economies

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Innovative Business Effort in a Mediterranean Region, Same Characteristics and/or Same Spatial Distribution?

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Abstract: Business innovation is fundamental for sustained economic growth at the regional level. Knowing the common characteristics of innovative companies and their location is essential to carry out appropriate economic policies. To this end, we have carried out a double analysis: one grouping of companies according to characteristics and another by geolocation. This study focused on one of Spain's 17 autonomous communities, the Comunitat Valenciana, a region characterised by significant industrial diversity. Our results show, among other things, that size is not a differentiating factor when it comes to innovation, and that there is a positive relationship between physical clustering and productivity.

Keywords: regional economy; innovative companies; industrial activity

Citation: García-Alcober, María P., Ana Isabel Mateos-Ansótegui, and María Teresa Pastor-Gosálbez. 2023. Innovative Business Effort in a Mediterranean Region, Same Characteristics and/or Same Spatial Distribution? *Economies* 11: 274. https://doi.org/10.3390/economies11110274

Academic Editor: Richard J. Cebula

Received: 29 September 2023
Revised: 19 October 2023
Accepted: 24 October 2023
Published: 3 November 2023

1. Introduction

In a globalised and constantly changing world, business innovation has become an unignorable necessity for companies to survive. Innovative activity increases business productivity and, consequently, local economic growth. This activity is characterised by a series of features such as novelty, creativity, and the transferability of results to society as a whole, which makes it a field of study of special interest. For all of these reasons, it is essential to know the characteristics of the companies that carry out innovation in order to help the different agents involved in promoting local economic development in making decisions.

There is no consensus in the literature on certain relationships between firm characteristics and innovation. In particular, the relationship between firm size and innovation has been much debated. Although the literature tended to link firm size with innovation in a positive way, for example Audretsch and Acs (1991); Mowery et al. (1996); or Camisón-Zornoza et al. (2004), we now ask ourselves: do smaller firms really innovate less? In this sense, as Baumann and Kritikos (2016) has pointed out, although smaller firms have more problems in obtaining financing and being able to innovate, it is also true that they need innovation to survive. In a globalised and continuously evolving competitive environment, small firms have to adapt quickly to constant changes in order to avoid closure, as they do not have the financial cushion or support of a stronger business group. Along the same lines, the study carried out by Calvo (2000) concludes that innovative companies in the Spanish manufacturing sector are small and belong to small and medium-sized technology sectors. This discrepancy of opinions, as indicated in a 1996 OECD report (Symeonidis 1996), has led to a debate regarding policy decisions over whether to concentrate on promoting market concentration and firm size or on giving subsidies or grants to smaller firms to increase innovation.

Another variable linked to innovation is the existence of agglomeration economies, which can arise from the geographical concentration of firms (Jacobs 1969). In this case, we might also ask whether innovative firms are geographically clustered. Here, Carlino and Kerr (2015) offer an extensive literature review on the relationship between innovation and business agglomeration.

The innovative behaviour of companies is not homogeneous across the territory. In this study, we will focus on the analysis of innovative companies located in Spain's Valencia Region. The Regional Innovation Indicator 2021 published by the European Union presents a ranking of the different regions. The Valencia Region is classified as a region of moderate innovation, slightly above the Spanish average and below the European average. This, together with its sectoral diversity, as described by Galleto and Boix Doménech (2006), justifies the choice of this territory for our analysis. There is extensive existing literature on this region. Studies by Pérez et al. (2006), Hervás-Oliver et al. (2021), and García-Alcober et al. (2021) provide overall analyses. At a sectoral level, there are studies on the footwear sector, such as those by Ruiz-Ortega et al. (2016) and Marco-Lajara et al. (2021); the ceramics sector has been analysed by, among others, Molina-Morales et al. (2017), Hervás-Oliver et al. (2018), and Albors-Garrigos and Hervás-Oliver (2019); the textile sector has been studied by Pla-Barber and Puig (2009) and Molina-Morales and Expósito-Langa (2013), not to mention other sectors and/or authors.

Firms are usually classified according to the productive sector to which they belong when considering their level of technological innovation. However, following the approach of Gkotsis et al. (2018) regarding EU firms, in this study we will analyse firms that innovate independently of their activity, as we are more interested in their innovative behaviour than in their affiliation to a certain productive sector.

In short, this paper aims to classify innovative companies in the Valencia Region according to certain economic and financial characteristics and, subsequently, it will analyse their geographical location in order to determine whether or not there are economies of agglomeration. Knowing what companies that innovate have in common is fundamental when it comes to implementing appropriate policies for the promotion and support of such companies, which, as mentioned previously, are essential for sustained local economic growth in the medium and long term.

As a methodology, we will use the k-means clustering algorithm, as described by Likas et al. (2003), which will allow us to group the companies according to different economic-financial and size characteristics. At the same time, we will use a geographical location methodology, SaTScan, to analyse the level of territorial concentration of the studied firms. Geographic Information Systems software, using geolocation coordinates, will allow us to determine the existence of statistically significant business groupings.

Our results highlight, for example, that size and age do not limit the possibilities for innovation, that there is evidence that physical clustering enhances productivity, and that smaller, newly created or highly indebted firms tend to be geographically dispersed.

The paper is structured as follows: in Section 2, following this introduction, we analyse the data and methodologies used, both k-means and SaTScan. In the subsequent section, we present the results obtained by both methodologies. Then, in the fourth section, we compare and discuss the results within the context of the current literature and, present conclusions.

2. Materials and Methods

2.1. Materials

In general, studies of business clusters focus on manufacturing companies or on companies in a particular sector. In this study, we analyse innovative companies in the Valencia Region as a whole. The concept of innovation can be understood in different ways. Some authors, such as Molina-Morales and Expósito-Langa (2013), take into account the innovation effort variable and define it as R&D expenditure over total turnover. Other authors consider innovation to be the result of this expenditure and measure innovation as patents or new products obtained. In this sense, Belso-Martínez et al. (2020) link innovation

to the production of new products or production processes. However, as Bell (2005) points out, innovation can also be considered as the development and implementation of new ideas to solve problems. For this reason, Galleto and Boix Doménech (2014) speak of two different innovation models: STI (Science, Technology, and Innovation) and DUI (Doing, Using, and Interacting). Given the difficulty of measuring innovation and the diverse criteria used in the existing literature, in this paper we will consider innovative companies as those that make an innovative effort, in line with Molina-Morales and Expósito-Langa (2013). In this sense, we are going to consider the companies that have any expenditure in R&D in their accounts. Moreover, we will add the companies that receive any public subsidy, because there are companies that have R&D expenditures that cannot be accounted for as such because they do not satisfy all the requirements of the Spanish General Accounting Plan. For instance, to be added to the Plan, they have to be identifiable, measurable, or susceptible to economic valuation, among other limitations. We use the SABI[1] database to conduct the study. The year being analysed is 2019, as the following financial years, 2020 and 2021, would not be representative for a study of this type due to the impact of the COVID-19 pandemic. For the Valencia Region (Comunitat Valenciana), in 2019, we found a total of 1429 companies that can be considered innovative, distributed across the different branches of activity indicated by the National Statistics Institute (INE).

