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Patterns of spatial clustering of Spanish Start-ups and the formation of entrepreneurship in the manufacturing sector

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Abstract

Entrepreneurship is spatially unequally distributed in Spain and manufacturing entry rates have not been high in the last three years. Using data from the Spanish National Institute of Statistics (INE) and SABI databases, this study explores the factors that influence manufacturing entrepreneurship clusters in the Spanish provinces by highlighting the importance of industrial localization and urbanization factors. At the industry level, our results support the existence of a significant Marshallian effect in the manufacturing sector, as more manufacturing entrepreneurship is likely to occur where there is a concentration of upstream firms and a strong labor market. In the case of urbanized economies, population size is positively related to manufacturing entrepreneurship, while population density is negatively related to it. Based on Marshallian theory, our paper's analysis of the spatial clustering of start-ups in the Spanish manufacturing sector can be useful to local and national policy makers planning to encourage entrepreneurship.

Keywords: Marshallian effect, spatial clusters, entrepreneurship, start-ups

Resumen

La iniciativa empresarial está distribuida espacialmente de forma desigual en España y las tasas de entrada en el sector manufacturero no han sido elevadas en los últimos tres años. Utilizando datos de las bases de datos del Instituto Nacional de Estadística (INE) y SABI, este estudio explora los factores que influyen en los clusters de emprendimiento manufacturero en las provincias españolas destacando la importancia de los factores de localización industrial y urbanización. A nivel industrial, nuestros resultados apoyan la existencia de un efecto Marshall significativo en el sector manufacturero, ya que es probable que se produzca más emprendimiento manufacturero allí donde existe una concentración de empresas ascendentes y un mercado laboral fuerte. En el caso de las economías urbanizadas, el tamaño de la población está positivamente relacionado con la iniciativa empresarial en el sector manufacturero, mientras que la densidad de población lo está negativamente. Basado en la teoría de Marshall, el análisis de nuestro trabajo sobre la agrupación espacial de las empresas de nueva creación en el sector manufacturero español puede ser útil para los responsables políticos locales y nacionales que planean fomentar el espíritu empresarial.

Palabras clave: Efecto Marshall, agrupaciones espaciales, iniciativa empresarial, start-ups

Introduction

Nowadays, entrepreneurship is a hot topic of study and has been highly persistent for some time (Fossen & Martin, 2018). The entrepreneurial spirit was initially proposed by Schumpeter (1939), who considered entrepreneurs as primarily involved in inventive activities and as a relatively limited number of persons capable of recognizing novel resource combinations and market prospects. Entrepreneurial activity is a hallmark of the new economic boom and is seen as an important driver of growth for countries and regions (Reynolds et al., 2002). Entrepreneurship is an important indicator of the economic dynamism of a country or region (Li et al., 2020). It is a comprehensive reflection of the local legal environment, market environment, innovation and entrepreneurship environment and business environment, and is closely related to regional economic development (Estrin, 2006). Many studies have shown that entrepreneurship has a significant impact on economic growth (Acs et al., 2018; Acs & Szerb, 2007; Carree & Thurik, 2010). The formation of new enterprises represents entrepreneurship and plays an important role in the reconfiguration of industrial space, stimulating new employment and catalysing technological progress (Fritsch & Storey, 2014).

The topic of entrepreneurship is often associated with industrial clustering. There is a consensus among many scholars that there is growing evidence that regional, rather than national, economies are the decisive units of economic growth (Cheshire & Malecki, 2003). The spatial and sectional clustering of economic activity is one of the central issues in economic geography, as it involves explaining why certain geographical locations are more competitive or dynamic than others (Zander, 2004). Regional or local systems have three main characteristics: inter-firm division of labor, productive specialization, and knowledge accumulation (Belussi, 1996). This coincides with the three advantages of industrial agglomeration proposed by Marshall (1890). So many policymakers now say they want their region to "become the next Silicon Valley" (Chatterji et al., 2014).

The decision to locate a new company has important implications for regional economic development (Fritsch & Mueller, 2008). Young and growing companies in particular are a potential asset for a country's economic development (Hellwig, 2023). Therefore, understanding the factors that determine the choice of location for a start-up is essential for effective decision-making (Y. Lee, 2008). And the analysis of start-ups is useful for understanding the long-term development of regional entrepreneurial models (Hellwig, 2023). Besides, manufacturing companies are the main forces behind the expansion and development of an economy, and the rate of change in this sector may be increased by social, economic, and environmental factors (Khan et al., 2021). This paper therefore seeks to address the following three research questions:

1, what are the spatial clusters of entrepreneurship in Spain?

