

## **Spatial Agglomerations in the Spanish Food Industry: Does Sectorial Disaggregation Matter?**

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José Miguel Giner-Pérez<sup>1</sup> and María Jesús Santa-María

Department of Applied Economics and Economic Policy, University of Alicante, Spain

### **Abstract**

The food industry is the most important industrial activity in Spain in terms of production and employment; its spatial concentration is considerable. However, there is a lack of quantitative research on its agglomerations, especially at high levels of spatial and sectorial disaggregation. With the study presented, this deficit is addressed, using systematic and quantitative methods to examine the spatial agglomeration in the subsectors that the food industry is specialized. Spanish food industry clusters have been identified by applying a top-down quantitative methodological approach—the cluster index—and following a high level of territorial and sectorial disaggregation. Clusters were identified at the three- and four-digit sectorial disaggregation. The number of four-digit-level relevant clusters was higher than three-digit disaggregation. This evidence was verified using nonparametric statistical tests (Wilcoxon signed-rank test). Furthermore, the analysis of four significant three-digit subsectors allows us to advance two alternative explanations for the divergent results at the different levels of the analysis (three digits vs. four digits). This partly explains the potential competitiveness of Spain in the food industry and shows the possibility of establishing policies for the development of clusters.

### **Keywords**

cluster, food industry, sectorial disaggregation, Spain, spatial agglomerations

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<sup>1</sup> Corresponding Author:

José Miguel Giner-Perez, Department of Applied Economics and Economic Policy, University of Alicante, P.O. Box 99, E-03080 Alicante, Spain.

Email: [giner@ua.es](mailto:giner@ua.es)

## **Introduction**

The scholarship generally recognizes that firms tend to agglomerate geographically. Since Alfred Marshall's initial reflections on localized industries (Marshall 1920), it has been argued that firms in the same sector tend to concentrate geographically due to the benefits derived from external economies. Industrial organization models, such as industrial districts (Becattini 1979, 1989, 1992; Bellandi 1986; Sforzi 1987, 1990; Brusco 1992; Signorini 1994; Dei Ottati 1995) or clusters (Porter 1990, 1998, 2003; Delgado et al. 2010) explain how spatial concentrations emerge, forming a system that conditions the operating modes, efficiencies, and results of the companies that are part of them. These models emphasize the idea that locating with other related companies allows the firm to enjoy external economies, such as those derived from access to qualified human resources, specialized suppliers, and technological spillovers (Krugman 1991) with benefits of lower costs and productivity improvements. These positive agglomeration externalities are locally limited and only nearby firms can enjoy them (McCann and Folta 2008).

The territorial agglomeration concept has permeated existing theoretical and applied economic analysis. Renewed interest in considerations of the spatial dimension of the economy has generated a broad and diversified body of literature, which had an extraordinary boom in the 1990s (Porter 1990; Krugman 1991; Fujita and Mori 2005). The ever-increasing number of publications worldwide on clusters and industrial districts (see literature reviews by Ketels 2003; Cruz and Teixeira 2010; Martínez-Fernández et al. 2012; Capo-Vicedo et al. 2011; Lazzereti et al. 2014; Hervás-Oliver et al. 2015) reflects the popularity and relevance of these models.

Most studies have emphasized the influence of location on firm performance. Production costs can be lower in agglomerated spaces, due to local access to specialized labor and inputs such as suppliers or manufacturing facilities (Krugman 1991). However, the greatest impact derives from the generation and diffusion of innovation and knowledge caused by the proximity among space members (Signorini 1994; Fabiani et al. 2000; Camisón and Molina-Morales 1998; Spencer et al. 2010; Li and Geng 2012, Feldman 2014). In bounded geographical contexts, proximity to similar organizations favors formal and informal networks, providing a dense structure and strong ties that improve the quality of mutual exchanges of knowledge (Tsai and Ghoshal 1998; Zahra et al. 2000; Yli-Renko et al. 2001; Boschma and Ter Wall 2007; Molina-Morales and Martínez-Fernández 2010). In fact, many authors have considered that firms in geographical clusters with an abundance of social interactions improve their position to access new information, ideas, and opportunities, which explains the potential advantages of clustered firms (McEvily and Zaheer 1999; Trigilia 2001; Cooke 2002; Wolfe 2002). Factors that boost knowledge exchange and innovation processes are linked to the intensity of interactions between cluster members, face-to-face interactions, short cognitive distances, common language, trustful relations between various actors, easy observations, and immediate comparisons (Malmberg and Maskell 2002).

From this approach, the idea that has been strengthened is that specialized agglomerations can improve industrial and regional competitiveness. Therefore, in many cases, clusters have become a very attractive model to foster regional development, and governments strive to create an environment that supports them (Preissl and Solimene 2003; Commission of the European Communities 2008). In the last two decades, cluster policies have been widely promoted by international organizations, such as the Organization for Economic Cooperation and Development (OECD) and the European Union, and have

been proliferated worldwide both regionally and nationally (Benneworth et al. 2003; Sölvell, Lindqvist and Ketels 2003; Ketels et al. 2006; Europe Innova 2008). By supporting the development of clusters, policymakers hope to boost innovation, increase job creation, and increase regional competitiveness (Feser 2008; Huggins and Williams 2011). Policymaker action must be directed predominantly toward areas of existing strength: that is, areas where clusters or emerging clusters already exist (Sölvell et al. 2003; Ketels 2013). Therefore, prior to the implementation of actions, information about the geographical area and the sector of activity in which the cluster operates is required. A useful tool is a cluster map that provides a geographic footprint of specific clusters and the specialization profile of a given region (Ketels 2017). A cluster map could confirm the existence of known phenomena, but it can also point to new emerging clusters.

A literature review on clusters and industrial districts shows that different methodologies have been used to identify these agglomerations (Bergman and Feser 2020). Two approaches have emerged: top-down analysis, which generally relies on quantitative data to deduce the industrial structure of a regional economy; and bottom-up analysis, or qualitative-type case studies in a given region which examine the inner workings and interfirm connections of a particular cluster in a particular location.

In the context of the second approach—qualitative-type case studies in a specific sector/location—numerous studies have focused on specialized food-related industries. The first studies in this field emerged in the early 1990s (Iacoponi 1990; Fanfani 1994). Since then, several empirical studies have shown the presence of agrifood districts in Italy for specialized products (Bertolini 1988; Brasili and Ricci Maccarini 2003; Bertolini and Giovannetti 2006). Following this approach, other studies have focused on different European countries (Lagnevik et al. 2003). Agrifood clusters in Spain have also been analyzed, such as olive oil in Andalusia (Sanz Cañada and Macías Vázquez 2005), the

case of Valencian citrus (Gallego Bono 2009), the Iberian ham cluster (Diez-Vial 2011), and the foodstuffs (nougat) cluster in the Valencia region (Molina-Morales et al. 2015). Numerous documented examples of clustering activity in the food sector focus on wine clusters (Porter 1998; Giuliani and Bell 2005; Morrison and Rabelloti 2009; Beebe et al. 2013; Hira and Swartz 2014; Aldecua et al. 2017). Studies have also considered Latin American countries (Dirven 1999; Boucher and Requier-Desjardins 2005; Mancini 2013; Crespo et al. 2014).

On the other hand, the literature review shows that very few studies have sought to identify agrifood clusters in a territory using systematized methods and based on quantitative data. Quantitative techniques have been used to identify clusters (Porter 2003; Delgado et al. 2016) and industrial districts, such as, notably, the methodology used in Italy by Sforzi (1987, 1990) and ISTAT (1996, 2006) and applied to the case of Spain by Boix and Galletto (2006, 2008), Ybarra et al. (2008), and Boix et al. (2015). There are also some studies with quantitative methodologies that have added a qualitative analysis to refine their results (Hernández et al. 2005; Aranguren et al. 2008, 2011). The analyses that they offer of the food processing industry are mainly based on aggregate sectorial classification—usually with a sectoral disaggregation at two digits—or are limited to specific regions. However, the food-related industry has specific characteristics that make it difficult for studies carried out at a high level of sectoral aggregation to detect specialized areas. We highlight two facts that are characteristic of this industry that can hinder cluster identification. On the one hand, the sector presents heterogeneity because it is made up of very different subsectors. The spatial distribution is very complex, with different spatial patterns observed based on different conditions: proximity to natural resources, proximity to demand, etc. Furthermore, this heterogeneity means that there are subsectors that include very different activities within each. In many cases, these activities

have a very different participation in the complete subsector (e.g., number of companies, employment, etc.) and they present diverse location patterns. Secondly, there is a wide dissemination of these types of activities throughout the territory (dispersed location). The agrifood industry is characterized by a predominance of small-sized companies that are diffusely distributed at a spatial level. All these localization patterns may hide specialized food-related industry agglomeration processes in which external economies have a relevant role.

The Spanish food industry is a major industry sector. However, it is not known in detail if there are agrifood industry spatial agglomerations and, specifically, if there are spatial agglomerations of its subsectors and where the different specializations are located. This paper tries to identify agglomerations which specialize in agrifood industry subsectors throughout the Spanish territory. The heterogeneity of the Spanish agrifood industry, with over 360,000 employees belonging to 35 different subsectors, means that aggregate-level analyses are inadequate (Cluster Competitiveness Group 2007). The present research sought to overcome this gap in the literature and evaluate whether food industry spatial agglomerations exist at the 3-to-4-digit level of disaggregation throughout the Spanish territory, based on Statistical Classification of Economic Activities in the European Community (NACE—Rev.2). Some analyses have applied a high degree of sectorial disaggregation (Unioncamere 2009; Giner and Santa-María 2017, 2018b; Hoffmann et al. 2017) but in the case of Spain no study has been carried out at a 4-digit sectorial disaggregation level.

Therefore, our research can contribute to enriching the mapping of industrial agglomerations using quantitative methods by the advantages of the applied methodology, because of both the high sectorial (4-digit level) and territorial (local labor systems) disaggregation and the applied index. The cluster index (CI) used in this research

corresponds to that suggested by Sternberg and Litzenger (2004) to identify industrial clusters and has as its main advantage that a value for each analyzed area/sector can be derived. Other advantages of this index are based on its multidimensional nature, incorporating the information and dimensions of three relevant location aspects: relative industrial stock, relative industrial density, and relative plant size. Another advantage is its continuous character. The outstanding advantages outweigh the possible limitations of the Italian methodology used in the mapping of industrial districts applied to Spain (Boix and Galletto 2006, 2008; Boix et al. 2015).

Regarding other similar studies, our methodological contributions and results are based on two fundamental features. Differential results according to sectorial disaggregation (3-digit versus 4-digit level) are verified through nonparametric statistical hypothesis testing. This means that we can identify clusters that do not appear in another research. Furthermore, the analysis of spatial location of some significant 3-digit subsectors in the Spanish food industry with quantitative measures allows us to explain the divergent results at different levels of the analysis (3 digits vs. 4 digits).