Data Description

We now undertake a purely descriptive analysis of the companies under review, with the aim of finding out which productive sector they belong to, their size, whether or not they receive research subsidies, and their degree of openness to the outside world. Table 1 shows their distribution by sector:

Table 1. Distribution of innovative companies by productive sector in Comunitat Valenciana.

Sectors	% Innovative Companies over Total Innovative Companies in CV	% Innovative Companies over Total Companies in CV by Sector
Agriculture, livestock, forestry, fisheries and extractive industries	0.98%	0.64%
Manufacturing industry	16.79%	4.80%
Chemicals, pharmaceuticals and metallurgy	29.39%	8.68%
Furniture manufacture, energy supply, water and waste treatment	7.63%	2.92%
Construction and ground transport	21.27%	0.73%
Maritime transport, air transport and postal services, accommodation services	2.17%	0.38%
Telecommunications, financial services, insurance	8.82%	0.68%
Research and development, veterinary, rental and employment-related activities	10.01%	2.11%
Security and research, education and health activities	2.59%	0.58%
Creative, artistic and performing arts activities, libraries	0.35%	0.16%

Source: Own elaboration with CNAE data.

It can be seen that "Chemicals, pharmaceuticals and metallurgy" is the productive sector with the highest proportion of innovative companies at 29.39%. Moreover, it is the sector with the highest proportion of innovative firms, 8.68% of the firms in this sector. At the other extreme, the "Creative" sector represents the lowest percentage of the sample.

Table 2 shows that two thirds of the innovating companies are small (small and micro-businesses), and only 5.11% of those innovating are large companies. It can be pointed out that near 50% of the Chemicals, pharmaceuticals and metallurgy innovation companies have a medium or large size; in sum, they are the biggest ones.

Table 3 shows the distribution of the firms according to whether they receive R&D subsidies, showing that 1 in 10 firms innovate without resorting to subsidies. By sector, we can observe that "Maritime transport, air transport and postal services, accommoda-

tion services", "Agriculture, livestock, forestry, fisheries and extractive industries" and "Construction and ground transport" are the sectors with the lowest subsidy levels.

Table 2. Distribution of innovative companies by size and sector.

Sector	% Large	% Medium	% Small	% Micro
Agriculture, livestock, forestry, fisheries and extractive industries	0.0%	14.29%	64.3%	21.43%
Manufacturing industry	4.2%	31.25%	55.0%	9.58%
Chemicals, pharmaceuticals and metallurgy	5.7%	41.67%	42.1%	10.48%
Furniture manufacture, energy supply, water and waste treatment	11.9%	25.69%	43.1%	19.27%
Construction and ground transport	3.6%	24.34%	52.6%	19.41%
Maritime transport, air transport and postal services, accommodation services	6.5%	22.58%	45.2%	25.81%
Telecommunications, financial services, insurance	4.8%	11.11%	38.9%	45.24%
Research and development, veterinary, rental and employment-related activities	1.4%	16.78%	38.5%	43.36%
Security and research, education and health activities	13.5%	24.32%	32.4%	29.73%
Agriculture, livestock, forestry, fisheries and extractive industries	0.0%	0.00%	60.0%	40.00%
Overall total	5.11%	28.55%	46.05%	20.29%

Source: Own elaboration with CNAE data.

Table 3. Distribution of innovative companies according to whether they receive R&D subsidies or not by sector.

Sector	% No R&D Subsidies	% Receive R&D Subsidies
Agriculture, livestock, forestry, fisheries and extractive industries	21.4%	78.6%
Manufacturing industry	6.7%	93.3%
Chemicals, pharmaceuticals and metallurgy	8.6%	91.4%
Furniture manufacture, energy supply, water and waste treatment	4.6%	95.4%
Construction and ground transport	21.1%	78.9%
Maritime transport, air transport and postal services, accommodation services	38.7%	61.3%
Telecommunications, financial services, insurance	5.6%	94.4%
Research and development, veterinary, rental and employment-related activities	1.4%	98.6%
Security and research, education and health activities	5.4%	94.6%
Agriculture, livestock, forestry, fisheries and extractive industries	0.0%	100.0%
Overall total	10.29%	78.6%

Source: Own elaboration with CNAE data.

In the context of foreign trade, Table 4 shows that 37% of the companies do not carry out any type of foreign trade, and the "Chemicals, pharmaceuticals and metallurgy" sector is the one with the highest level of foreign trade.

Table 4. International trading activity by sector.

Sector	% Export Activity	% Import Activity	% Export/Import	% No Foreign Trade
Agriculture, livestock, forestry, fisheries and extractive industries	21.4%	7.1%	28.6%	42.9%
Manufacturing industry	15.8%	7.9%	55.8%	20.4%
Chemicals, pharmaceuticals and metallurgy	21.9%	6.0%	56.2%	16.0%
Furniture manufacture, energy supply, water and waste treatment	9.2%	8.3%	35.8%	46.8%
Construction and ground transport	11.5%	9.5%	43.8%	35.2%
Maritime transport, air transport and postal services, accommodation services	16.1%	3.2%	16.1%	64.5%
Telecommunications, financial services, insurance	13.5%	4.8%	7.9%	73.8%
Research and development, veterinary, rental and employment-related activities	14.0%	6.3%	11.2%	68.5%
Security and research, education and health activities	5.4%	0.0%	0.0%	94.6%
Agriculture, livestock, forestry, fisheries and extractive industries	20.0%	0.0%	20.0%	60.0%
Overall total	15.61%	6.93%	40.45%	37.02%

Source: Own elaboration with CNAE data.

2.2. Methods

Based on this information, the aim of this work is to identify those innovative companies in the Valencia Region that, because they share a series of characteristics, could be seen as belonging to a particular category of company. This would enable these groups to be categorised and so facilitate decision-making in the provision of incentives for innovation-related activities.

The methodology that we use to group the companies that carry out R&D activities in the Valencian Region is the k-means algorithm. This is one of the most widely used unsupervised machine learning algorithms and can be implemented using different software (KNIME, MATLAB Spectral, Python, R, etc.). This type of analysis has already been used in the field of industry, e.g., Gkotsis et al. (2018) and Rastogui et al. (2020). The k-means[2] cluster analysis technique[3] is a multivariate technique that groups the cases of a data set (variables) according to the similarities between them. This algorithm uses quantitative variables to calculate the Euclidean distance and detect patterns of behaviour. This analysis allows us to detect the optimal number of groups and their composition solely on the basis of similarities across the data (assuming no specific distribution for the quantitative variables). We use the library developed in RStudio to implement this algorithm[4].