2, what is the spatial clustering of manufacturing start-ups in Spain?

3, what factors drive the outcome of such manufacturing clusters?

In recent years, the study of start-ups has attracted a great deal of attention in academic circles. Some scholars have analysed the distribution patterns and spatial clustering characteristics of start-ups (Bishop, 2019; Ghani et al., 2014; Glaeser & Kerr, 2009), others have explored the factors that influence the location decisions of start-ups (Chatterji et al., 2014; Oyarzo et al., 2020; Zheng & Zhao, 2017), and still others have focused on theories related to entrepreneurial activity (Bernhard et al., 2020; Cheshire & Malecki, 2003; Fratesi & Senn, 2009). And most academics prefer to use high-tech start-ups as the unit of analysis. However, studies with a Spanish focus have been very limited. One of the least known aspects of the Spanish economy is the trade between the various regional economies that make up the Spanish economy (Becattini et al., 2002). As a result, much of the previous research has focused on topics related to the external economy (Sanromà & Ramos, 1999; Sanromá & Ramos, 2001; Fornielles & Costa, 1995).or the spatial mobility of the regional markets (Callejón & Costa, 1996; Ramos & Sanromá, 2013). In addition, Fornielles & Costa (1995) analyse the impact of external economies on the localisation of industrial activities; Costa et al. (2000) compare the impact of innovation on the competitive position of different Spanish industries; Marsal & Costa (1999) examine the impact of integration processes on the concentration of different industrial activities; Gómez-Antonio & Sweeney (2021) pay particular attention to the role of knowledge spillovers on the choice of location of firms engaged in technology, and Hervas-Oliver et al. (2017) focus on the role of cluster economies and knowledge heritage on the tile role of firm evolution. The study most similar to our theme is that of Cantarero et al. (2017) who analyse the spatial model created by the Spanish social economy companies and compare the evolution and differences between this model during the growth phase and the general crisis phase. There are also Costa Campi et al. (2004), who have found that the location decisions of companies vary according to the technology density and life cycle of the industry.

However, none of them have fully analysed the phenomenon of spatial agglomeration of start-ups in all sectors in Spain and discussed the factors influencing manufacturing from a Marshall's theory perspective. This paper will attempt to fill this gap.

This paper makes two main contributions. Firstly, it examines entrepreneurial spatial clusters in Spain particularly in the manufacturing sector, using a framework previously used to analyse similar spatial clusters in the United States (Glaeser & Kerr, 2009), India (Ghani et al., 2014) and China (Zheng & Zhao, 2017). Our findings will answer some of the future-oriented research questions posed by these articles and explore whether the Marshall Agglomeration advantage also plays a role in the Spanish manufacturing sector. Secondly, this article provides a broad picture of the general entrepreneurial landscape in Spain. Based on Marshallian theory, this is an analysis of the factors affecting the spatial clustering of manufacturing start-ups in Spain, which can be said to be recent, and our results are likely to be useful for other subsequent researchers investigating related areas or building on them.

Based on the above, we propose the objective of the study: this paper aims to find the spatial clustering patterns of start-ups in Spain and to analyse the reasons the reasons for the formation of entrepreneurship in manufacturing in particular.

The remainder of the paper is organised as follows. Section 2 is a literature review which reviews and summarises the results of previous experience. Section 3 describes the definition of the data and variables used and provide descriptive statistics. Section 4 contains the results of our econometric analysis. In the concluding section, we examine our key findings, comment on their consequences, highlight the limits of our work, and suggest promising future research directions.

Literature Review

From birth to demise, enterprises can be divided into four stages: start-up, growth, maturity and metamorphosis (Zoltners et al., 2006). Therefore, by start-ups in this paper, we mean companies in their infancy. The choice of location for new and emerging industries can relate to the theory of regional industrial bifurcation in economic geography. According to the theory of regional branching, local industrial base and geographic proximity may have a substantial influence on emerging industries, and existing industrial connections can provide better regional innovation policies for entrepreneurship. Regional branching theory suggests that local industrial base and geospatial proximity can have a significant impact on new industries, and that existing industrial linkages can provide better regional innovation policies for entrepreneurship (Zhao et al., 2017). This theory coincides with one of the traditional Marshall theories.