The paper is in line with the research on statistical methods and technical tools that tries to provide more objective ways to identify clustering processes using quantitative techniques with top-down approaches. The results of our research, along with our empirical analysis, provide an analytical identification framework applicable in the case of the identification of clusters in industries with a complex structure of subsectors with heterogeneous spatial patterns. This analytical framework can be implemented in the future to other industries with these features. In addition, this new analytical framework can promote the development of new qualitative research and assist in supporting the decisions of cluster policymakers.

The present study is structured in five further sections: the second section presents a literature review—spatial agglomeration theories, social network approaches, and agrifood industry agglomerations—and a preliminary analysis of the Spanish agrifood industry. Following a theoretical review, the third section describes the methodology used in this study to identify and analyze agrifood clusters. Analytical data are presented in the fourth section, and the results are described in the fifth section. The final section presents our conclusions. The results may be of interest to researchers in this field and can assist policymakers in formulating policy measures aimed at supporting the development of clusters.

## **Theoretical Background**

### Spatial Agglomeration Theories: a Review

Theories on spatial agglomeration have existed in the academic literature for many years and have recently aroused greater interest in the domain of economic geography analysis. These studies are rooted in the pioneering ideas of Alfred Marshall on the advantages of territorial firm agglomerations and the notion of industrial districts, which the author put forward at the beginning of the twentieth century (Marshall, 1920). Since then, various theories have been proposed to explain the formation of spatial agglomerations. Thus, during the 1970s and 1980s, three theoretical approaches arose that share both a geographic perspective, based on proximity, and a sociological one, based on social networks (Martin and Sunley, 2003). One of these theoretical streams comes from the Italian school that focuses on the conceptualization of the industrial district (Becattini 1979, 1989, 1992; Bellandi 1986; Sforzi 1987, 1990; Brusco 1992). This way of



organizing the production activity and the cooperative and competitive relationships are the origin of some competitive advantages that can only be enjoyed by companies located within the district. In particular, the solid bonds of trust generated foster the dissemination of formal and informal knowledge (Sengenberger and Pyke 1992; Bellandi 1996).

A second approach comes from the Groupe de Recherche Européen sur les Milieux Innovateurs (GREMI) with the notion of “innovative milieu” (Aydalot 1986; Aydalot and Keeble 1988; Camagni 1995). The innovative milieu literature highlights the territorial nature of innovation, often at a local or sub-regional level. It is not territory as a medium that is important, but the bringing together of economic players and non-material resources (training, research), which, through their interactions, lead to the development of specific skills, know-how and rules, among others (Maillat 1998). In addition, the history of an area, its collective behavior and its internal structure of unanimity becomes especially relevant in the innovation process (Aydalot 1986). The concept of innovative milieu highlights that the quality of relational capital within a milieu determines its success.

Other related territorial innovation models are regional innovation systems (Iammarino 2005; Lundvall 1992; Braczyck et al. 1998; Cooke et al. 1997; Capello and Lenzi 2018), smart regions, learning regions or learning territories (Asheim 1996; Florida 1995; Morgan 1997; Antonelli and Ferrão 2001; Jambes 2001). These models share the notion that relationships among companies themselves and with other agents in the environment are decisive to build knowledge and to improve companies’ learning mechanisms and capacity to innovate.

The third approach derives from the Californian school (Storper and Scott 1989) with the concept of ‘new industrial spaces’ (Scott 1988) that try to explain how territorial enterprise systems emerge and function after the crisis of Fordism. Their research

highlights how the agglomeration of activities allows for the flexible organization of production that, in turn, leads to decreasing costs and greater efficiency and competitiveness of companies. The agglomeration not only contributes to lower production costs, but also to a reduction in transaction costs, since “proximity translates into lower costs and greater opportunities to combine needs and capabilities” (Scott and Storper 1992).

Subsequently, the analysis of the spatial dimension of the economy and industrial agglomerations will be widely disseminated with the emergence of the cluster concept (Porter, 1990). Porter's cluster theory stems from his research, in the late 1980s and early 1990s, on international competitiveness and national competitive advantage (Martin and Sunley 2003). He focused mainly in his early study on industrial phenomena, emphasizing that competitive sectorial clusters are determined, within a nation, by strong vertical and horizontal relationships. Porter (1998) turned towards the territorial dimension, regarding geographical concentration as inherent to the cluster concept. The clusters are, in most cases, trans-sectorial (vertical and lateral) networks that include complementary companies that are specialized in a specific link in the value chain. An important factor is the relationship between companies and partner institutions, such as universities, consultancies, research associations or institutes and knowledge-intensive service companies (Porter 1998, 2000). On the other hand, with regards to the relationships that take place between the companies, Porter points out how clusters intensify both competition and cooperation relations. Cooperation agreements allow for the exploiting of complementarities and economies of scale and scope, as well as increasing companies' flexibility and speed of reaction to environmental changes (Porter 1998). In addition, competitive pressure and constant comparison with other companies

promote research and development (R&D) strategies and the introduction of new technologies.

The study of firms' agglomerations has been revitalized in the framework of the "new economic geography" (NGE; Krugman 1991). Since the 1990s, the NGE has tried to explain the broad range of forms of economic concentration in geographical areas (Fujita et al. 2001). The theoretical arguments of these contributions to explain the concentration is that the initial location decisions – which may come from the initial advantages of a geographical area, for example, due to the presence of natural resources or transport facilities – can cause effects positive diffusers generating an inertia that, in turn, guarantees greater efficiency and, therefore, maintains the activity in that area, although the initial conditions are modified or may even disappear. The NGE shows the renewed interest of conventional economists in spatial analysis through the development of a new generation of spatial agglomeration models.

All the theories and studies cited have tried to explain the reasons that led to the formation of a firm's agglomeration in the territory and how these agglomerations can catalyze regional competitiveness. As key elements present in all of them, spatial proximity, the interrelatedness of capabilities and activities, interactions between agents and institutional endowment stand out. However, although the literature highlights the benefits of firm agglomeration, there are also studies that have shown possible disadvantages of being in an area of agglomeration (Folta et al. 2006; Shaver and Flyer 2000). A higher number of companies in the same location can generate congestion costs within the region, with negative implications for company performance (Prevezer 1997). In addition, competition for workers, land and public services increases, leading to scarcity and higher costs. There is also a greater risk that knowledge will be expropriated by geographically close rivals (Shaver and Flyer, 2000). Such congestion costs increase the possibility of

the appearance of diseconomies of agglomeration. These agglomeration diseconomies play an increasingly important role in the way the cluster evolves (Folta et. al 2006) by creating a deterrent effect for the location of companies in that area. Finally, recent studies have shown how companies do not benefit equally from being in an agglomeration, since knowledge flows may be contingent upon firm characteristics, such as firm size, the strategic orientation of the firm or alliance activity (McCann and Folta 2011).

### Agglomeration of Firms: Social Network Approaches

Most of the literature on firms' agglomerations emphasize that proximity facilitates the exchange of knowledge, especially tacit knowledge, between companies and among their own employees. This idea is what sustains the so-called relational turn within economic geography. The relational approach highlights the role of socio-institutional networks in the economic success of certain territories, especially in the exchange of knowledge and in the improvement of the innovation process. In this relational approach, the concept of social capital and network analysis stand out. In fact, many authors have considered the idea of social or relational capital to be inherently spatial (Martin, 1994; Staber 2001). In bounded geographical contexts, proximity among similar organizations favors diverse forms of social capital (McEvily and Zaheer 1999) and has been considered a factor explaining the potential advantages of clustered firms (Trigilia 2001; Cooke 2002; Wolfe 2002).

Existing literature already supports the connection between the concepts of clusters and networks. A cluster can be defined as a network within a production context in a geographically defined area (Boschma and Ter Wal 2007; Parrilli and Sacchetti 2008). Contexts of geographical proximity, such as those defined as industrial clusters (Porter

1998; Tallman et al. 2004; Inkpen and Tsang 2005), can be viewed as networks, since many different actors, including final product firms, suppliers, customers, service providers, local institutions and policy agents, interact, evolve and contribute to a specific geographical context performance. Firms in clusters are connected through a variety of formal and informal networks, providing greater strength to local relations. These networks have a decisive role in building trust and disseminating tacit knowledge, which favors competitiveness and innovation (Scott 1988). Clusters and industrial districts represent local configurations that are high in social capital and are characterized by mutual trust, cooperation and an entrepreneurial spirit, as well as by a multitude of small local firms with complementary specialized competencies (Trigilia 2001; McEvily and Zaheer 1999).

There is evidence that intensive social interactions in these areas foster knowledge exchanges and enable actors to gain access to other actors' resources (Zahra et al. 2000; Yli-Renko et al. 2001; Boschma and Ter Wall 2007). Proximity facilitates the redundancy of relationships and face-to-face contacts, as well as the building of common norms and values. Information and trust are referred to in terms of qualities that would restrict opportunism as a resource that prevents cheating or fraud in business (Trigilia 2001; Staber 2001). On the other hand, a shared vision allows for more fluent transmission. A shared vision is identified as a shared code or paradigm, which facilitates a common understanding of the collective objectives and the proper ways to act within a social system (Nahapiet and Ghoshal 1998). In addition, as intermediaries, local institutions facilitate the acquisition of competitive capabilities by compiling and disseminating knowledge and by reducing search costs (Baum and Oliver 1992; McEvily and Zaheer 1999; Molina-Morales and Martínez-Fernández 2010; Belso-Martínez 2015; Belso-Martínez et al. 2018). Consequently, a firm with an abundance of social interactions is

likely to have a greater capability to combine and exchange resources with other actors, and so enhance its innovation capacity (Tsai and Ghoshal 1998).

However, as Yli-Renko, Autio and Sapienza (2001) have argued, the degree to which companies use their external networks to acquire and exploit knowledge is regulated by the amount of social capital they possess. Firm-level characteristics, such as basic knowledge, determine how the firms are joined in local networks, benefiting from external resources (Boschma and Ter Wal 2007). These attributes will determine the differences between companies in the cluster when it comes to exploiting the advantages of the location.