The following variables are used to group the companies reviewed:

- Years of activity: Years since the company was founded until 2019;
- Number of employees: Total number of employees according to SABI data in 2019;
- Intangible fixed assets: Net volume of "Intangible assets", i.e., as shown on balance sheets, net of accumulated depreciation. Sum of Research and Development, Patents, Administrative Concessions, etc.;
- Tangible fixed assets: Net volume of "Property, plant and equipment", i.e., as shown in the balance sheets, net of accumulated depreciation. Sum of Land, Buildings, Technical Installations, Vehicles, etc.;
- Value added: The result of correcting the profit or loss for the year by adding certain items that were subtracted as expenses for the year. Therefore, VA is calculated by adding to the profit and loss for the year the amount of corporate income tax, staff costs, depreciation and amortisation payments, and financial expenses for the year;
- EBITDA: Earnings Before Interest, Taxes, Depreciation, and Amortisation;
- Bank debt: Debts contracted with financial institutions, which generate both long- and short-term financial outgoings;
- SE: Shareholder Equity (or Core Funding): Comprises the sum of Share Capital, Reserves, and Profit and Loss for the financial year;
- Cash-Flow: sum of Profit for the year (Profit after tax) and the depreciation and amortisation expenses for the year.

On the other hand, another of the aspects that we are interested in analysing is whether innovative companies are physically grouped together and how to locate these groupings in the studied territory. To carry out this analysis, we use a geographical location methodology, in this case the SaTScan software tool[5] (https://www.satscan.org/)[6] (accessed on 14 June 2021). This is a geographic information system that uses geolocation coordinates to identify statistically significant business clusters. This software allows us to detect the existence of spatial agglomerations that are statistically significant by applying the Kulldorff (1997) scan. In our study, we analyse the existence of circular zones containing a minimum of 15% of technology firms—calculated over the total business population—in order to take into account economies of proximity and scale.

This methodology has previously been used by López and Páez (2017) for Canadian high-tech companies and García-Alcober et al. (2021) for technology companies in the Valencia Region.

So far, studies on clustering have focused only on spatial location. However, with this paper we go a step further to identify whether there is also the clustering of firms with similar characteristics in nearby locations. Both clusters, physical location and according to

characteristics, are fundamental when it comes to understanding and being able to boost the innovative effort of companies in this Spanish region.

3. Results

First, we proceeded to detect whether there are any shared characteristics in the innovative firms. Using a k-means technique, we identified whether the innovative firms have common characteristics in terms of age, size (measured by the number of employees), corporate indebtedness (calculated as the ratio of bank debt to equity, bank debt to cash-flow, and cost of debt to EBITDA) in order to capture the portion of profits that goes to cover the financial burden, and cost of debt to EBITDA in order to capture the share of profits that goes to cover the financial burden of debt, productivity (measured by the value added per employee and EBITDA per employee), installed capacity—property, plant, and equipment (proxied by the volume of tangible fixed assets per employee), and R&D expenditure (proxied by the volume of intangible fixed assets per employee).

Each of the types of company grouped together by these characteristics is termed a cluster.

In Table 5, we can see that there are 11 clusters. However, Clusters F, G, H, I, J, and K consist of only one or two companies, which have such particular characteristics that they cannot be aligned with other companies. Therefore, we consider only Clusters A, B, C, D, and E, which have more than 25 companies each, to be relevant. According to these results, we can distinguish five different clusters of innovative companies, whose characteristics are described below.

Table 5. K-means results based on SABI data for innovative companies in 2019.

Cluster ID	No. Companies	Years Active	No. Employees	Intangible Fixed Assets per Employee	Property, Plant, and Equipment per Employee	Value Added per Employee	EBITDA per Employee	Bank Debt/SE	Financial Expenses/ EBITDA	Bank Debt/ Cash-Flow
A	761	−0.65	−0.24	0.00	−0.19	−0.14	−0.23	−0.01	−0.04	−0.11
B	79	−0.11	−0.09	0.35	0.96	1.21	2.78	−0.10	−0.05	−0.21
C	522	0.93	0.07	−0.13	0.07	−0.03	−0.06	−0.05	−0.04	−0.07
D	28	−0.14	−0.06	0.04	−0.15	−0.23	−0.41	0.53	0.14	4.95
E	30	0.63	5.23	−0.12	0.19	0.00	0.00	−0.08	−0.13	−0.15
F	2	−0.01	0.27	−0.18	0.32	0.21	−0.26	−0.12	0.56	0.39
G	2	−0.81	−0.50	21.09	1.14	1.04	2.47	−0.17	0.11	−0.21
H	1	−0.78	−0.21	−0.03	0.17	33.58	−4.23	−0.20	−0.13	−0.28
I	1	−0.56	−0.50	−0.18	28.12	−0.05	0.48	−0.13	0.39	0.02
J	2	−0.42	−0.42	0.21	0.16	−0.20	−0.55	−0.02	23.43	0.10
K	1	0.48	0.63	−0.18	0.20	−0.19	−0.53	33.25	4.85	2.78

Source: Own elaboration with k-means results.

Cluster A: Comprising 761 companies, it is the largest. It is characterised by younger and smaller firms, both in terms of number of employees and net investment in property, plant, and equipment, with both variables being below average. This indicates that start-ups are usually small;

Cluster B: Comprising 79 companies, it is characterised by high productivity, based on both Value Added per employee and EBITDA per employee;

Cluster C: The main characteristic of companies of this type, composed of 522 companies, is their age; that is, they are the most experienced companies in the sample;

Cluster D: This category groups together companies that are characterised by a higher level of indebtedness, both in terms of bank debt itself and the cost of this debt and its proportion in relation to the company's equity;

Cluster E: Characterised by the fact that they are larger companies in terms of the number of employees.

We then relate the different types of clusters to the variables that define the composition of the sample: size, openness to the outside world, and being in receipt or not of R&D subsidies. These relationships are analysed in the tables below.

As shown in Table 6, more than half of the firms in Cluster A are small or micro-businesses (80%), which is consistent with one of the main characteristics of this cluster, being the smallest firms in the sample.

Table 6. Characterisation of clusters by firm size.

	K-MEANS CLUSTER				
Size	**A**	**B**	**C**	**D**	**E**
Large	1.7%	6.3%	4.6%	3.6%	100.0%
Medium	17.9%	24.1%	46.6%	28.6%	0.0%
Micro-business	31.3%	27.8%	3.6%	21.4%	0.0%
Small	49.1%	41.8%	45.2%	46.4%	0.0%
Overall total	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Own elaboration.

Cluster B, which comprises the most productive companies, although small companies and micro-enterprises again predominate, accounting for almost 70% of the total number of companies in this cluster, is larger in size than Cluster A.

In Cluster C, which includes the oldest enterprises, the number of micro-enterprises is not very significant (3.6%), with small and medium-sized enterprises predominating.

