered districts. In this connection, 124 enterprises were analysed by means of social network methodologies. The results show significantly stronger inter-organizational network structures for the two clustered districts as compared to the non-clustered ones. This implies that spatial agglomeration might, despite the endowment with natural resources, emerge as an important driver for interrelations between enterprises. Such clusters are what

[18] Mayen-Koblenz is not one of the seven most relevant districts as it is related to the third category ("potential cluster"). In this relation, the district is solely mentioned due to the common borders with the other two districts.
[19] Explicit knowledge refers to information that can easily be traded while tacit knowledge cannot easily be exchanged.

Iammarino and McCann (2006) refer to as social networks*,* that are characterized by interrelations that enhance the exchange of tacit knowledge.

Furthermore, the two districts of Cloppenburg and Vechta, have been identified as relevant meat processing clusters, are both located in the area referred to as the Oldenburger Münsterland. Despite its high density of factory farming and meat processing enterprises, this area is characterized by a mediocre to bad soil quality implying that additional fodder has to be imported in order to allow for sufficient earnings potential in this region (von Laer, 2002; Freisinger and Windhorst, 2005; Teller, 2007; Bauer et al., 2010). This points towards clusters which emerge independently of natural resource endowments.

While further insights are needed for a complete picture of cluster classification for the remaining subsectors, the two given examples illustrate that clusters in the German food industry are likely not exclusively pure agglomerations driven by natural resource endowment.

6. Discussion and Conclusions

In this study we have analyzed in which of the 429 German districts cluster tendencies for the 4-digit food industry subsectors can be found. The analysis is based on the Cluster Index (CI) which has the advantage that the size of analyzed districts as well as the relative size of establishments is considered. Another advantage of this indicator is the exact specification of the geographical districts in which the clusters of the analyzed sector can be found, whereas other measurement methods only state if a certain sector is concentrated in general or not. Thus the CI enables to identify potential clusters for regional political initiatives as well as already existing cluster structures.

Contrary to the results of previous studies, the findings of this analysis show that clusters in the German food processing industry exist. These agglomerations have become identifiable by using quantitative measurement methods on a more disaggregated level. It has to be pointed out that it is important to choose the right aggregation level in this branch, because the structure of the food processing industry with more than thirty subsectors and about 651,560 employees is too complex and too heterogeneous to be analyzed at a highly aggregated level (3-digit) or in its entirety.

While several previous studies of German manufacturing sectors were conducted at a highly aggregated sectoral level (2 or 3-digit), this paper shows why the use of quantitative measurement methods such as the CI for 3-digit categories or for the whole food processing industry are inadequate.

Two problems that can occur when applying the CI at a highly aggregated level are presented. First, as illustrated for the meat industry, cluster tendencies can remain concealed if large subsectors with low cluster tendencies are analyzed together in the same category with smaller subsectors characterized by high cluster tendencies. While experts in the German meat sector directly confirm cluster tendencies, Sternberg and Litzenberger (2004), along with others, negate this fact in their empirical studies which are based on highly aggregated data. For the meat sector this controversy is caused by the dominating number of establishments and employees in the very dispersedly distributed subsector "production of meat products (DA 1513)". The fact that the other two subsectors "processing and preserving of meat (DA 1511)" and "processing and preserving of poultry meat (DA 1513)" are characterized by strong cluster tendencies is concealed in an aggregated quantitative analysis, as these subsectors only account for 7% of all establishments in the main category.

The second problem was illustrated based on the "manufacture of beverages" and the "manufacture of other food products", two sectors that are characterized by strong heterogeneity of their subsectors. While in the meat sector the relationship between the different subsectors is rather strong and size issues between the categories can be seen as the reason for concealed cluster tendencies at the 3-digit level, in the case of the "manufacture of other food products" or "manufacture of beverages" the heterogeneity of most of the subsectors can be seen as the main reason for concealed cluster tendencies at highly aggregated data levels. It is therefore also difficult to compare CI studies that are based on diverging industry classifications (Litzenberger, 2007; Klein, 2004; Boddin, 2009).

As this is one of the first analyses of potential agglomerations in the German food sector at a more disaggregated level, the results of this study can provide meaningful insights on where possible clusters in the German food industry are located. However, although the CI provides useful results, it can, like all other quantitative measuring methods, only be seen as a first step that identifies cluster structures in a specific region. Further studies need to be implemented in order to assess if high CI values e.g. in the "manufacture of mineral waters (DA 1598)" are simply caused by the given natural resources of mineral springs in the respective districts, or due to the previously defined cluster characteristics as defined in section 2. Similar to most of the other subsectors of the food processing industry, natural resources play a crucial role for the choice of launching an establishment in the "manufacture of mineral waters". Nevertheless, in section 5.3 we have provided two examples of industries where clusters do not solely emerge through natural resource endowment. Furthermore, Nestlé for instance has relocated its headquarters for bottled water to France due to the competitive environment (Porter, 2000). Therefore, an analysis of the location attractiveness of regions for establishments tends to be of particular importance and should be considered by future studies.

Furthermore, it has to be noted that geographical proximity of firms does not necessarily imply that establishments cooperate and that intersectoral relations between firms, spatial knowledge spillover, and linkages with research institutions cannot be identified by the given method (Bathelt and Glueckler, 2003). Such functional relations between firms within clusters can be analyzed by means of network analysis or (in the case of intersectoral relations) by a combination of the CI with input-output analysis. In our view, social relationships of actors are considered to be a crucial element of clusters. Thus, in further studies it is important to analyze if network effects and other cluster-inherent structures are relevant for a specific region (Dannenberg and Kinder, 2004).

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