On the other hand, an extensive body of literature exists that directs its attention in the spillovers of knowledge. It is a popular idea that firms located in clusters benefit from local knowledge spillovers. Spillovers are the unintentional transmission of knowledge to others beyond the intended boundary. Knowledge created by a local agent can be accessed and used by other agents without market interaction and financial compensation for the producer of the knowledge (Asheim 1996; Morgan 1997; Malmberg and Maskell 2002; Bathelt et al. 2004). Taking up the idea of Marshall's 'industrial atmosphere', current debates often involve similar ideas on local knowledge flows such as the neologism's local 'buzz' (Bathelt et al. 2004; Storper and Venables 2004) and 'noise' (Grabher 2002). Knowledge spillovers are highly localized, and physical proximity matters since it increases the actors' probability of contacts and, hence, the flow of information exchange among them (Audretsch and Feldman 1996; Jaffe et al. 1993). This is especially important in the case of tacit knowledge exchange, which is highly contextualized and impossible to codify, and it therefore requires face-to-face interactions, regular co-presence and a shared local social context (Morgan 2004; Storper and Venables 2004). It has been argued that the co-location of economic actors leads to greater face-to-face interaction (Bathelt

et al. 2004; Depner and Bathelt 2005; Gertler 2003; Rekers and Hansen 2015) and that much of this interaction is not planned, but mostly the result of happenstance and chance meetings associated with living and working in high-density and diverse environments. Density generates opportunities “for repeated contacts and the serendipity of casual exchange in a known local milieu” (Amin and Cohendet 2005). In this way, frequent chance, casual and/or serendipitous interactions between economic actors in clusters lead to greater innovation (Lee and Rodriguez-Pose 2013).

However, a few recent empirical contributions have suggested that the knowledge advantages of clusters might not be so clear-cut (Giuliani 2007; Moodysson 2008). Even in cases in which interaction leads to economically viable knowledge being exchanged, the knowledge in circulation may be not new or even redundant. In addition, in relatively closed systems, the knowledge exchange may be at risk of lock-in, effectively limiting the potential for implementation of new technologies or the identification of new market possibilities (Boschma 2005). In the same way, it is not clear that companies in clusters collaborate more, or that this collaboration is the result of face-to-face interactions (Grillitsch and Nilson 2015). Recent studies have shown that most relationships tend to be purpose-built and firms that rely on partnerships based on casual encounters do not innovate significantly more than firms without any self-declared important partners (Fitjar and Rodriguez Pose 2017).

#### Agri-food Industry Agglomerations: Literature Review

Industrial district and cluster theories have been the starting point for numerous studies focused on specialized food-related industries. In these cases, food processing firms, farmers, suppliers of inputs (such as fertilizers and chemicals, packaging, plastics and

machinery), service companies and public and private institutions are located within a well-defined area. The first studies in this field arose in the early 1990s. Iacoponi (1990) was the first to introduce the concept of industrial districts into agricultural research. In his work, he pointed out how in the *distretto agro-industriale*, all enterprises are bound together in a sort of collective production process, in which semi-finished products are exchanged at very low transaction costs in a quasi-market. Fanfani (1994) analyzed certain areas of Northern Italy and showed the main characteristics of the agrifood districts not only in terms of their origin, but also in terms of their structural organization and dynamic transformation. Since then, several empirical studies have shown the presence of agrifood districts in Italy for specialized products. One example is the research into *parmigiano reggiano*, in which a synergistic combination between a local agricultural tradition, technological innovation and entrepreneurial modernity was verified (Bertolini 1988). The meat processing industry has also been analyzed, confirming the economic role of small producers and highlighting the dense network of relationships between the players, as well as their capability for creating institutions that co-ordinate and defend the local dimension of their work (Bertolini and Giovannetti 2006). There are also specific studies on Italian agrifood districts that highlight the better results of firms inside the agrifood districts, like the research into the meat and fruit and vegetable processing sectors (Brasili and Ricci Maccarini 2003).

Following this approach, other studies have focused on different European countries. Lagnevik et al. (2003) analyze the highly successful food cluster in the Öresund region (across the borders of Denmark and Sweden), proposing the notion of dynamic food innovation clusters, where non-firm actors play a key role in the evolution and success of such clusters. Agrifood clusters in Spain have also been analyzed, such as olive oil in Andalusia (Sanz Cañada and Macías Vázquez 2005). This analysis find that collective



organization, institutional framework, and territorial identity can enhance local competitiveness. In the case of Valencian citrus, it has been shown that the regional interaction between suppliers and citrus growers favors the innovation and competitiveness of the cluster, increasing international interactions, which over time become more creative by feeding back into the original internal relations (Gallego Bono 2009). The Iberian ham cluster has also been studied (Diez-Vial 2011), and the positive effect that geographical concentration has on performance has been demonstrated. This effect is explained by access to valuable natural resources, workers, higher demand, knowledge spillovers and lower transaction costs. In the case of the foodstuffs (nougat) cluster in the Valencian region, research has shown that social proximity and geographical proximity favor the formation of inter-firm relationships and reinforce the organizational dimension (Molina-Morales et al. 2015). In the case of Spain, there are other studies with a more descriptive methodological approach for specialized clusters: olive oil in Andalusia (García Brenes and Sanz Cañada 2012; Rodríguez Cohard and Parras 2011); horticultural production located in Murcia (Martínez-Carrasco and Martínez Paz 2011); the horticultural cluster in Vega Baja – Alicante (Giner and Santa-María 2018a); the agro-industrial cluster that emerged around the intensive horticulture of Almería (Aznar Sánchez 2011); and the agrifood production systems of Castilla and León (Juste Carrión 2011).

Numerous documented examples of clustering activity in the food sector focus on wine clusters. Perhaps the reason for this is that Porter (1998) had chosen the California wine industry as an example illustrating the application and use of his cluster approach. In the 1998 study, Porter describes the wine cluster as a group of interconnected wineries, grape growers, suppliers, service providers and wine-related institutions located in California.

One such study in this sector was carried out by Beebe et al. (2013) on the wine production cluster in Paso Robles, California. This research emphasizes how identity in wine clusters has economic value, and there is therefore a strong interest for all actors to build a common strategy to outline a positive cluster identity. On the other hand, social networks and the knowledge exchange are important factors for cluster innovation, and many authors evidence this in the context of wine clusters. Thus, the research focusing on the wine cluster in the region of El Priorat, Spain verified the importance of creating and strengthening intra-regional links based on trust and solidarity, links that enable the efficient diffusion of this innovative information, in such a way that the knowledge can be shared (Aldecua et al. 2017). Similarly, Hira and Swartz (2014) analyzed the Napa wine cluster and found that social capital and the efforts of entrepreneurs to work together to develop the technological breakthroughs give them a comparative advantage. Another example is the research on the Chilean wine cluster by Giuliani and Bell (2005), focusing on the intra-cluster knowledge system and its interconnection with extra-cluster knowledge. This work highlights a wide range of different communication and learning behaviors in the cluster, showing that it was the capacities of individual firms to absorb, spread and creatively exploit knowledge that shaped the learning dynamics of the cluster. A work in a similar vein is the study conducted by Morrison and Rabelotti (2009), which focused on the nature and extent of knowledge and information networks in an Italian wine cluster. The empirical findings show that knowledge flows are restricted to a tightly connected community of local producers, differing in terms of knowledge assets, innovation behaviour and overall economic performance with respect to the rest of the firms in the cluster. Other, more descriptive studies have been carried out in Spain for the wine clusters in Rioja (Larreina et al. 2011), Castilla and León (Sánchez Hernández 2011)

and Jerez (Soler Montiel 2011), as well as the analysis of the Galician wine system (Macías Vázquez 2011).

There are also numerous works on the specific concentrations of small firms specialized in a particular food-processing industry and how these systems appear as catalysts for rural development, agriculture modernization and a better market reachability for farmers. Research has also considered Latin American countries, contemplating the dairy clusters (Dirven 1999), the local cheese production system in Nicaragua (Mancini 2013), rural cheese factories in Peru (Boucher and Requier-Desjardins 2005) and the cheese production community in Mexico (Crespo et al. 2014). It should be point that in many cases, these agrifood systems are in possession of tangible and intangible cultural and institutional resources that confer differential attributes to the food products linked to these territories. In addition, there is certainly a role played by social capital, as a crucial local resource for successful collective actions, since it is a source of trust and collective commitment within a community. In sum, this territorial framework is usually adopted by small enterprises as the best way to generate innovation and economic growth through an embeddedness of social and knowledge links (Molina-Morales and Martínez-Fernández 2010; García Alvarez-Coque et al. 2015).

### The Spanish Agrifood Industry

The agrifood industry is the top industrial branch in Spain. According to the Structural Business Statistics (2017) of Spain's National Institute of Statistics, the food and beverage industry accounted for 28,212 companies, that is, 14.7% of the manufacturing industry. These companies employ 404,338 workers (18.8% of the industrial sector). Overall, the sector generated €118,833 million net turnover (19.2% of the industrial

sector). After France, Germany and Italy, Spain is the country with the highest turnover in the EU. In addition, it is the fourth export economy of agrifood products of the EU-27. However, the investment effort (R&D/GDP) of the agrifood sector in Spain (0.5%) is 28% lower than the value registered at the community level (0.7%).

The Spanish food industry by subsector (see Table 1) shows as the processing of meat sub-sector, followed by the manufacture of bakery products and pastries, are the ones with the highest percentages of employed, with 23.9% and 21.5% respectively. The sub-sectors with the largest number of companies are bakery products and pastry, with 36.4% of the firms' total, beverage manufacturing with 17.9% and meat processing with 12.9%. The sub-sector with the highest turnover percentages of this industry in 2017 was meat processing (22.1%), followed by beverage manufacturing (14.5%). Fruits and vegetables are the main agrifood products exported and accounted for 17.7% of the total sector in 2018.

#### **Insert Table 1**

With regard to the spatial distribution of the agrifood industry (see Table 2), the regions with the greatest weight in this industry are Catalonia, Andalusia and the Valencian region and Castilla and León. Catalonia concentrates 21.8% of total employment in the sector and 12.4% of total companies. Despite the fact that certain regions register a higher percentage of companies and employment in the food industry, this industry is diffusely located in the national territory, with 3,400 municipalities that have registered an establishment in this sector (out of a total of 8,126 municipalities).

#### **Insert Table 2**

It is noteworthy that the sector is characterized by business atomization: 95.6% of businesses have fewer than 50 employees, and 77.8% have fewer than 10 employees, a fact that hinders innovation and internationalization. Thus, the Spanish agrifood industry

has a small number of large companies that concentrate a substantial market share in certain sub-sectors. In parallel, it is common that a large number of small agro-industrial enterprises, generally more closely linked to the rural environment, undertake first-stage processing activities, thus encouraging the tertiarization of the rural economy whose services are often exploited by the agrarian activity itself (Pereira-Sánchez and Vence-Deza 2017).

Furthermore, substantial structural changes have been detected in recent years in the Spanish agrifood industry. Since the end of the 1980s, distribution activities have progressively concentrated, and the joint market share of the sector's five main distributors has increased from 27% to 56% (Asensio 2015). This has led the traditional distribution structure to shrink, as it used to be constituted by very small stores that protected the agrifood sector against increased competition from other countries. This significant concentration of the distribution sector puts competitive pressure on food processing companies. In addition, the industry is characterized by market saturation and high competition, making it necessary to approach innovation processes that allow for consolidation of national and international market presence (Barciela 2017). The challenges facing the agrifood industry may make the agrifood clusters significant, as they provide greater competitiveness to the companies included within them. Spanish agrifood clusters can play a major role by fostering the food industry and supporting the development of rural areas.