In Cluster D, whose main characteristic is a high level of debt, the presence of large companies is very low (3.6%), with most being small businesses (46.4%).

Finally, Cluster E consists solely of large firms, which is consistent with its main characteristic.

The results shown in Table 7 allow us to deduce that companies are not receiving R&D subsidies based on their age, since more than 90% of the youngest (Cluster A) as well as more than 90% of the oldest (Cluster C) receive subsidies. However, there is a relationship between debt and receiving or not receiving subsidies. Half of the companies characterised by a high level of debt do not receive subsidies (Cluster D). What is not clear is whether this lack of subsidies is a cause or an effect of their financial problems.

Table 7. Cluster relationship according to receipt of R&D support.

	K-MEANS CLUSTER				
R&D Subsidy	**A**	**B**	**C**	**D**	**E**
0	8.5%	13.9%	9.8%	50.0%	16.7%
1	91.5%	86.1%	90.2%	50.0%	83.3%
Overall total	100%	100%	100%	100%	100%

Source: Own elaboration.

Table 8 indicates whether there is any relationship between the different clusters and foreign trade.

As can be seen, half of the Cluster A companies (the youngest and smallest) have no foreign activity, as is also the case with Cluster D companies, which are the most indebted. Cluster B companies, which, as we have seen, are the most productive, also tend to have more foreign activity (two thirds of these companies). Companies in Clusters C (the oldest) and E (the largest) engage in more international trade. In short, company size and experience also imply greater openness to foreign trade.

Table 8. Relationship between clusters and foreign trade activity.

	K-MEANS CLUSTER				
Exp/Imp	**A**	**B**	**C**	**D**	**E**
No foreign trade activity	50.9%	31.6%	18.0%	50.0%	13.3%
Does export	11.6%	16.5%	20.5%	21.4%	23.3%
Does import	7.5%	8.9%	5.4%	10.7%	13.3%
Exp/Imp	30.1%	43.0%	56.1%	17.9%	50.0%
Overall total	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Own elaboration.

Once the innovative companies in the Valencia Region have been analysed according to the criteria obtained via k-means, we proceed to study their link to the territory using a georeferencing technique, SaTScan.

The SaTScan analysis indicates that there are six significant business clusters, as set out in Table 9.

Table 9. Statistically significant business groupings[7].

	1	**2**	**3**	**4**	**5**	**6**
Radius	26.71 km	15.88 km	11.34 km	12.22 km	6.36 km	8.04 km
Population	8697	11,310	5418	1746	3025	4100
Number of cases	220	232	113	46	55	63
Expected cases	66.14	86.02	41.21	13.28	23.01	31.18
Observed/expected	3.33	2.7	2.74	3.46	2.39	2.02
Relative risk	3.75	3.03	2.89	3.55	2.45	2.07
Percent cases in area	2.5	2.1	2.1	2.6	1.8	1.5
Log likelihood ratio	121,013,856	93.456707	44,585,636	25,126,552	16.482704	12.981459
p-value	<0.00000000000000001	<0.00000000000000001	1.1×10^{-16}	7.4×10^{-9}	0.000026	0.0007

Source: Own elaboration with k-means results.

Once these data have been collected, we located these clusters on a map of the Valencia Region. As shown, there are two clusters (numbers 1 and 5) in the province of Alicante (the localities of El Comtat and Baix Vinalopó), one cluster (number 4) in the province of Castellón (the locality of L'Alcora), and three clusters in the province of Valencia (numbers 2, 3, and 6) (the localities of Buñol, La Ribera and Sagunto) (Figure 1).

The productive activities of each SaTScan grouping can be seen in Table 10.

The physical groupings of innovative companies broadly coincide with the location of the clusters and/or industrial districts found in the previous literature on the Valencia Region. Thus, three geographically concentrated traditional regional industries stand out in the Valencia Region: the textile sector in the Alcoi/Ontinyent area (inland Alicante), footwear in the Vinalopó area (a little further south than the previous area), and ceramics in the province of Castellón. Our Cluster 1 is located in the interior of the province of Alicante, an area where the traditional textile industry was predominant, as indicated by Miret-Pastor et al. (2011), Pla-Barber and Puig (2009), and Molina-Morales and Expósito-Langa (2013). Our analysis in Table 10 shows that one of the most frequent activities found in this grouping continues to be the textile sector. We also find plastics and rubber, machinery, and wholesale trade, which can be considered complementary to the textile sector. In the interior of the province of Valencia we find Cluster 2. This cluster contains the greatest diversity of economic activity, with the food, chemical, plastics, rubber, machinery, and wholesale trade industries predominating. As Membrado-Tena et al. (2019) point out, the food industry in the Valencia Region has shown great resilience over the past decade thanks to its innovation and international outlook.