Marshall (1890), a classical economist, was the first to identify the major characteristics and causes of location-specific economies of scale, often known as agglomeration or external economies. In his theory on the localisation of industry, Marshall (1890) highlighted three advantages of agglomeration in terms of transporting goods, people and ideas. This was confirmed in subsequent studies (Armington & Acs, 2002). The extant texts are essentially based on these three theories of Marshall, which also form the theoretical basis for the analysis in this paper.

The first advantage of agglomeration is that companies benefit from lower transport costs due to the close proximity of suppliers and customers Marshall (1890). Relationships between buyers and sellers as well as suppliers and buyers might reveal industry clusters (Porter, 2014). Although transportation costs have dropped substantially over the last two centuries as technology has advanced, fundamentals still matter, especially in developed economies (Ghani et al., 2014). An industry cluster's extensive network of suppliers might be advantageous to entrepreneurial businesses (Helsley & Strange, 2002), and it might be especially important for start-ups (McCann, 2013). And the quality of input matching is enhanced by this clustering (Huber, 2012). To measure the extent to which the city is full of potential customers and suppliers of new entrepreneurs, (Glaeser & Kerr, 2009) created two related Marshall indicators. And these indicators have been perpetuated by subsequent scholars (Ghani et al., 2014; Zheng & Zhao, 2017). Each of these two indicators utilises the input-output tables published by each country, with certain calculations to capture the relative strength of the input-output relationship in a given market.

The second advantage of agglomeration is that it provides a dense labour market with an abundance of specialist workers Marshall (1890). Access to skilled labor is crucial for the growth of businesses because it may be expensive and time-consuming to find and (re)train employees in several ministries (Puga, 2010). Geographical clusters boost workers' desire to acquire human capital particular to their sector (Rotemberg & Saloner, 2000). Silicon Valley is a prime example of a region where job mobility across businesses enables greater fit between person and business (Fallick et al., 2006). Cities o regions must build areas that offer the traits individuals require to live and work in order to attract and retain highly competent personnel (Currid & Williams, 2010; S. Lee, 2010). As a result, it is critical to effectively create metropolitan regions with a tolerant and accepting attitude toward social diversity, which necessitates start-up cities improving their own circumstances (e.g. active government policies, etc.) (Gómez-Antonio & Sweeney, 2021; Florida, 2002).

The third advantage of aggregation is the ability to transfer old ideas and create new ones through the clash of ideas Marshall (1890). One of the probable reasons why some places are creative hotspots is their capacity to foster fresh ideas (Glaeser & Kerr, 2009). In Silicon Valley, for example, the flow of ideas between companies drives the occurrence and existence of entrepreneurial clusters (Saxenian, 1993). Therefore, in order to quantify the flow of ideas, many previous studies have relied on patent data to measure the similarity of technologies between industries (Glaeser & Kerr, 2009; Griliches, 1998). The knowledge spillover viewpoint emphasizes the importance of extensive industrial variety in order to foster cross-fertilization, which can lead to new ideas and entrepreneurial success. According to Gómez-Antonio & Sweeney (2021), a company's main source of benefit from knowledge spillovers is its proximity to other companies in the same industry, rather than from technology or research universities. There are also opposite views: Porter (1985) highlights the importance of Stanford University in the rise of Silicon Valley and MIT in the rise of the Route 128 cluster. Cluster policies are justified by the occurrence of substantial cross-firm spillovers, which naturally produce clusters and justify geographically focused entrepreneurial strategies (Chatterji et al., 2014; Saxenian, 1993).

In addition to Marshall, there are many other scholars who have studied other factors that influence the spatial clustering of start-ups. Chinitz (1961), for example, also emphasises the role of input suppliers. Chinitz initially proposed the relevance of small enterprises in agglomeration economies, which was intensively explored by many academics throughout the previous century (Grunberg, 1985; Piore & Sabel, 1984； Saxenian, 1993) and has been dubbed “the Chinitz effect” by later academics.

A number of academic studies have demonstrated that small business employees are more likely to launch companies of their own because they have access to networks and environments that support small businesses in addition to working in a variety of jobs and gaining extensive experience in starting and running small businesses (Dobrev, 2023; Parker, 2009). Employees at smaller businesses often have a better skill balance, whereas employees in bigger businesses tend to have a lower skill balance (Lechmann & Schnabel, 2014). This is why employees in smaller companies are more exposed to many different tasks and are more likely to stimulate a self-starting mind-set (Stuetzer et al., 2013). Bade & Nerlinger (2000) found that the highest rates of entrepreneurship were found near core cities, which had the absolute highest number of start-ups. This affirms the importance of the competitiveness of the city itself. According to Audretsch et al. (2012), the proclivity to start a firm among local employees is greatest in metropolitan agglomerations and their surrounding areas. Researchers have also often distinguished between two latitudes when analysing cluster patterns: industry or city. Other more common factors include the level of local human capital, the population and age structure of the city, and the natural resources of the city itself, among others.