## **Methodology**

The literature review on clusters and industrial districts shows that different methodologies have been used to identify these agglomerations. Bergman and Feser

(2020) examine a set of methods for identifying and analyzing industry clusters. There are a variety of tools available for the task, from simple measures of specialization (location quotients) to input-output based techniques. They begin by making a distinction between highly stylized studies of pre-determined sectors (often in the Porterian tradition) and studies that attempt to infer the identity of clusters embedded within a very diverse and reasonably comprehensive set of regional industries. The first kind, which they label “micro-level cluster applications,” are typically driven by specific regional interests or policy concerns. For the second kind, techniques that permit a comprehensive investigation of virtually all sectors in the regional economy are needed. They label analysis based on such techniques “meso-level cluster applications” following terminology adopted by the OECD. Bergman and Feser (2020) identify several ways of identifying industry clusters, with most of the detailed focus placed on input-output based methodologies. They list six basic analytical approaches, with certain advantages and pitfalls, ordered roughly in terms of how commonly they have been used: expert opinion, location quotients, trade-based input-output analysis, innovation-based input-output analysis, network analysis and surveys.

Broadly speaking, two approaches have emerged: top-down analysis, which generally relies on quantitative data to deduce the industrial structure of a regional economy; and bottom-up analysis, or qualitative-type case studies in a given region, which examine the inner workings and interfirm connections of a particular cluster in a particular location. Each approach is illuminating, but neither is complete (Cortright 2006). Indeed, it probably makes most sense to conceive of regional cluster analysis as a two-stage process: 1) an initial scan of the regional economy, using detailed quantitative sources; 2) then a detailed, perhaps painstaking, investigation of specific industrial features/clusters identified in the scan (Bergman and Feser 2020). A large part of the methods used in the

first stage process have used analytical-statistical tools, attempting to systematically and objectively identify clusters and uncover their precise location in the territory. Our research is framed within this context. Algorithms or methods can be found in the literature allowing us to apply some of these techniques in a quasi-automated way, making it easier to compare results (Porter 2003; Delgado et al. 2016). Quantitative techniques have also been used to identify industrial districts, such as, notably, the methodology conducted in Italy by Sforzi (1987, 1990) and ISTAT (1996, 2006), and applied to the case of Spain by Boix and Galletto (2006, 2008), Ybarra et al. (2008) as well as Boix et al. (2015).

Concerning the agrifood industry, the literature review showed that very few studies have sought to identify agrifood clusters in a given territory using systematized methods and based on quantitative data. However, some analyses have applied a high degree of sectorial disaggregation, such as the identification in Italy of agrifood districts and quality agrifood districts by Unioncamere (2009). Following this methodology, Giner and Santa-María (2017, 2018b) identified agrifood districts in Spain. The study by Hoffmann et al. (2017), identifying food industry clusters in Germany, is also relevant.

In the case of Spain, no study has been carried out that reveals the agrifood industry's agglomeration level at a 4-digit sectorial disaggregation level. The present study attempts to address this gap and identifies agrifood clusters at a high level of spatial and sectorial disaggregation, following the methodology used by Hoffmann et al. (2017). In a study on cluster identification in Germany's food industry, the authors used the cluster index (CI) put forward by Sternberg and Litzberger (2004). Sternberg and Litzberger (2004) proposed the CI as a measure to identify industrial clusters. The CI is composed of the following three components: relative industrial stock (IS); relative industrial density (ID); and relative plant size (PS). To identify industrial clusters at a spatial level, these

components are related through multiplication, with the CI corresponding to territorial unit i (area i) and sector j:

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

where:  $e_{ij}$  is the number of employees in area i and sector j;  $b_i$  is the number of inhabitants in area i;  $a_i$  is the area's surface size in km<sup>2</sup>;  $p_{ij}$  is the number of companies in area i and sector j;  $\sum_{i=1}^n e_{ij}$  is the number of employees in sector j throughout the region;  $\sum_{i=1}^n b_i$  is the number of inhabitants throughout the region;  $\sum_{i=1}^n a_i$  is the size of the entire region measured in km<sup>2</sup>; and  $\sum_{i=1}^n p_{ij}$  is the number of companies throughout the region in sector j.

The main advantage of the CI is that a value for each analyzed area/sector can be derived. Therefore, comparison between areas/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 areas). This makes comparisons of values for areas of different size unreliable (Litzenberger and Sternberg 2006).

One advantage of this index is based in its multidimensional nature, incorporating the information and dimension of three relevant location aspects. 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. The ID is included as otherwise scarcely populated regions, in which most of the inhabitants work in the same sector and 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.

Another advantage is based on its continuous character. All three components of the CI (ID, IS and PS) are defined between zero and infinity, implying that the whole index also has the potential range from zero to infinity. Values below one indicates below average



economic activity of sector  $j$  in area  $i$ , while values in excess of one point towards an overrepresentation. The multiplicative connection of the CI components implies that extreme values of single components have a higher influence than, for example, 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 area, clusters will be identified through a possibly high IS, although the ID can be below one (Sternberg and Litzenberger 2004).

The outstanding advantages outweigh the possible limitations of the Italian methodology used in the mapping of industrial districts applied for Spain (Boix and Galletto 2006, 2008; Boix et al. 2015): The taxonomy is rigorously dichotomous (a local system is a district or not a district, that is, intermediate situations are not contemplated), and there is restrictive multi-criteria methodology (if one of the criteria is not verified, the LLS can no longer be considered a district).

In any case, using the CI to identify potential clusters implies setting a minimum value threshold. Since no specific value threshold exists to define a cluster, the threshold should be determined individually in each cluster study (Koschatzky and Lo 2007; Titze et al. 2011). Therefore, one of the possible limitations of the index is the subjectivity when setting the minimum threshold to identify relevant or potential clusters. On the other hand, several authors (Hoffmann 2014) have shown that sectors with a small number of establishments and dispersed distribution lead to overestimating the CI.

Also, the following drawbacks of the CI need to be pointed out (Hoffmann et al. 2017): The inclusion of the ID in the calculation can lead to a greater difficulty to detect clusters in larger territorial units than in smaller ones. However, without this element, biases with

unidentified clusters in highly populated areas (e.g. cities) might occur. Additionally, correcting with the PS could obscure clusters mainly consisting of large firms. More significant is the fact that functional relations between firms and industries cannot be identified with the CI (Koschatzky and Lo 2007; Titze et al. 2011), and information about the sectoral or spatial interdependence of industrial clusters cannot be derived (Brachert et al. 2011).

On the other hand, as Martin and Sunley (2003) point out, the importance of the type of industry/area classification is highlighted when implementing top-down approaches, such as the CI. The use of these code-based classifications – as the Statistical Classification of Economic Activities in the European Community (NACE) – faces to potential difficulties and errors that can produce distorting results (Kile and Phillips, 2016). In fact, these classifications present levels of inconsistency and unreliability within the same category and in the comparison analyses (Jacobs and O’Neill, 2003). Bean (2016) has summarized three main limitations of these classifications: first, businesses currently classify themselves as other, which means that we have little understanding about an important part of the activities of the economy; second, some businesses are engaged in types of economic activity which do not sit well within code classification. In fact, it fails to capture the new sectors, resulting in a lack of evidence that hinders observer. And third, as businesses become increasingly more dynamic, innovative, and technology-driven, they also perform cross-sector activities then classifications fail to accurately capture the variety of business activities.

The top-down methodological approach of quantitative type can identify as clusters some areas of agglomeration that are not functionally clusters. Therefore, our methodological approach used to identify clusters are not meant to be necessarily conclusive and it should be completed with more qualitative analyses. An evaluation of these initial findings can

be done by analyzing the structure and nature of inter-firm relationships and the presence and role of the local and regional institutional framework, enabling a better understanding of the cluster (Porter 1998; Tallman et al. 2004; Inkpen and Tsang 2005).

In the present study, to identify Spain's food industry clusters, the thresholds used by Hoffmann et al. (2017), based on the classification established by Litzenger (2007), were used. To determine the index interpretation categories, the authors distinguished between the values of one, double, quadruple and eightfold for each component, fixing the CI quadruple value of 64 as the threshold for relevant clusters, and a CI of 512 for highly relevant clusters.

Once the food clusters have been identified, a descriptive analysis will be carried out at a territorial and sectorial level. In the sectorial domain, we tried to uncover any differential results – especially regarding relevant clusters – existing between 3-digit and 4-digit sectorial classifications. Evidence from other research (Hoffmann et al. 2017) has shown a greater presence of relevant clusters when a higher disaggregation (4 digits) of sectorial classification was used. That is, at a more aggregate level of sectorial classification (3 digits), cluster-type spatial agglomerations were underestimated.

This aspect will be addressed using a statistical analysis of nonparametric tests of hypothesis testing. Specifically, we tested the hypothesis of significant CI value differences at a given 3-digit level sector with its different 4-digit sub-sectors.

Nonparametric tests compare the distributions of two related variables. The appropriate test depends on the type of data. If the data are continuous – as in our case, CI – the sign test or the Wilcoxon signed-rank test can be applied. The sign test calculates the differences between the two variables for all cases and classifies the differences as positive, negative or null. If both variables have a similar distribution, the number of positive and negative differences does not significantly differ. Wilcoxon's signed-rank

test (Wilcoxon 1945) considers the information of the sign of the differences and the magnitude of the differences between the pairs. Since the Wilcoxon signed-rank test incorporates more information about the data, it is more powerful than the sign test, and therefore, was applied in our analysis using the statistical program SPSS©. This test is normally applied in the field of experimental sciences, although there have also been applications in economics (e.g. Salvati et al. 2018).

To complete this analysis, we studied the spatial location of some significant 3-digit sub-sectors of the Spanish food industry (both in terms of number of companies and employment) – (101) Processing and preserving of meats and processing of beef products; (105) Manufacture of dairy products; (107) Manufacture of bakery products and pastries; and (108) Manufacture of other food products – to try to explain the divergent results at different levels of sectorial disaggregation (3 digits vs. 4 digits). At the methodological level, we have analyzed different quantitative measures of the spatial distribution of these sectors (employment, number of relevant clusters) and several sectorial indicators.

## **Data**

The territorial unit of analysis was the market or LLS, constructed based on residence-labor mobility data. Specifically, the 806 LLSs identified by Boix and Galleto (2006) were used for the whole of Spain. The territorial units ultimately analyzed were the 768 LLSs with activity in the agrifood industry.