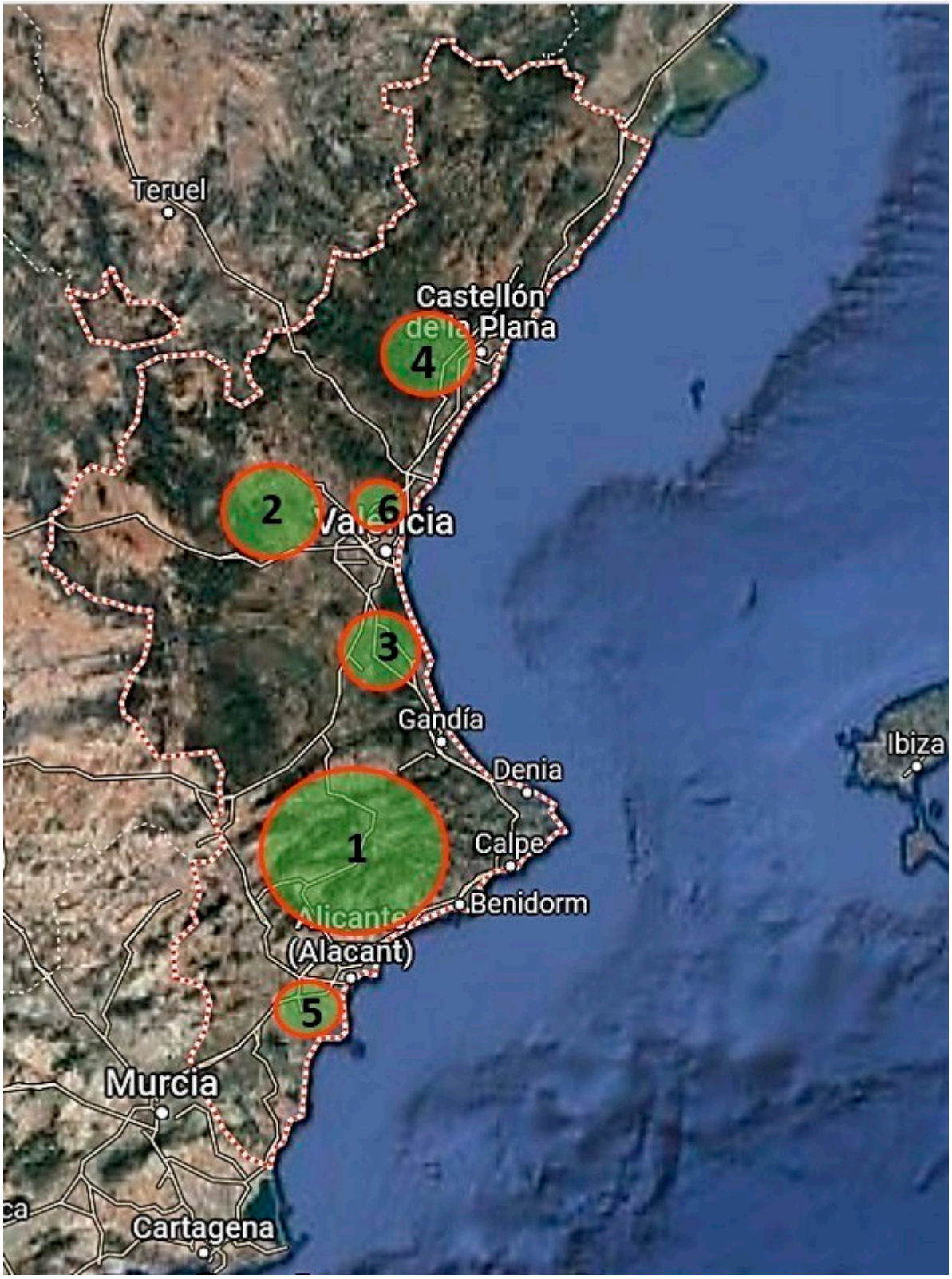

Figure 1. Map of business clusters in the Valencian Region. Source: Own elaboration.

Cluster 3, to the south and inland of the city of Valencia, in the locality of La Ribera, has as its main activities chemistry, auxiliary furniture, and wholesale trade.

The ceramics cluster is located in the province of Castellón. Specifically, the locality of L'Alcora—our Cluster 4—is where most of the companies in this sector are located, as

indicated by the studies conducted by Molina-Morales et al. (2017), Hervás-Oliver et al. (2018), and Albors-Garrigos and Hervás-Oliver (2019).

Table 10. Distribution of productive activities according to SaTScan groupings.

SaTScan Grouping	Most Frequent CNAE	Most Frequent Activity
1	13–22–16–46	Textiles, plastics and rubber, machinery and wholesale trade
2	12–20–22–25–46	Food industry, chemicals, plastics and rubber, machinery and wholesale trade
3	13–16–46	Chemicals, furniture auxiliaries and wholesale trade
4	23	Glass and ceramics
5	46	Wholesale trade
6	20-46	Chemicals and wholesale trade

Source: Own elaboration.

Our Cluster 5 is in Baix Vinalopó, in the southern part of the province of Alicante, where wholesale trade is identified as the main activity. This area is where the footwear sector was traditionally located, as shown by the studies by Ruiz-Ortega et al. (2016) and Marco-Lajara et al. (2021). In this grouping, this sector retains a clear influence, as many of the companies registered under the CNAE as wholesalers are former footwear sector companies.

Finally, to the north of the city of Valencia, comes Cluster 6, where the chemical sector and wholesale trade predominate.

In short, we have found six different physical clusters of innovative companies, two of which clearly coincide with the traditional sectors of textiles and ceramics. However, we also found subsidiary activities in these clusters and in the rest. As Becattini (1990) pointed out, an industrial district is a space in which a local community specialises in a certain productive activity and, alongside this main industry, subsidiary companies emerge. This is reflected in how the chemical sector encompasses a wide variety of products that include supplies for the food industry, phytosanitary products, and also support for the ceramics or textile sectors. Something similar occurs with the plastics and rubber sectors. With regard to wholesale trade, as mentioned above, many traditional industrial companies, mainly due to globalisation, have changed their main activity from production to wholesale trading.

We now proceed to analyse the physical grouping of the enterprises according to their characteristics, that is, we will compare the results of the georeferencing of the enterprises with the characteristics "size", "subsidised or not", and "foreign activity (import and/or export)", as we have done with the results obtained via k-means. These results are shown in Tables 11–13.

Clusters 1 and 5—both in the province of Alicante in the Valencia Region—are characterised by being comprised by around 70% of small enterprises (both micro and small), and at the opposite extreme, Cluster 4—in the province of Castellón in the Valencia Region—is comprised by more than 50% of enterprises of above average size (medium and large enterprises). Clusters 2, 3, and 6—in the province of Valencia in the Valencia Region—are intermediate, characterised by consisting of between 42% and 46% small enterprises followed by medium-sized enterprises, which represent slightly more than a third of the business make-up.

Although receiving some kind of R&D support was a condition for choosing a sample for this study, Table 12 corresponds only to the receipt of public R&D subsidies. It can be seen that, although the distribution is similar between groups, in group 1 (El Comtat), more than 94% of the companies receive some type of research subsidy, and in group 5 (Baix Vinalopó), 14.5% of the companies do not receive any type of aid.

As can be seen in Table 13, the companies that do not belong to any grouping correspond to those that do not engage in significant international trade activity (neither export nor import). Group 4 stands out, with a clear export profile, coinciding with the type of companies it comprises, companies in the ceramics sector with a clear orientation

toward international markets. In the other groupings (1, 2, 3, 5, 6), around two thirds of the companies have some type of activity related to foreign trade.

Table 11. Distribution of companies in each grouping according to size.

	STATSCAN GROUPING						
Size	**1**	**2**	**3**	**4**	**5**	**6**	**Rest**
Large	1.8%	6.9%	4.4%	6.5%	3.6%	3.2%	5.86%
Medium	29.1%	34.5%	39.8%	47.8%	23.6%	33.3%	23.29%
Microbusiness	18.6%	15.9%	10.6%	6.5%	12.7%	17.5%	25.57%
Small	50.5%	42.7%	45.1%	39.1%	60.0%	46.0%	45.29%
Overall total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Own elaboration.

Table 12. Distribution of companies in each grouping according to whether or not they receive R&D subsidies.

	STATSCAN GROUPING						
R&D Subsidy	**1**	**2**	**3**	**4**	**5**	**6**	**Rest**
No subsidy	5.9%	11.2%	12.4%	8.7%	14.5%	9.5%	10.86%
Receives subsidy	94.1%	88.8%	87.6%	91.3%	85.5%	90.5%	89.14%
Overall total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Own elaboration.

Table 13. Distribution of companies in each grouping according to whether they are active internationally or not.