Furthermore, numerous researchers have investigated this topic using theoretical frameworks other than Marshall and Chinitz's theory. On the basis of a literature review methodology, Alvedalen & Boschma (2017) seek to explain (ambitious) entrepreneurship from a systemic or ecosystemic viewpoint. (Chatterji et al., 2014) also discuss academic work on the concentration of entrepreneurial and innovative spaces in the US by way of a systematic literature review, making recommendations for local policies on local entrepreneurship and innovation. Adler et al. (2019) compare the “Jacobsian” and “Marshallian” approaches and find that the two spatial mechanisms do not work in opposition to each other, but work together to shape the geographic pattern of entrepreneurial activity. Based on the Kernel density and standard deviation ellipsoid approach, a spatial-temporal model of entrepreneurship and innovation performance is put out by Li et al. (2020), who also investigate the spatial spillover mechanism of entrepreneurship on innovation performance by developing a spatial Durbin model. In conclusion, there are many different ways and theories to study the spatial pattern of entrepreneurship, each of which is worth examining.

Methodology

The definition of entrepreneurship remains inconclusive. Some scholars have used self-employment rates as a measure of entrepreneurship, linking entrepreneurship to the number of people leading independent businesses (Evans & Jovanovic, 1989; Blanchflower & Oswald. 1998). But later scholars found that the vast majority of self-employed businesses found in the Labour and Population Censuses do not create jobs for other workers, and they may even be the product of a lack of employment opportunities for business owners (Astebro et al., 2010; Schoar, 2009). Therefore we will not use this indicator. An alternative approach is to use average firm size as a measure of entrepreneurship (Glaeser, 2007). However, Glaeser & Kerr (2009) has since found that this indicator barely captures the dynamic aspects of entrepreneurship and may reflect as much competition as entrepreneurship itself. Therefore we will not use this indicator either. When evaluating the influence of entrepreneurship on economic growth, a regional composite indicator of innovation activity is typically employed to represent entrepreneurship (Hong et al., 2022). In recent years, scholars have tended to measure entrepreneurship in terms of new firms. Some researchers describe this as the number of private start-ups (Guo et al., 2016), while others define it as the number of employees employed by new enterprises (Glaeser & Kerr, 2009; Zheng & Zhao, 2017) or the population share of company owners (Armington & Acs, 2002). Based on the framework of (Glaeser & Kerr, 2009), (Ghani et al., 2014) and (Zheng & Zhao, 2017), this paper defines entrepreneurship as the number of workers employed by a new, unincorporated business established within one year (Q1 2022 to Q1 2023).

In total, our sample includes 52 provinces (of which, 17 autonomous regions and 2 special cities). In the last three years, there were 22,396 new start-up companies, of which 22,250 were limited liability companies and public limited companies. In total, therefore, over 99% of new companies are included. In our sample, the total number of active companies is 1,487,520, of which 127,250 are manufacturing companies. Typically, defining the scope of a labour market area first requires the use of inductive and deductive methods (Van der Laan & Schalke, 2001). However, we simply used the Spanish provinces as the unit of study, dividing each province into a functional area, because it fulfils two requirements for functional areas to be used for decision-making and statistical purposes, namely, no overlap between regions and full coverage (each spatial basic unit must be assigned to a region)(Flórez-Revuelta et al., 2008).

To measure entrepreneurship and the state of the local industry, the main data for this study was obtained from the Spanish National Statistics Institute and the SABI database. For each company, the data provides a wide range of company characteristics, including company location, year of company establishment, type of company ownership, total number of employees, etc. The data also provides general city characteristics, including city population, city employment rate, etc.

Table 1 shows the regional differences in entry rates by city. The entry rate compares the number of persons employed in new firms in a city to the number of people employed in existing firms (Klapper et al., 2010). The table shows the entry rates in the 52 provinces, from which we can see that each province has a low entry rate. The highest is Segovia, with around 2%. The rest are below 2%. The top five provinces in terms of entry rates are Segovia, Badajoz, Murcia, Almería, and Valencia. The bottom five provinces are Melilla, León, Palencia, Toledo, and Salamanca. Melilla, in particular, has an entry rate as low as 0.2338%. This shows that there has not been much entry of start-ups in Spain for three years, possibly due to the Covid-19 effect.