The classification system used was Statistical Classification of Economic Activities in the European Community (NACE – Rev.2). Although most analyses were conducted at a 3-digit level, studies on clusters have argued that functional relationships can be better detected at the 4-digit or even 5-digit level. The 4-digit level of the NACE-Rev.2

comprises 35 classes or sub-sectors for division 10 “food industry” and division 11 “beverage manufacturing,” which represent the sectorial scope of our analysis.

The data on the number of companies and their use in each food industry sub-sector, as well as the population data and the size of the LLS, were needed at a disaggregated level to calculate the CI. Thus, the main data were obtained from the Iberian Balances Analysis System (SABI) managed by Bureau van Dijk, which provides information on 1.25 million companies in Spain. Starting from a database with the individualized records of existing industrial companies in the available time period, secondary variables were generated on the number of companies and industrial employment at the indicated territorial level. Data were available at the 4-digit industry disaggregation level for any of the LLSs. The data used in this analysis were from 2016, which was the latest period available with complete available data at the required sectorial and territorial levels.

In addition to food industry data, the number of inhabitants per LLS and the size of the LLS (surface area) were needed to calculate the CI. These data were obtained from the Spanish Ministry of Transportation (Atlas of Urban Areas), and they provided the measures of surface size (km<sup>2</sup>) as well as the number of inhabitants for each of the 768 LLSs with activity in the food and beverage industry.

Some aspects of the sectorial and territorial dimension of the analysis have been noted in a previous subsection. Table 3 shows the descriptive statistics (average, median, standard deviation). LLSs with activity in the food industry account for an average surface area of 648.5 km<sup>2</sup> and an average population of 50,185 inhabitants. The high values of the standard deviation statistics show that the LLSs vary significantly in size (both in area and in population). Average firms’ number and employee in each LLS were 18.5 and 362.8, respectively. Average employment in the industry’s 14,203 companies was 19.6.

**Insert Table 3**

As mentioned above, several authors (Hoffmann 2014) have shown that sectors with a small number of establishments and dispersed distribution lead to overestimating the CI. To avoid this bias, only sub-sectors at the 4-digit level with at least 100 companies were considered. This meant that we had to exclude ten of the 35 sub-sectors at the 4-digit level from the analysis. However, these sub-sectors only represented 334 companies, which means that only 2.4% of food and beverage industry companies were excluded from the cluster identification and analysis.

## **Results**

The first subsection is a preliminary analysis of the results of the identification of agrifood clusters in Spain. The differential results according to sectorial disaggregation (3-digit vs. 4-digit level) and the sensitivity of results according to sectoral disaggregation will be verified using non-parametric statistical tests (Wilcoxon signed-rank test) in the second subsection. In addition, the analysis of four significant 3-digit sub-sectors in the Spanish food industry in the third subsection will allow us to advance alternative explanations for the divergent results at the different levels of the analysis (3 digits versus 4 digits).

### **Identification and Preliminary Analysis**

We analyze the 25 sub-sectors of the Spanish food and beverage industry (4-digit level) with at least 100 active companies, together with the ten 3-digit sectorial categories. Since smaller sectors may introduce a bias in the analysis by oversizing index values, we verified the reliability of the results by conducting an exploratory analysis. We checked whether sub-sectors with a small number of companies or employees frequently showed

a higher number of relevant clusters ( $CI > 64$ ). The results of the corresponding regressions did not show a significant impact of the size of the sector on the CI. The correlation coefficient between the size of the territorial unit and the CI value average was shown to be close to zero (0.0206).<sup>2</sup> In addition, despite its high level of disaggregation, the 4-digit NACE-REV.2 is characterized by a high degree of heterogeneity, such as in the meat processing and preserving sub-sector (1011) and in the other processing and preserving of fruit and vegetables sub-sector (1039).<sup>3</sup> Therefore, the CI seems adequately and reliably to identify the existence of clusters, as well as their geographical location (Martin and Sunley 2003).

#### **Insert Table 4**

The results show that 540 relevant clusters (with  $CI > 64$ ) are identified in the 25 analyzed sub-sectors of the food and beverage industry at the 4-digit level. Table 4 shows the distribution of relevant clusters based on territorial units' types: rural areas in rural environments (65.7%); densely populated areas (18.3%); and 8% in rural areas around urban agglomerations and city areas. In the case of Germany (Hoffmann et al. 2017), most clusters were in densely populated areas and in large urban areas (approximately 80%). Other empirical studies (Boix and Vaillant 2009; Llorente-Pinto et al. 2014; Sánchez-Hernández et al. 2015) have shown the relevance of rural areas compared to urban areas in Spain's agrifood industry.

Figure 1 shows the spatial distribution of relevant clusters identified in our analysis for Spain (at a 4-digit level).

#### **Insert Figure 1**

A relevant aspect is the existence of many LLSs identified as relevant clusters in several sub-

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<sup>2</sup> The correlation between the size of the area and the number of clusters identified was also small (0.1281).

<sup>3</sup> For example, the 6-digit NAICS system used in the United States contains 49 fairly homogeneous sub-sectors compared to the 35 sub-sectors of the NACE\_Rev.2 4-digit level.

sectors at the 4-digit level; specifically, 44 LLSs were identified as relevant clusters in 3 or more 4-digit sub-sectors. Exceptional cases include the LLSs centered around Lorquí (Murcia), which appears as a relevant cluster in 8 sub-sectors; Cambados (Galicia), in 6 sub-sectors; and Barcelona, in 5 sub-sectors. Therefore, the 540 clusters identified are associated with 343 LLS (44.7% of LLS with agrifood activity) observing 214 single-specialized LLS (only appear in a single sector) and 129 multi-specialized LLS (appearing in two or more sectors). The spatial distribution of the relevant clusters at Autonomous Community-Autonomous Region levels (NUTS-2 Regions) shows a greater spatial concentration of clusters in the following Autonomous Communities (see Figure 1): Andalusia (20.7%), Catalonia (14,6%); Valencian Community (12.8%); Castilla-La Mancha (8.7%); Galicia (6.9%); Castilla and León (6.3%); Murcia (5.9%); and Extremadura (5.2%). These 8 regions concentrate 81.1% of the relevant clusters identified.

#### Differential Results According to Sectorial Disaggregation (3-Digit vs. 4-Digit Level)

To obtain a more detailed analysis, Tables 5 and 6 show the number of clusters in each CI category for the different sub-sectors at the NACE-Rev.2 3-digit and 4-digit level, respectively.

The results indicate that relevant clusters can be identified for almost all sub-sectors of the food and beverage industry at the 3-digit level (see the last two columns of Table 5). Of these, 196 relevant clusters are identified in the 10 analyzed sectors (3-digit), with an average of 19.6 relevant clusters per sector. Five sub-sectors show a higher value than average number of clusters.

#### **Insert Table 5**

The following sub-sectors presented a large number of relevant clusters in absolute terms



(there were at least 20 relevant clusters in each of them): (102) Processing and preserving of fish, crustaceans and mollusks; (103) Processing and preserving of fruits and vegetables; (104) Manufacture of vegetable and animal oils and fats; (109) Manufacture of products for animal feed; and (110) Manufacture of beverages. However, regarding the number of LLS with activity in each sub-sector, a bigger presence of relevant clusters was observed in the following sub-sectors: (102) Processing and preserving of fish, crustaceans and mollusks; (103) Processing and preserving of fruits and vegetables; (104) Manufacture of vegetable and animal oils and fats; and (106) Manufacture of mill products, starches and starchy products.

### **Insert Table 6**

By moving the analysis down to the 4-digit level (Table 6), the results again indicated that relevant clusters could be identified in almost all 4-digit level food and beverages industry sub-sectors (see the last two columns of Table 6). Of these, 540 clusters are identified in the 25 sub-sectors analyzed, with an average of 21.6 relevant clusters per sector. Eleven sub-sectors show a higher value than average number of clusters. The sub-sectors with the smallest presence of relevant clusters were: Manufacture of bread, fresh bakery and pastry products (1071); and Manufacture of beer (1105). The 4-digit sub-sectors with the largest number of relevant clusters (25 relevant clusters were identified in each of them) were: (1022) Manufacture of canned fish; (1032) Manufacture of fruit and vegetable juices; (1039) Other processing and preserving of fruits and vegetables; (1043) Manufacture of olive oil; (1044) Manufacture of other oils and fats; (1053) Manufacture of cheese; (1082) Manufacture of cocoa, chocolate and confectionery products; (1084) Preparation of spices, sauces and condiments; and (1102) Winemaking. If we compare the 4-digit level findings (Table 6) with respective 3-digit findings, the number of relevant clusters at the 3-digit level was generally much lower (Table 5). This

evidence, observed in a descriptive and intuitive way, was verified through nonparametric statistical hypothesis testing.

As noted in the methodological section, the non-parametric test applied calculated the differences between the two variables (3-digit CI – 4-digit CI) in all cases (LLSs) and classified the differences as positive, negative or null. If two variables have a similar distribution, the number of positive and negative differences does not differ significantly. Wilcoxon's signed-rank test (Wilcoxon 1945) considers the information of the sign of the differences and the magnitude of the differences between the pairs. The results obtained from Wilcoxon's signed-rank test (Table 7) allowed us to reject the hypothesis of null differences with a high statistical significance ( $p < 0.05$ ) of the median values of all analyzed pair combinations. The statistically significant differences were mainly negative differences (78.2% of the analyzed pairs). This provided a general and statistically relevant indication that the 4-digit CI values were greater than the 3-digit CI values.

### **Insert Table 7**

#### Explaining the Different Results According to the Sectorial Disaggregation

The analysis of four significant 3-digit sub-sectors in the Spanish food industry (both in terms of number of companies and employment) may help to explain the divergent results at the different levels of the analysis (3 digits vs. 4 digits) [(101) Processing and preserving of meats and processing of beef products, (105) Manufacture of dairy products, (107) Manufacture of bakery and pastry products, (108) Manufacture of other food products].

Processing and preserving of meats and processing of beef products (101)

In the 3-digit level sector (101), 14 relevant clusters were identified. The number of relevant clusters identified at the 4-digit level produced the following results:

- Processing and preserving of meat, 20 relevant clusters.
- Production of meat products and poultry, 14 relevant clusters.

#### **Insert Table 8**

The production of meat products and poultry (1013) is characterized by small and medium-sized businesses often closely linked to local suppliers and shows a low level of spatial concentration with very small values of the Gini index (0.0024) and the Ellison-Glaeser index (-0.0190) (see Table 8). Given the importance of this sub-sector in the 3-digit sector (101) – 36,048 jobs (62.2%) – it induces a bias regarding the lesser relevance of clusters at 3-digit level sectors. The distortion responds, therefore, to the effect of a sub-sector (4 digits) that is very large in size and whose spatial distribution is highly dispersed.