	STATSCAN GROUPING						
Exp/Imp	**1**	**2**	**3**	**4**	**5**	**6**	**Rest**
No international activity	30.0%	28.0%	28.3%	8.7%	30.9%	31.7%	46.43%
Exports	11.8%	17.7%	12.4%	58.7%	7.3%	14.3%	14.57%
Imports	10.0%	6.5%	8.8%	0.0%	7.3%	6.3%	6.29%
Exp/Imp	48.2%	47.8%	50.4%	32.6%	54.5%	47.6%	32.71%
Overall total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Own elaboration.

At this point we have, on the one hand, defined clusters, which allows us to classify companies according to their dominant characteristic—age, size, productivity, or level of indebtedness—and, on the other hand, we have grouped them geographically according to their physical proximity. We are, therefore, in a position to detect whether the different types of firms belong to a particular territorial grouping. Table 14 shows this relationship.

Table 14. Relationship between the different clusters and the geographical groupings.

	K-MEANS CLUSTER					
SaTScan Grouping	**A**	**B**	**C**	**D**	**E**	**Rest**
1	14.2%	8.9%	19.5%	10.7%	0.0%	0.0%
2	13.7%	24.1%	18.8%	3.6%	26.7%	22.2%
3	8.1%	7.6%	8.2%	0.0%	6.7%	0.0%
4	1.6%	5.1%	5.4%	0.0%	6.7%	0.0%
5	4.7%	5.1%	2.5%	3.6%	3.3%	0.0%
6	3.2%	11.4%	5.2%	0.0%	3.3%	22.2%
No grouping	54.5%	38.0%	40.4%	82.1%	53.3%	55.6%
Overall total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Own elaboration.

As shown in Table 14, more than half (54.6%) of the young and small companies (Cluster A) do not tend towards a geographical grouping, as is the case with the most-indebted companies (Cluster D), where 82.1% of the companies are geographically dispersed. In terms of this characteristic, it is worth noting that those that are grouped together are congregated in Cluster 1, in the El Comtat locality, at 10.7%.

However, the most productive firms (Cluster B) tend to be physically clustered. In fact, only 38% are not clustered. It should be noted, in particular, that the companies that are characterised by being the most productive are mainly located in Cluster 2, corresponding to the Buñol locality. The largest companies are also congregated in this area (Cluster E, with 26.7%).

Analysing each cluster in depth, for Cluster A, Figure 2 shows that, although these companies do not tend to concentrate together, those that do so are mainly in the interior of Alicante (El Comtat area), at 14.2%, and the interior of Valencia (Buñol), at 13.7%.

The companies in Cluster B, characterised by their productivity, are mainly concentrated in the locality of Buñol, in the interior of the province of Valencia, at 24.1%, and in Sagunto to the north of the city of Valencia, at 11.4%.

Regarding Cluster C (the most mature companies), Figure 2C shows that these companies are mostly located in Clusters 1 and 2 (in the localities of El Comtat and Buñol), both areas having a longstanding industrial tradition (19.5% and 18.8%, respectively).

The companies characterised by high debt (Cluster D) are mostly not in a geographical cluster (82.1%), although 10.7% are located in the inland Alicante cluster and 3.6% in inland Valencia.

Finally, more than half (53.3%) of the largest companies by number of employees (Cluster E) do not cluster, although 26.7% of those that do are located in the interior of the province of Valencia.

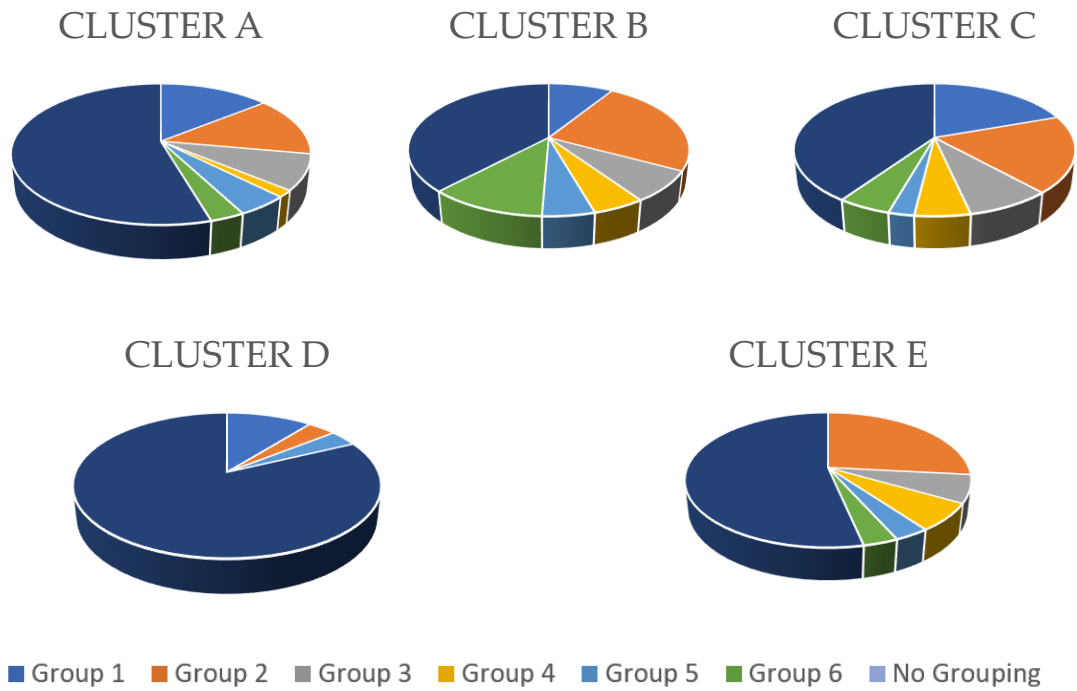

Figure 2. Distribution of companies by Clusters according to geographic groupings. Source: Own elaboration.

4. Discussion and Conclusions

In a highly competitive world, business innovation is essential for business survival. For this reason, many economic policies aim to promote such innovation, but in order to design and implement this correctly, it is necessary to know what kind of companies

carry out such innovation. In this study, so as to have better information in this regard, we have conducted a classification of innovative companies according to their characteristics. Subsequently, we have also looked for physical groupings of these companies.

First, we found five different types of companies, which we have classified according to their main characteristics as: young companies with an average of 16.7 years of age (this is the largest group), senior companies with an average of 40 years of experience, productive companies, indebted companies, and, finally, large companies.

Subsequently, we analysed them in terms of size, whether they receive subsidies, and whether they are active internationally. The main results with respect to size indicated that the senior firms are the largest and the younger firms are the smallest, so there is a relationship between seniority and size. However, we found no relationship between productivity and size. Regarding subsidies, the companies that receive the most subsidies are both young and senior companies, in contrast to indebted companies, which receive the least subsidies. With regard to foreign trade, it is the productive and large companies that are the most active in international trade. And young and indebted companies are the least active in international trade.