Table 1: Spatial variation in start-up entry rates by province

Province	Empl-Newfirms	Empl-Total	Entry rates
Almería	1912	128978	1.4824%
Cádiz	1240	146196	0.8482%
Córdoba	963	110549	0.8711%
Granada	909	117521	0.7735%
Huelva	741	95857	0.7730%
Jaen	804	72919	1.1026%
Málaga	3109	292869	1.0616%
Sevilla	3485	357621	0.9745%
Huesca	431	42344	1.0179%
Teruel	166	19286	0.8607%
Zaragoza	1772	235455	0.7526%
Asturias	1254	173882	0.7212%
Baleares	2228	285054	0.7816%
Las Palmas de Gran Canaria	1593	216055	0.7373%
Santa Cruz de Tenerife	1290	175831	0.7337%
Cantabria	783	96483	0.8115%
Avila	107	14375	0.7443%
Burgos	399	62693	0.6364%
León	304	62305	0.4879%
Palencia	119	22190	0.5363%
Salamanca	270	44471	0.6071%
Segovia	482	23275	2.0709%
Soria	188	14603	1.2874%
Valladolid	882	105317	0.8375%
Zamora	130	19040	0.6828%
Albacete	564	75592	0.7461%
Ciudad Real	680	75853	0.8965%
Cuenca	216	33647	0.6420%
Guadalajara	447	36688	1.2184%
Toledo	621	113831	0.5455%
Barcelona	11054	1574081	0.7023%
Girona	1375	187272	0.7342%
Lleida	775	92823	0.8349%
Tarragona	887	133726	0.6633%

Ceuta	69	6864	1.0052%
Alicante	3731	382578	0.9752%
Castellón	868	135030	0.6428%
Valencia	9992	728436	1.3717%
Badajoz	1360	84949	1.6010%
Cáceres	386	47103	0.8195%
a Coruña	2245	264313	0.8494%
Lugo	574	46471	1.2352%
Ourense	422	44197	0.9548%
Pontevedra	1894	200335	0.9454%
La Rioja	397	59936	0.6624%
Madrid	26867	3397674	0.7907%
Melilla	11	4704	0.2338%
Murcia	5375	343555	1.5645%
Navarra	1725	155072	1.1124%
Alava	671	67463	0.9946%
Guipuzcoa	1553	155364	0.9996%
Vizcaya	2426	303224	0.8001%

Table 2 shows the differences in the entry rates of manufacturing firms by province. Similarly, the manufacturing entry rate compares the number of people employed by new manufacturing firms in a province with the number of people employed by existing manufacturing firms. Since Melilla has not seen an increase in the number of manufacturing start-ups in the last three years, we include only 51 provinces (17 Autonomous Communities and 1 Special Municipality) in terms of manufacturing. Of these, only Jaen has an entry rate of more than 1%. From these two tables we can reasonably infer that there has not been much enthusiasm for entrepreneurship in Spain in the last three years.

Table 2: Spatial differences in entry rates of manufacturing start-ups by province

Province	Empl-new maft	Empl-maft	Entry rate
Almería	53	12774	0.4149%
Cádiz	90	19532	0.4608%
Córdoba	151	27759	0.5440%
Granada	45	14333	0.3140%
Huelva	47	10123	0.4643%
Jaen	274	16929	1.6185%

Málaga	136	21913	0.6206%
Sevilla	396	49920	0.7933%
Huesca	19	9897	0.1920%
Teruel	37	5877	0.6296%
Zaragoza	213	62776	0.3393%
Asturias	86	37836	0.2273%
Baleares	112	14100	0.7943%
Las Palmas de Gran Canaria	66	11561	0.5709%
Santa Cruz de Tenerife	71	10116	0.7019%
Cantabria	126	22502	0.5600%
Avila	2	1886	0.1060%
Burgos	109	20607	0.5289%
León	61	14098	0.4327%
Palencia	2	8505	0.0235%
Salamanca	30	9300	0.3226%
Segovia	36	5815	0.6191%
Soria	36	4901	0.7345%
Valladolid	24	33380	0.0719%
Zamora	15	3674	0.4083%
Albacete	78	18847	0.4139%
Ciudad Real	167	16813	0.9933%
Cuenca	18	8965	0.2008%
Guadalajara	25	7365	0.3394%
Toledo	111	33197	0.3344%
Barcelona	1525	326450	0.4671%
Girona	201	42613	0.4717%
Lleida	36	19189	0.1876%
Tarragona	102	25476	0.4004%
Ceuta	6	956	0.6276%
Alicante	964	89755	1.0740%
Castellón	184	41742	0.4408%
Valencia	1258	124479	1.0106%
Badajoz	81	14508	0.5583%
Cáceres	35	8721	0.4013%
a Coruña	133	42079	0.3161%
Lugo	76	8140	0.9337%