#### Manufacture of dairy products (105)

The sector's spatial agglomeration significantly diverged according to sectorial disaggregation (Tables 5 and 6). A total of 8 relevant clusters were identified at the 3-digit level (105). The number of relevant clusters identified at the 4-digit level produced these results:

- Production of ice cream, 20 relevant clusters.
- Manufacture of cheese, 33 relevant clusters.
- Preparation of milk and other dairy products, 18 relevant clusters.

In this case, the 4-digit level sub-sectors revealed the presence of relevant clusters that were not visible when the sector was analyzed at a 3-digit level. This can be explained by the fact that the 4-digit sub-sectors showed a high spatial agglomeration (see the spatial concentration indexes of Table 8), but their localization patterns were very

heterogeneous.<sup>4</sup> If we analyze the spatial distribution of employment and of the relevant clusters at the regional level, substantial differences are observed in the 4-digit sub-sectors analyzed (see Table 8). For example, if we look at the four main regions (top 4) in terms of employment in each sector, 11 different regions are identified; that is, there are substantial differences in their location and agglomeration. Similar results are observed in the spatial distribution of number of relevant clusters. This second type of distortion responded to the impact of heterogeneous subcategories.

#### Manufacture of bakery products and pastry products (107)

As shown in Tables 5 and 6, the sector's spatial agglomeration differed significantly according to the sectorial disaggregation. In the 3-digit level sector (107), 4 relevant clusters were identified. The number of relevant clusters identified at the 4-digit level produced the following results:

- Manufacture of bread, fresh bakery and pastry products, 4 relevant clusters.
- Manufacture of biscuits and long-life bakery and pastry products, 18 relevant clusters.

The manufacture of bread, fresh bakery and pastry products sub-sector (1071) is characterized by small businesses often closely linked to local demand; the sector is highly spatially dispersed (Gini index 0.0038, Ellison-Glaeser index -0.0001) (see Table 8). The analysis detected a reduced number of relevant clusters, being present in 601 LLSs (78% of the LLSs with activity in the food industry). Given the importance of this sub-sector in the 3-digit sector (107) – 3,337 companies (87.3%), 41,292 jobs (75.9%) – it induces a bias regarding the small relevance of clusters at 3-digit level sectors. The distortion is explained again to the effect of a sub-sector (4 digits) that is very large in size and whose spatial distribution is highly dispersed.

#### The Manufacture of other food products sector (108)

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<sup>4</sup> The correlations of the spatial distributions of these sectors (both in number of companies and in employees) were very small and statistically insignificant.

The sector's spatial agglomeration significantly diverged according to sectorial breakdown (Tables 5 and 6). A total of 12 relevant clusters were identified at the 3-digit level (108). The number of relevant clusters identified at the 4-digit level produced these results:

- Manufacture of cocoa, chocolate and confectionery products, 25 relevant clusters.
- Preparation of coffee, tea and infusions, 18 relevant clusters.
- Preparation of spices, sauces and condiments, 28 relevant clusters.
- Preparation of prepared dishes and meals, 18 relevant clusters.
- Preparation of homogenized food preparations and dietetic food, 16 relevant clusters.
- Preparation of other food products, 16 relevant clusters.

In this case, the 4-digit level sub-sectors revealed the presence of relevant clusters that were not apparent when the sector was analyzed at a 3-digit level. This can be explained by the fact that the 4-digit sub-sectors showed a high spatial agglomeration (see the spatial concentration indexes of Table 8), but their localization patterns were very heterogeneous. The correlations of the spatial distributions of these sectors (both in number of companies and in employees) were very small and statistically insignificant. If we analyze the spatial distribution of employment and of the relevant clusters at the regional level, substantial differences are observed in the sub-sectors analyzed (see Table 8). For example, if we look at the four main regions (top 4) in terms of employment in each sector, 10 different regions are identified. If we analyze the 5 most relevant clusters (top-5) of each 4-digit sector, 27 LLSs are identified for the 6 sectors analyzed; that is, the top-5 clusters are different depending on the sub-sector that we analyze. That is, in each 4-digit sector there are substantial differences in their location and agglomeration. This distortion responded to the impact of spatial heterogeneous subcategories.

## **Discussion and Conclusions**

Although most academic studies have focused on specialized productive agglomeration models centered on the traditional manufacturing industry, some studies have spread to other sectors, such as agrifood. However, to date, few studies have attempted to identify food clusters in a national territory based on systematized quantitative data methods with high territorial and sectoral disaggregation. A first important point to note is that, in the agrifood industry, these agglomerations can only be detected if measures and methods are used with a higher level of disaggregation than in the case of other industries. It is important to choose the right aggregation level in this industry because the structure of the Spanish food processing industry, with more than thirty-five subsectors and about 360,000 employees, is too complex and too heterogeneous to be analyzed at a highly aggregated level (3-digit) or in its entirety. This study contributes empirically to the body of knowledge about Spanish industry clusters and applies established conceptual approaches and methodologies to a new empirical context. In this research, we tried to make progress in this field by identifying food industry clusters in Spain.

Our results show geographical areas where agglomerations of agrifood subsectors are located, enabling the identification of clusters. In total, 196 relevant clusters are identified in the ten sectors (3-digit) and the 4-digit level analysis reveals the existence of 512 relevant clusters. Multi-specialization and spatial concentration are already shown in the studies of Boix and Galletto (2006, 2008) and Boix et al. (2015). The results of these studies—applying the Italian methodology—show us that the agrifood industry is one of the sectors with the largest number of industrial districts. Although most of the districts previously detected have been identified in our analysis as relevant clusters—mainly as very relevant clusters ( $CI > 512$ )—a differential result of our research is that other relevant and

potential clusters have been identified that are not visible in the results of the Italian methodology.

The quantitative relevance of the clusters detected in our research is consistent with the results of the few studies that have sought to identify agrifood clusters in a given territory using systematized methods and based on quantitative data: Italy (Unioncamere 2009), Spain (Giner and Santa-María 2017), and Germany (Hoffmann et al. 2017). Also, the research contributes to expanding studies focused on food-related industries, such as those developed in Italy (Iacoponi 1990; Fanfani 1994; Bertolini 1988; Brasili and Ricci Maccarini 2003; Bertolini and Giovannetti 2006) and other European countries (Lagnevik et al. 2003).

In our analysis, the subsectors with the largest number of relevant clusters are in line with the case studies about agrifood clusters in Spain: preparation of fruit and vegetable juices (29 clusters) and other processed and preserved fruits and vegetables (36 clusters) (Gallego Bono 2007; Aznar Sánchez 2011; Martínez-Carrasco and Martínez Paz 2011; Giner and Santa-María 2018a); manufacture of olive oil (45 clusters) (Sanz Cañada and Macías Vázquez 2005; García Brenes and Sanz Cañada 2012; Rodríguez Cohard and Parras 2011); manufacture of cocoa, chocolate, and confectionery products (25 clusters) (Molina-Morales et al. 2015); and winemaking (32 clusters) (Aldecua et al. 2017; Larreina et al. 2011; Macías Vázquez 2011; Sánchez Hernández 2011; Soler Montiel 2011). These studies highlight the geographical proximity between the components of the cluster as a factor which generates agglomeration economies through internal specialization and division of labor. The network of connections and the informal relationships within the cluster that favor transmission of knowledge are also analyzed. Such functional and social relationships between actors are a crucial element of clusters. It has been shown in the theoretical section that contexts of geographical proximity, such

as those defined as industrial clusters (Porter 1998; Tallman et al. 2004; Inkpen and Tsang 2005), can be viewed as networks because many different actors are involved, including final product firms, suppliers, customers, service providers, local institutions, policy agents, and so on. Thus, in further studies it will be important to analyze through qualitative analysis if network effects and other cluster-inherent structures are relevant for a specific subsector region, specifically in those clusters identified in our research and not detected previously.

On the other hand, in Spain, the cluster has been used as a policy instrument, due to its positive effects on competitiveness (Preissl and Solimene 2003; Commission of the European Communities 2008). In the last decade, the Spanish government designed and implemented an industrial policy aimed at supporting the development of innovative clusters identified as “associations of innovative enterprises” (Ybarra and Domenech 2014). Our results—especially for very relevant clusters—are consistent with the associations of innovative enterprises in the agrifood sector.

Regarding the location of clusters, the research shows that most of the 540 relevant clusters (with CI > 64; 84%) were in rural areas in rural environments (65.7%) and in densely populated areas (18.3%). In the case of Germany (Hoffmann et al. 2017—one of the few studies addressing the identification of clusters with high sectoral disaggregation for a country), most clusters are in densely populated areas and in large urban areas (approximately 80%). Therefore, relevant cluster location patterns in Spain are very different from those analyzed in Germany. Other empirical studies (Boix and Vaillant 2009; Llorente-Pinto et al. 2014; Sánchez-Hernández et al. 2015) have shown the relevance of rural areas compared with urban areas in Spain’s agrifood industry.

It is worth noting that the number of relevant clusters was higher at the 4-digit level, and concentrations in the industry were identified that would not have been detected at a



higher sectorial aggregation level. This aspect is consistent with the preliminary analysis of Ellison and Glaeser (1997) and subsequent developments; they discuss scope in the sense of an industrial definition (i.e., whether concentration is principally a phenomenon which exists at the level of individual industries or whether it is characteristic of broad industry classes as well). Our analysis applied different sectorial disaggregation (3 and 4 digits) which highlights how the results are substantially different.

Furthermore, the analysis of four significant 3-digit subsectors in the Spanish food industry made it possible to approximate an explanatory framework of the factors that generate a lower presence of relevant clusters in 3-digit sectorial disaggregation with respect to 4-digit disaggregation. Specifically, we highlight two facts: the impact of 4-digit subsectors with a high spatial agglomeration but with very heterogeneous localization patterns and the effect of a subsector (4 digits) that is very large in size and whose spatial distribution is highly dispersed. This is another of the contributions of our research at the methodological and results level.

In the present study, identifying agrifood clusters made it possible to further our understanding of the phenomenon of agro-industrial firm agglomerations, as well as their localizations and main specializations. We thus compensated for the lack of significant studies on Spanish food sectors by applying our top-down methodological approach and following a high level of territorial and sectorial disaggregation. The index used in our research (CI) can provide a starting point to identify clusters and is a standard method of identification for these industrial structures.

However, some limitations of our investigation cannot be ignored. One such limitation relates to the source of information used in the analysis: only the location data of the firms were used, whereas it would be ideal to use business units or establishments.

A second set of limitations is associated with methodological aspects. One limitation refers to the use of the statistical classification of economic activities by NACE. The use of these code-based classifications faces potential difficulties and errors that can produce distorting results (Kile and Phillips 2009). In fact, these classifications present levels of inconsistency and unreliability within the same category and in the comparison analyses (Jacobs and O'Neill 2003). Bean (2016) has summarized the main limitations of these classifications.