Second, we studied the physical groupings using the SaTScan georeferencing programme, obtaining six business-type groupings: two in Alicante province, one in Castellón province, and three in Valencia province. The province of Alicante is shown to have a high concentration of the smallest companies, with 69.1% and 72.7% in both groupings being small or microbusinesses. At the opposite end of the scale comes Castellón, where the larger companies congregate, with 54.3% being medium or large companies. This grouping in inland Castellón corresponds to the area where the ceramic sector has a strong presence, as confirmed by the analysis of the main activity of the companies, which also explains the strong export activity of the companies in this sample.

Of the six groupings that we obtained, there are two, one in Alicante province and one in Castellón province, that coincide with areas where the textile and ceramics sectors have traditionally been strong, and that is precisely the main activity characterising the companies currently in these locations. It is worth highlighting that it is precisely these two groupings that receive the most subsidies, indicating the ongoing financial support for these traditional sectors.

However, our analysis of the locations of the companies indicates that there is a tendency towards geographic aggregation on the part of innovative companies, with more than half of these being located in one or another of the geographical groupings identified. Additionally, it is the most productive businesses that are particularly prone to geographic clustering. It would seem that a tendency for businesses to cluster serves to increase the innovative drive of businesses as well as their productivity. It should also be noted that the companies with the highest levels of debt are also more geographically dispersed. Both these traits point to the benefits of business clustering. Glaeser et al. (1992) define the Marshall–Arrow–Romer (MAR) model whereby the spatial concentration of a particular industry generates external links between companies and encourages innovation. In this instance, in addition, the most productive companies are grouped in the interior of the province of Valencia. As mentioned previously, this area has a wide variety of industries, suggesting the existence of positive inter-industrial externalities, as described by Jacobs (1969).

This study is intended to help policy makers to design regional R&D and innovations systems. For instance, our results can be interesting for the RIS3 (Research and Innovation Smart Specialisation Strategy) Agenda. After the financial crisis, the European Commission proposed five EU targets for 2020, and they are described in the Europe agenda 2020. One of the targets is research and innovation. In the context of this project, the Spanish government promoted the development of the various regional RIS3s. Specifically, the RIS3 Agenda in the Comunitat Valenciana (RIS3-CV) aims to constitute a regional strategic framework for R&D policies that promotes the necessary structural changes that will promote research and innovation in order to contribute to economic and social progress.

Our work analyzes the common characteristics of the companies that make an innovative effort in the Comunitat Valenciana.

One of the main conclusions reached in this study shows that the productivity of companies and their location in areas of high business concentration are positively related. This behavior is especially observed in the interior of Valencia, where the Paterna Technology Park is located. We understand that this evidence, and the actions that could be derived from it, could be of interest for the RIS3 Agenda.

Moreover, this study of the types of business that undertake innovation in the Valencian Region, in terms of their characteristics and geographic location, provides a deeper understanding that can, in turn, be applied to implement appropriately targeted economic policies. Another result to take into account is, for example, that business size is shown not to be an obstacle to engaging in innovation, contrary to what might be expected. Physical clustering, on the other hand, does indeed offer intra-industrial and inter-industrial advantages.

Some further topics of research are unexplored. For example, one of them is to see how industrial parks/areas influence business development, to study the existence of localization economies and their effect on innovative effort.

One of the main limitations of this work is that, on the one hand, given the nature of the data, it is not possible to distinguish the type of innovation (product, process, etc.) resulting from this innovative effort. On the other hand, this analysis only allows us to establish a picture of the innovative effort and not to identify the cause–effect relationship.

Author Contributions: Conceptualization, M.P.G.-A., A.I.M.-A. and M.T.P.-G.; methodology, A.I.M.-A. and M.T.P.-G.; software, M.T.P.-G.; validation, M.P.G.-A., A.I.M.-A. and M.T.P.-G.; resources, A.I.M.-A.; data curation, A.I.M.-A.; writing—original draft preparation, M.P.G.-A.; writing—review and editing, M.P.G.-A., A.I.M.-A. and M.T.P.-G. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was founded by the ESI International Chair@CEU UCH.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data are available in SABI (Iberian Balance sheet Analysis System) Database.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

1 SABI (Iberian Balance sheet Analysis System) Database is developed by INFORMA D&B in colaboration with Bureau Van Dijk. This database is widely used in the academic world. It contains annual accounts of over 2.7 million Spanish companies and more htan 800,000 Portuguese ones.

2 K-means is a clustering method which starts from a set of observations divided into K groups, where each observation belongs to a group whose mean value is closest. The term k-means was first used by McQueen (1967).

3 The versatility of hierarchical cluster analysis lies in the possibility of using different types of measures to estimate the distance between cases or variables, the possibility of transforming the original metric of the variables, and the possibility of selecting from a wide variety of agglomeration methods. But there is no combination of these possibilities that optimises the solution obtained. In general, it is more practical to evaluate different solutions to choose the one that is most consistent.

4 Starting from the individual sample elements considered separately, it creates groups until a single group or cluster is formed, incorporating all the elements of the sample.

5 The k-means method enables the processing of an unlimited number of cases, but only one agglomeration method can be used and it requires the number of clusters to be set out in advance.

6 It has three characteristics of interest (López and Páez 2017): first, it allows micro-information to be processed, considering the space to be continuous since it uses each company's geographic co-ordinates. Second, it enables hypotheses to be compared, thereby enabling an analysis of statistical significance. Lastly, this software is able to identify the location of each companies in the possible agglomerations (each time it does so is called an "event").

7 Spatial analysis can be performed for different statistical distributions. In our case, we have assumed that the distribution of variables follows a Bernoulli distribution to carry out the analysis. The underlying principle of this statistical spatial measurement is as follows. Basically, a test is designed to identify areas where the intensity of a particular event (in this case, the emergence of technology firms) within the space is higher or lower than expected using a specific null hypothesis. In order to test the

hypothesis, we define a predetermined type. The statistical software progressively changes the size of this zone, and each time it changes, the intensity of the event is measured inside and outside the zone, thus identifying areas where the intensity is different. The concentration of technology companies within the zone is measured against that outside the zone, thus identifying areas where the concentration is different. The process was repeated to cover the entire area under study (the Valencia Region). Finally, the values observed for the event (the identification of technology companies) in each area were compared with the values predicted by the null hypothesis (López and Páez 2017) explain this process in detail.

References

Albors-Garrigos, José, and José Luis Hervás-Oliver. 2019. Disruptive innovation in traditional clusters: The case of the Kerajet ceramic tile cluster in Spain. *Applied Sciences* 9: 5513. [CrossRef]

Audretsch, David B., and Zoltan J. Acs. 1991. Innovation and size at the firm level. *Southern Economic Journal* 57: 739–44. [CrossRef]

Baumann, Julian, and Alexander S. Kritikos. 2016. The link between R&D, innovation and productivity: Are micro-firms different? *Research Policy* 45: 1263–74. [CrossRef]

Becattini, Giacomo. 1990. The Marshallian district as a socio-economic notion. In *Industrial Districts and Intra-Firm Collaboration in Italy*. Edited by Frank Pyke, Giacomo Becattini and Werner Sengenberger. Geneva: International Institute for Labor Studies.