Ourense	93	-32841	0.2832%
Pontevedra	401	43862	0.9142%
La Rioja	82	21725	0.3774%
Madrid	1013	259646	0.3901%
Murcia	343	66205	0.5181%
Navarra	971	62000	1.5661%
Alava	157	26824	0.5853%
Guipuzcoa	342	51524	0.6638%
Vizcaya	203	58643	0.3462%

We will then discuss the determinants that may contribute to manufacturing entrepreneurship clusters in Spain. The determinants fall into two categories: Marshallian characteristics and city-level characteristics.

Based on the theory of industrial localisation developed by Marshall (1890), we propose the following three indicators. Firstly, in terms of the intensity of customers and suppliers, we start with the Spanish input-output tables published by the Spanish National Institute of Statistics. We define Input $_{i \leftarrow k}$ as the share of manufacturing industry i's inputs that come from industry k, and Output $_{i \rightarrow k}$ as the share of manufacturing industry i's outputs that go to industry k. These shares vary from zero (full independence from inputs or outputs) to one (total reliance) (Glaeser & Kerr, 2009). There are asymmetries in pairs of customer and supplier dependency ($Input_{i \leftarrow k} \neq Output_{k \rightarrow i}$) due to differences in industry size and the importance of flows to or from all other industries and end consumers (Ghani et al., 2014; Glaeser & Kerr, 2009). Based on (Zheng & Zhao, 2017)， According to Marshall (1890) and Krugman (1991), supplier/customer linkages are the main source of localization economies, so we set the variable Input $_c$ to measure the extent to which city c provides suitable upstream firms for manufacturing:

$$Input_c = \sum Input_{i \leftarrow k} * Empl_{ck} \quad (1)$$

The variable Outputc measures the extent to which city c provides suitable downstream firms for manufacturing:

$$Output_c = \sum Output_{k \rightarrow i} * Empl_{ck} \quad (2)$$

where i here stands for the manufacturing sector and $Input_{i \leftarrow k}$ stands for the percentage of sector k's inputs that go into sector i. $Empl_{ck}$ stands for sector k's employment in city c, and $Input_c$ for the possible input connection that city C offers to newly established companies in sector i. In a similar way, $Output_{k \rightarrow i}$ represents the portion of sector i's output that sector k purchases, while $Output_c$ represents the prospective consumers that city C offers new sector i enterprises. The comparative advantage of supplier links (SUPPLIER) and customer links (CUSTOMER) are measured, respectively, using the location quotient of input and output (Guo et al., 2016).

The second variable of interest is labour market strength. Local labor markets imply a geographically "aggregated" interplay of labor supply and demand (Casado-Díaz & Coombes, 2011). The labor market is described as a separate and coherent area in terms of commuting flows (Flórez-Revuelta et al., 2008), which also applies to Spain (Casado-Díaz, 2000), and is especially developed for the study of local labor phenomena (Feria et al., 2015). The research in the United States was able to model direct employment mobility between industries because of the availability of industry occupational matrices in the relevant databases (Glaeser & Kerr, 2009). Some Chinese scholars have also created related matrices through Chinese databases (Zheng & Zhao, 2017). Instead, we have adopted an alternative, less direct and simpler approach. We will use the number of local manufacturing employees as a share of the number of employees in all local industries as an indicator of the potential local workforce. We therefore define:

$$Labor_c = Empl_{ic} / Empl_c \quad (3)$$

The third relevant variable is the flow of ideas. As the territorial source of such patents was not available for the time being for our study, it must be noted that this is a potential limitation.

In terms of industry factors, we will also use the variables $Employment\_M_c$ and $EntryRate_c$, which represent the number of employees of manufacturing firms in a province and the entry rate of manufacturing firms in that province, respectively.