The CI used in the identification shows a series of limitations. One of the possible limitations of the index is subjectivity when setting the minimum threshold to identify relevant or potential clusters. The following drawbacks of the CI need to be pointed out: The inclusion of the relative industrial density (ID) in the calculation can lead to greater difficulty in detecting clusters in larger territorial units than in smaller ones. Additionally, correcting with the relative plant size (PS) could obscure clusters mainly consisting of large firms. A main disadvantage of the CI is that it does not allow identification of the functional relationships between companies and industries (Koschatzky and Lo 2007; Titze et al. 2011). Lastly, the research approach based on a quantitative analysis can identify clusters that do not fit the conceptual and empirical framework of clusters. Therefore, it is important to highlight the benefits of using both quantitative and qualitative techniques together (De Propris 2005).

We propose several lines of future research. On the one hand, it is necessary to perform a more in-depth quantitative analysis based on CI components (relative industrial stock, relative industrial density, and relative plant size); on the other, improvements in innovative research techniques would allow for the development of a new index that could help overcome CI's methodological limitations.

Based on the results of our analysis, researchers can now consider the spatial dimension of clusters based on their geolocations. For example, through exploratory spatial data analysis it can be shown if there is a significant trend of grouping similar CI values (cluster typology) in nearby areas in the territory with significant spatial patterns in statistical terms.

Because the use of code-based sectorial classifications faces potential difficulties and errors that can produce distorting results, a future line of research may be the analysis of agrifood clusters without the constraints of sectorial classifications, such as that carried out by Molina-Morales and Martínez-Fernández (2019) in the ceramics sector.

It is also important to complement CI-based identification with the use of more qualitative (bottom-up) approaches. It would be relevant to analyze food industry sectors with numerous clusters in more detail, combining quantitative and qualitative techniques (De Propriis 2005), thus describing the characteristics of these areas, how they operate, and their temporal dynamics. Relational approaches, social capital, and network of knowledge should be included in future research.

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## Tables-figures

**Table 1.** Spanish food industry by subsector, 2017.

	N° of firms	%	Turnover	%	N° of employees	%
Processing and preserving of meats and processing of beef products (101)	3,661	12.98	26,291,329	22.12	96,576	23.88
Processing and preserving of fish, crustaceans and molluscs (102)	607	2.15	6,050,416	5.09	20,367	5.04
Processing and preserving of fruit and vegetables (103)	1,424	5.05	10,090,839	8.49	36,355	8.99
Manufacture of vegetable and animal oils and fats (104)	1,613	5.72	12,323,697	10.37	12,970	3.21
Manufacture of dairy products (105)	1,585	5.62	9,449,263	7.95	26,542	6.56
Manufacture of mill products, starches and starch products (106)	409	1.45	3,326,700	2.80	6,696	1.66
Manufacture of bakery products and pastry (107)	10,279	36.43	8,415,402	7.08	87,009	21.52
Manufacture of other food products (108)	2,811	9.96	13,031,626	10.97	53,203	13.16
Manufacture of products for animal feed (109)	762	2.70	12,598,280	10.60	13,124	3.25
Beverage Manufacturing (110)	5,061	17.94	17,256,122	14.52	51,496	12.74
Total	28,212	100.00	118,833,674	100.00	404,338	100.00

Source: Structural Business Statistics, Spain's National Institute of Statistics (2017).

**Table 2.** Spanish food industry by Region, 2017.

	N° of firms	%	Turnover	%	N° of employees	%
Andalusia	5,653	18.66	18,192,186	15.35	53,189	13.19
Aragón	1,042	3.44	4,659,467	3.93	12,005	2.98
Asturias	690	2.28	1,948,647	1.64	7,367	1.83
Balearic Islands	533	1.76	613,519	0.52	4,606	1.14
Canary Islands	1,109	3.66	1,520,585	1.28	11,222	2.78
Cantabria	416	1.37	1,549,838	1.31	5,853	1.45
Castile-Leon	3,043	10.04	10,135,428	8.55	36,503	9.05
Castile-La Mancha	2,421	7.99	8,147,447	6.88	25,142	6.24
Catalonia	3,754	12.39	27,939,485	23.58	88,032	21.83
Valencian Region	2,339	7.72	9,803,868	8.27	37,526	9.31
Extremadura	1,381	4.56	3,454,096	2.92	11,012	2.73
Galicia	2,587	8.54	9,018,658	7.61	30,050	7.45
Madrid	1,612	5.32	5,718,789	4.83	23,227	5.76
Murcia	901	2.97	5,982,360	5.05	21,632	5.36
Navarre	626	2.07	3,451,433	2.91	13,912	3.45
Basque Country	1,409	4.65	4,243,000	3.58	14,517	3.60
Rioja, La	742	2.45	2,071,839	1.75	7,183	1.78
Ceuta	19	0.06	23,950	0.02	158	0.04
Melilla	17	0.06	2,760	0.00	72	0.02
Total	30,294	100.00	118,477,355	100.00	403,208	100.00

Source: Structural Business Statistics, Spain's National Institute of Statistics (2017).

**Table 3.** Descriptive statistics (2016)<sup>a</sup>

	Mean	Median	Stdv.
LLS size (km <sup>2</sup> )	648.5	405.3	818.9
No. of inhabitant per LLS	50,185.0	12,682.0	230,759.2
Employees per LLS	362.8	298.0	1,310.7
Establishments per LLS	18.5	28.0	43.4
Establishments per sub-sector	1,420.3	277.5	1,253.9
Establishments per sub-sector and LLS	1.8	2.0	7.4
Employees per establishment	19.6	9.4	75.6

*Source:* Own calculations.

*Notes:* <sup>a</sup> In order to provide a better overview, the descriptive statistics is based on the 3-digit level while the statistical analysis in Section 5 is based on the 4-digit level.

**Table 4.** Distribution of relevant clusters on territorial units types

LLS type <sup>a</sup>	No. of 4-digit sectors with $64 < CI \leq 512$	No. of 4-digit sectors with $CI > 512$	Total	%	
Rural areas in rural environment	271	84	355	65.7	
Rural areas around urban agglomerations	29	14	43	8.0	
Densely populated areas	56	43	99	18.3	
City areas	39	4	43	8.0	
	Total	395	145	540	100.0

*Source:* Own calculations.

*Notes:* <sup>a</sup> Classification of LLS/regions. Rural LLS in rural environment: <100 inhabitants/sq. km.; Rural LLS around urban agglomerations: <150 inhabitants/sq. km.; Densely populated LLS: >150 inhabitants/sq. km.; City LLS: city LLS with >100,000 inhabitants.

**Table 5.** Distribution of 768 LLS on the different CI-categories for (sub)sectors of the Spanish food Industry (3-digit sectors)

3-digit sectors	CI=0	0<CI≤1	1<CI≤8	8<CI≤64	64<CI≤512	CI>512
Processing and preserving of meats and processing of beef products (101)	332	237	140	45	11	3
Processing and preserving of fish, crustaceans and molluscs (102)	670	24	28	22	12	12
Processing and preserving of fruit and vegetables (103)	536	85	62	50	23	12
Manufacture of vegetable and animal oils and fats (104)	491	77	87	78	33	2
Manufacture of dairy products (105)	472	122	102	64	8	0
Manufacture of mill products, starches and starch products (106)	636	16	44	53	13	6
Manufacture of bakery products and pastry (107)	153	363	202	46	4	0
Manufacture of other food products (108)	401	180	117	58	10	2
Manufacture of products for animal feed (109)	534	47	104	63	18	2
Beverage Manufacturing (110)	365	226	96	56	18	7
Total	4,590	1,377	982	535	150	46
Average per sector	459.0	137.7	98.2	53.5	15.0	4.6

Source: Own calculations.

**Table 6.** Distribution of 768 LLS on the different CI-categories for (sub)sectors of the Spanish food Industry (4-digit sectors)

4-digit sectors	CI=0	0<CI≤1	1<CI≤8	8<CI≤64	64<CI≤512	CI>512
1011 Processing and preserving of meat	515	94	96	45	11	7
1013 Elaboration of meat products and poultry	399	191	121	43	11	3
1021 Processing of fish, crustaceans and molluscs	722	6	6	19	6	9
1022 Manufacture of canned fish	686	17	17	20	14	14
1032 Manufacture of fruit and vegetable juices	693	12	18	16	17	12
1039 Other processing and preserving of fruit and vegetables	591	45	49	47	19	17
1043 Manufacture of olive oil	516	60	74	73	38	7
1044 Manufacture of other oils and fats	690	6	13	34	23	2
1052 Elaboration of ice cream	661	19	38	30	19	1
1053 Manufacture of cheese	568	38	66	63	30	3
1054 Preparation of milk and other dairy products	685	20	19	26	13	5
1061 Manufacture of Milling Products	640	14	38	58	12	6
1071 Manufacture of bread, fresh bakery and pastry products	173	331	215	45	4	0
1072 Manufacture of cookies and long-life bakery and pastry products	578	48	69	55	17	1
1082 Manufacture of cocoa, chocolate and confectionery products	649	28	39	27	16	9
1083 Preparation of coffee, tea and infusions	683	7	30	30	14	4
1084 Preparation of spices, sauces and condiments	711	7	12	10	13	15
1085 Preparation of prepared dishes and meals	667	25	32	26	13	5
1086 Preparation of homogenised food preparations and dietetic food	715	13	16	8	12	4
1089 Processing of other food products	497	105	93	57	16	0
1091 Manufacture of products for the feeding of farm animals	550	43	87	66	21	1
1101 Distillation, rectification and mixing of alcoholic beverages	654	20	30	42	18	4
1102 Winemaking	456	138	72	70	20	12
1105 Manufacture of beer	692	31	25	15	4	1
1107 Manufacture of non-alcoholic beverages; Production of mineral waters and other bottled waters	687	15	18	31	14	3
Total	15,078	1,333	1,293	956	395	145
Average per sector	603.1	53.3	51.7	38.2	15.8	5.8

Source: Own calculations.