Bell, Geoffrey G. 2005. Clusters, networks, and firm innovativeness. *Strategic Management Journal* 26: 287–95. [CrossRef]

Belso-Martínez, José Antonio, Francisco Más-Verdú, and Lorenzo Chinchilla-Mira. 2020. How do interorganizational networks and firm group structures matter for innovation in clusters: Different networks, different results. *Journal of Small Business Management* 58: 73–105. [CrossRef]

Calvo, José L. 2000. Una caracterización de la innovación tecnológica en los sectores manufactureros españoles: Algunos datos. *Economía Industrial* 331: 139–50.

Camisón-Zornoza, César, Rafael Lapiedra-Alcamí, Mercedes Segarra-Ciprés, and Montserrat Boronat-Navarro. 2004. A Meta-analysis of Innovation and Organizational Size. *Organization Studies* 25: 331–61. [CrossRef]

Carlino, Gerald, and William R. Kerr. 2015. Agglomeration and innovation. *Handbook of Regional and Urban Economics* 5: 349–404. [CrossRef]

Galleto, Vittorino, and Rafael Boix Doménech. 2006. Sistemas industriales de trabajo y distritos industriales mashallianos en España. *Economía Industrial* 359: 165–84.

Galleto, Vittorino, and Rafael Boix Doménech. 2014. Distritos industriales, innovación tecnológica y efecto I-distrito:¿ Una cuestión de volumen o de valor? *Investigaciones Regionales-Journal of Regional Research* 30: 27–51.

García-Alcober, María Pilar, Ana Isabel Mateos-Ansótegui, and María Teresa Pastor-Gosálbez. 2021. A geospatial analysis of concentrations of technological sectors in the Valencia Community region. *Regional Science Policy & Practice* 13: 1423–41. [CrossRef]

Gkotsis, Petros, Emanuelle Pugliese, and Antonio Venazi. 2018. A Technology-Based Classification of Firms: Can we learn something looking beyond industry classifications? *Entropy* 20: 887. [CrossRef] [PubMed]

Glaeser, Edward L., Hedi D. Kallal, José A. Scheinkman, and Andrei Shleifer. 1992. Growth in cities. *Journal of Political Economy* 100: 1126–52. [CrossRef]

Hervás-Oliver, José Luis, Francisco Sempere-Ripoll, Sofía Estellés-Miguel, and Ronald Rojas-Alvarado. 2021. Radical vs. incremental innovation in Marshallian Industrial Districts in the Valencian Region: What prevails? In *Rethinking Clusters*. London: Routledge, pp. 46–61.

Hervás-Oliver, José Luis, José Albors-Garrigos, Sofía Estellés-Miguel, and Carles Boronat-Moll. 2018. Radical innovation in Marshallian industrial districts. *Regional Studies* 52: 1388–97. [CrossRef]

Jacobs, Jane. 1969. *The Economies of Cities*. New York: Vintage.

Kulldorff, Martin. 1997. A spatial scan statistic. *Communications in Statistics-Theory and Methods* 26: 148196. [CrossRef]

Likas, Aristidis, Nikos Vlassis, and Jacob J. Verbeek. 2003. The global k-means clustering algorithm. *Pattern Recognition* 36: 451–61. [CrossRef]

López, Fernando A., and Antonio Páez. 2017. Spatial clustering of high-tech manufacturing and knowledge-intensive service firms in the Greater Toronto Area. *The Canadian Geographer* 61: 240–52. [CrossRef]

Marco-Lajara, Bartolomé, Patrocinio C. Zaragoza Sáez, Javier Martínez Falcó, and Pedro Seva Larrosa. 2021. Los distritos industriales zapateros de las comarcas españolas del Vinalopó: Un análisis detallado. *Revista Espacios* 42: 185–202. [CrossRef]

McQueen, J. B. 1967. Some methods of classification and analysis of multivariate observations. Paper presented at the 5th Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, CA, USA, January 1; pp. 281–97.

Membrado-Tena, Joan Carles, Jorge Hermosilla-Pla, and Ghaleb Fansa. 2019. Declive y resiliencia industrial en la periferia mediterránea europea. Análisis territorial y sectorial en la Comunitat Valenciana durante la década de 2010. *Investigaciones Geográficas* 72: 209–233. [CrossRef]

Miret-Pastor, Lluis, María Del Val Segarra-Oña, and Ángel Peiró-Signes. 2011. Identificación de sectores de servicios y de alta tecnología en la Comunidad Valenciana: ¿Un nuevo cluster mapping? *Revista de Estudios Regionales* 90: 71–96.

Molina-Morales, Francesc Xavier, and Manuel Expósito-Langa. 2013. El efecto saturación del esfuerzo innovador. Una aplicación al distrito industrial textil valenciano. *Revista Europea de Dirección y Economía de la Empresa* 22: 107–14. [CrossRef]

Molina-Morales, Francesc Xavier, Luis Martínez-Cháfer, and David Valiente-Bordanova. 2017. Disruptive technological innovations as new opportunities for mature industrial clusters. The case of digital printing innovation in the Spanish ceramic tile cluster. *Investigaciones Regionales-Journal of Regional Research* 39: 39–57.

Mowery, David C., Joanne E. Oxley, and Brian S. Silverman. 1996. Strategic alliances and interfirm knowledge transfer. *Strategic Management Journal* 17: 77–91. [CrossRef]

Pérez, José Miguel Giner, María Jesús Santa María Beneyto, and Antonio Fuster Olivares. 2006. Los sistemas productivos locales en la Comunidad Valenciana: Análiis para su identificación y localización territorial. In *La economía regional ante la globalización*. Alicante: Publicaciones de la Universidad de Alicante, pp. 109–26.

Pla-Barber, José, and Francisco Puig. 2009. Is the influence of the industrial district on international activities being eroded by globalization?: Evidence from a traditional manufacturing industry. *International Business Review* 18: 435–45.

Rastogui, Rachit, Ritika Jaiswal, and Raj K. Jaiswal. 2020. Renewable energy firm's performance analysis using machine learning approach. *Procedia Computer Science* 175: 500–7. [CrossRef]

Ruiz-Ortega, María José, Gloria Parra-Requena, and Pedro Manuel García-Villaverde. 2016. Do Territorial Agglomerations Still Provide Competitive Advantages? A Study of Social Capital, Innovation, and Knowledge. *International Regional Science Review* 39: 259–90. [CrossRef]

Symeonidis, George. 1996. Innovation, Firm Size and Market Structure: Schumpeterian Hypotheses and Some New Themes. In *OECD Economics Department Working Papers. No. 161*. Paris: OECD Publishing. [CrossRef]