At the city level, there are a number of other variables that deserve our attention. The first is demographic data. The basic demographic characteristics of an area include three things: population, age distribution of the population and population density (Ghani et al., 2014). Demographic data can and will reflect the supply of potential entrepreneurs to some extent. We name this variable *Totalpop*, which represents the total number of people living in a province. It has been demonstrated that the age structure of a region can have an additional impact on entry rates (Bönte et al., 2009). And the probability of having more entrepreneurs seems to be positively correlated with age (Evans & Leighton, 1989). In this study, we categorize the age structure of the population in each region into four stages, 19 years old and below, 20-39 years old, 40-59 years old, and 60 years old and above, and define these four pointers as *A19*, *A20_39*, *A40_59*, and *A60*, respectively. Population density, on the other hand, is used to represent agglomeration effects (Rosenthal & Strange, 2008) and can partially control market size and accessibility (Arauzo Carod, 2005). So density is also associated with a stronger flow of knowledge (Arzaghi & Henderson, 2008). We use *Density* as one of the variables.

Another important control factor is the level of education in the local area. We measure the general level of education in an area by the percentage of adults with a bachelor's degree. Research has shown that general education in the workforce is associated with higher entry rates (Doms et al., 2010). And this element is important for the development and growth of the region (Gennaioli, 2012). The last variable is the number of migrants. First off, immigrants are more likely to engage in entrepreneurial activities as they might not be able to get employment in non-private sectors due to personal traits or employment bias (Zheng & Zhao, 2017). Second, they may give business owners the essential and reasonably priced labor (Zheng & Zhao, 2017).

It is crucial to note that not all of the variables were taken into account while developing our controls. Inadequate local policy environments, for instance, may be a barrier to the growth of the private sector. Nevertheless, variables assessing these environments are not included. There are also financial systems, levels of local infrastructure, natural cost advantages (e.g. Ellison & Glaeser, 1999), local industrial diversity (Jacobs, 2016) and entrepreneurial culture (Hofstede, 1980; Florida, 2003) that are not controlled for.

To explain the spatial clustering of manufacturing entrepreneurship, we estimate the following model:

$$\mathrm{Ln}(\mathrm{Employment}_c) = \eta\alpha + \gamma\cdot \mathrm{Employment\_M}_c + \gamma \mathrm{I}\cdot \mathrm{EntryRate}_c + \gamma \mathrm{I}\cdot \mathrm{Input}_c + \gamma \mathrm{O}\cdot \mathrm{Output}_c + \gamma \mathrm{L}\cdot \mathrm{Labor}_c + \beta\cdot X_c + \varepsilon_c. \quad (4)$$

where $Ln(Employment_c)$ represents the logarithm of the number of employees of new firms in the manufacturing sector. $Employment\_M_c$, $EntryRate_c$, $Input_c$, $Output_c$ and $Labor_c$ represent the number of employees of manufacturing firms in a given province, entry rate of manufacturing firms in the province, strength of clients and suppliers, and labor market strength, respectively. X_c is a vector of regional characteristics such as population and education level. Besides, α is a constant and ε is an error term.

Table 3 summarises the variables used in this paper for the Spanish manufacturing sector, and the interpretation of the variable names.

Table 3: Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
ln_Employment	1.948088	0.6151809	0.30103	3.18327
Employment_M	36019.55	58610.11	-32841	326450
EntryRate	0.0052436	0.0033913	-0.0028318	0.0161852
Totalpop	951.9464	1879.889	31.35178	12517.86
Input	2961.101	6454.773	23.71622	41878.36

Output	0.1957711	0.1606077	-0.7430595	0.3998143
Labor	932004.4	1213718	82147.08	6825005
A19	178339.8	242676.2	14793.71	1347251
A20-39	210541.1	289511.7	18254.17	1638944
A40-59	293517.6	382303.3	23512.48	2164163
A60	249606	301638.1	15955.25	1674648
Density	214.4617	611.8348	8.686108	4323.531
Education	249899	390907.3	16453	2310257
Immigration	9378.804	17307.5	477	97079

Results

Empirical Results

Table 4 reports the empirical results for the estimated manufacturing sector. In order to investigate the effects of Marshall's agglomeration theory and city-level effects, we add these variables one by one for analysis. The first column includes only the city's manufacturing population and the urban population. The results confirm that more on-the-job manufacturing employment and the city's total population do not appear to be related to the entry of new manufacturing firm personnel.