**Table 7.** Differences between the 3-digits Cluster Index (CI) – 4-digits Cluster Index (CI)<sup>a</sup>

3-digit sector – 4 digit sector	Differences (%)		Sig.	Average	Median
	Negative	Positive			
CI101-CI1011	69.6	30.4	0.000	-21.14	-0.55
CI101-CI1013	66.1	33.9	0.000	-0.81	-0.15
CI102-CI1021	76.1	23.9	0.007	1.96	-7.79
CI102-CI1022	75.6	24.4	0.000	-123.1	-1.62
CI103-CI1032	74.7	25.3	0.000	-342.12	-5.91
CI103-CI1039	83.6	16.4	0.000	-425.84	-1.65
CI104-CI1043	82.1	17.9	0.000	-21.22	-1.55
CI104-CI1044	83.3	16.7	0.000	-69.04	-21.91
CI105-CI1052	82.2	17.8	0.000	-39	-4.28
CI105-CI1053	86.5	13.5	0.000	-31.75	-4.34
CI105-CI1054	80.7	19.3	0.000	-81.1	-4.05
CI106-CI1061	97.7	2.3	0.000	-14.1	-1.62
CI107-CI1071	79.2	20.8	0.000	-0.46	-0.13
CI107-CI1072	70.5	29.5	0.000	-21.32	-1.54
CI108-CI1082	70.6	29.4	0.000	-350.32	-3.53
CI108-CI1083	81.2	18.8	0.000	-155.3	-5.75
CI108-CI1084	86.0	14.0	0.000	-2364.9	-56.08
CI108-CI1085	73.3	26.7	0.000	-119.54	-3.41
CI108-CI1086	71.7	28.3	0.000	-269.66	-4.14
CI108-CI1089	67.9	32.1	0.000	3.51	-0.32
CI109-CI1091	91.7	8.3	0.000	-5.04	-0.93
CI110-CI1101	76.3	23.7	0.000	50.46	-5.44
CI110-CI1102	81.1	18.9	0.000	-125.95	-0.59
CI110-CI1105	64.5	35.5	0.006	-244.79	-0.77
CI110-CI1107	84.0	16.0	0.000	-62.22	-8.4

Source: Own calculations.

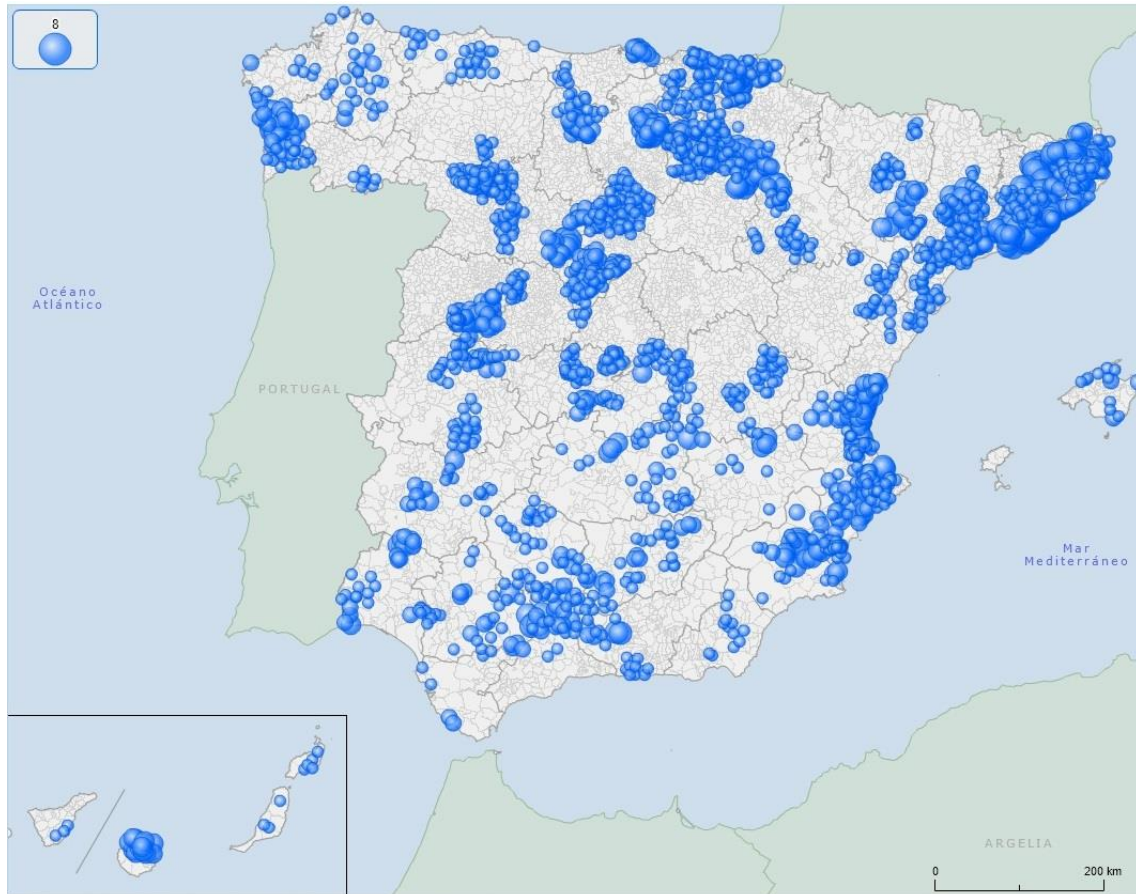
Notes: <sup>a</sup> See Tables 3 and 4 to code sector. Sig.: Statistical significance of Wilcoxon's signed rank test (p-value).

**Table 8.** Spatial distribution of employment and relevant clusters in some 4-digit sectors

3-digit sectors	101		105			107		108					
4-digit sectors	1011	1013	1052	1053	1054	1071	1072	1082	1083	1084	1085	1086	1089
% 3-digit sector	36.2	62.2	22.4	27.1	50.5	75.9	20.6	19.3	9.5	5.6	9.0	6.2	47.7
G index	0.0065	0.0024	0.1211	0.0626	0.0291	0.0038	0.0527	0.0163	0.0372	0.0835	0.0648	0.0471	0.0076
EG index	-0.0345	-0.0190	0.0626	0.0445	-0.0313	-0.0001	0.0331	-0.0055	0.0191	0.0563	-0.0350	-0.0043	0.0019
Regional distribution of sector employment (% of the national total)													
Regions	1011	1013	1052	1053	1054	1071	1072	1082	1083	1084	1085	1086	1089
Andalusia	11.5	5.5	7.2	4.2	8.7	13.8	11.5	6.4	5.6	10.0	5.3	2.6	8.2
Aragón	2.7	5.2	1.4	1.0	0.2	2.9	2.5	4.2	1.5	0.2	4.2	2.4	1.5
Asturias	0.8	1.3	0.4	0.8	21.0	2.3	0.4	1.4	12.9	0.6	1.5	0.1	0.5
Balearic Islands	0.5	0.8	2.1	4.7	0.5	2.0	1.9	1.1	1.8	0.1	0.5	0.4	0.9
Canary Islands	0.2	0.2	32.0	3.5	3.9	5.8	3.7	0.2	6.8	1.4	12.7	0.3	3.2
Cantabria	0.4	0.7	2.9	5.7	4.5	1.1	0.2	0.0	0.9	0.0	0.2	0.0	0.5
Castile-Leon	10.8	13.2	1.8	20.6	11.1	5.6	29.0	1.7	13.2	0.4	21.0	12.0	4.4
Castile-La Mancha	6.3	5.5	3.6	21.8	8.0	3.6	2.9	8.5	1.8	1.1	3.2	5.4	2.7
Catalonia	32.5	30.6	6.0	4.3	21.6	24.2	11.2	34.2	22.4	20.7	19.0	41.5	41.0
Valencian Region	9.1	4.6	23.6	3.4	1.3	9.0	15.8	18.7	13.6	24.2	4.6	7.2	10.8
Extremadura	3.2	2.6	0.8	4.3	0.9	1.5	0.4	1.3	0.4	4.7	0.2	0.0	0.7
Galicia	5.7	4.2	0.1	3.4	10.3	8.3	1.1	1.1	7.5	0.2	2.9	0.1	3.4
Madrid	10.6	10.2	1.7	16.8	0.9	8.8	10.5	5.0	4.5	2.1	13.8	25.7	6.5
Murcia	2.6	12.2	1.8	1.9	2.7	1.6	0.9	10.5	2.3	23.8	0.3	1.3	4.8
Navarre	1.0	1.2	0.1	1.9	0.5	3.5	1.8	0.6	0.7	0.6	7.5	0.6	4.0
Basque Country	0.8	0.8	14.3	0.7	3.9	4.9	4.4	4.8	2.1	0.1	1.7	0.3	2.9
La Rioja	1.4	1.1	0.2	1.1	0.0	1.0	1.8	0.3	1.9	9.8	1.5	0.0	3.8
National Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Regional distribution of relevant clusters (% of the national total)													
Regions	1011	1013	1052	1053	1054	1071	1072	1082	1083	1084	1085	1086	1089
Andalusia	16.7	7.1	10.0	3.0	5.6	50.0	22.2	24.0	16.7	7.1	16.7	6.3	12.5
Aragón	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	5.6	0.0	0.0
Asturias	0.0	0.0	0.0	0.0	11.1	0.0	0.0	0.0	5.6	0.0	0.0	0.0	0.0
Balearic Islands	0.0	0.0	20.0	12.1	5.6	0.0	11.1	0.0	0.0	3.6	0.0	6.3	12.5
Canary Islands	0.0	0.0	5.0	6.1	5.6	0.0	0.0	0.0	5.6	0.0	5.6	0.0	0.0
Cantabria	0.0	0.0	0.0	3.0	5.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Castile-Leon	11.1	21.4	5.0	12.1	5.6	0.0	27.8	0.0	5.6	3.6	5.6	6.3	6.3
Castile-La Mancha	5.6	7.1	0.0	33.3	5.6	0.0	0.0	12.0	5.6	3.6	5.6	12.5	0.0
Catalonia	33.3	35.7	15.0	3.0	22.2	25.0	5.6	24.0	16.7	14.3	22.2	25.0	25.0
Valencian Region	16.7	0.0	40.0	0.0	5.6	25.0	27.8	24.0	27.8	21.4	5.6	25.0	12.5
Extremadura	11.1	14.3	0.0	12.1	0.0	0.0	0.0	0.0	5.6	17.9	0.0	0.0	0.0
Galicia	5.6	0.0	0.0	6.1	16.7	0.0	0.0	4.0	5.6	0.0	5.6	0.0	0.0
Madrid	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.3	0.0
Murcia	0.0	7.1	5.0	3.0	5.6	0.0	0.0	4.0	5.6	17.9	0.0	6.3	18.8
Navarre	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	16.7	6.3	6.3
Basque Country	0.0	0.0	0.0	0.0	5.6	0.0	5.6	4.0	0.0	0.0	5.6	0.0	0.0
La Rioja	0.0	7.1	0.0	3.0	0.0	0.0	0.0	0.0	0.0	10.7	5.6	0.0	6.3
National Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: Own calculations.

Notes: On a gray background the most relevant regions (top-4) are indicated. In case of ties in the fourth place, more than 4 regions may appear. In sector 1054 only the top-3 regions are indicated (the rest are tied in fourth place).



**Figure 1.** Number of relevant food industry clusters in Spain (all 4-digit sectors)

*Notes:* Map elaborated through the GIS platform of the Ministry of Development of Spain.