Table 4: Estimation for Manufacturing

	DV: ln(Employment in new manufacturing firms)			
	（1）	（2）	（3）	（4）
Employment_M	3.30E-06	0.00000671*	6.11E-07	0.0000143***
	（0.0000026）	（0.00000399）	（0.0000035）	（0.0000049）
EntryRate	83.69694***	89.26579***	83.94946***	96.45122***
	（16.69486）	（17.56368）	（15.90885）	（14.85428）
Totalpop	1.41E-07	1.66E-07	3.43E-06	0.00000823*
	（0.000000125）	（0.000000278）	（0.00000474）	（0.004072）
Input		5.62E-05		0.0006411**
		（0.0002957）		（0.0002899）
Output		-5.45E-05		-0.0001175*
		（0.0000827）		（0.0000676）
Labor		-0.8400793*		-1.517899***
		（0.4700878）		（0.4216631）
A19			4.58E-06	-5.41E-07

			（0.00000703）	（0.00000659）
A20-39			-1.45E-05	-0.0000243***
			（0.00000903）	（0.000009）
A60			-1.43E-06	-9.05E-06
			（0.00000727）	（0.00000764）
Density			-0.0001911**	-0.0002246***
			（0.0000821）	（0.0000741）
Education			-6.66E-07	-1.82E-06
			（0.000000992）	（0.00000166）
Immigration			-4.52E-06	-1.61E-05
			（0.000014）	（0.0000149）
constant	1.259089***	1.356284***	1.119222***	1.421208***
	（0.1114987）	（0.1439768）	（0.1172987）	（0.141229）
R-squared	0.6095	0.6588	0.7443	0.8166
Adj R-squared	0.57846	0.6123	0.6882	0.7587

Notes: Standard errors are reported in parentheses. The dependent variable is the log employment in new manufacturing firms by city. The models are estimated using OLS.
∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$.

Column 2 presents our supporting evidence on the agglomeration of Marshall. Unfortunately, customer and supplier intensity is not supported, which is very different from the conclusions reached by previous academics. However, the point that the local labor market is considered to be the most important is exactly the same as the findings of the (Glaeser & Kerr, 2009).

Column 3 contains city characteristics: demographics, education and migration data. Surprisingly, demographics have a very limited role in explaining manufacturing entry patterns. This is consistent with the initial findings for the US and India, but not with the case of China (Ghani et al., 2014; Glaeser & Kerr, 2009; Zheng & Zhao, 2017). Of the urban characteristics in this column, only population density is significant. However, cities with higher population densities are negatively correlated with the number of entrants, which might reflect congestion in provinces with higher density. At the same time, spillover effects may ensue: by locating close to higher density provinces, firms can gain at least some of the agglomeration effects while avoiding some of the negatives such as higher land prices.

The complete ones are reported in column 4. Most of the characteristics differed from their respective previous estimates, both in terms of city and industry characteristics. Overall, the results confirm that the significance of city characteristics and the significance of industry characteristics interact.

With regard to the effect of the diocesan factor, our findings suggest that higher levels of manufacturing entrepreneurship tend to emerge wherever upstream firms are concentrated; suggesting that the entry of manufacturing newcomers is more inclined to be closer to more suppliers. The opposite effect is observed where downstream firms are concentrated. Another finding is that the share of local manufacturing employees has a negative significant effect, suggesting that the local manufacturing labour market is negatively associated with the entry of new manufacturing firms and that new manufacturing talent prefers to open up new manufacturing markets.

As for the effect of city characteristics, the coefficient on urban population is positive and significant, and the coefficient on population density is negative and significant. It indicates that maybe due to the factor of congestion, entrepreneurship is more likely to be found in cities that are populated but not densely populated.

At the same time some educational factors become significant. 20 to 39-year-olds is negatively significant (the omitted category is 40 to 60-year-olds), which is the exact opposite of the results of Zheng & Zhao (2017). Glaeser & Kerr (2009) find that the number of older people in a region has a relatively insignificant impact on manufacturing entrepreneurship in the U.S. This is the same as it is shown for manufacturing entrepreneurship in Spain, as our study exhibits that the population aged 60 and over is insignificant. In this study, more migrants are not associated with manufacturing start-ups. This is corroborated by part of the findings of Zheng & Zhao (2017), which show that a higher proportion of migrants do not seem to be associated with manufacturing start-ups, but are positively associated with the entry of new service firms. So industry does matter and it seems that immigrants have a greater role in the service sector.

Robustness

To ensure the robustness of our findings we use heteroscedasticity tests to account for possible violations of the homoscedasticity assumption in our data. The purpose of these tests is to check the sensitivity of our results to potential sources of model misspecification, outliers and other biases. In order to explore possible heteroscedasticity in the model, we conducted the White test and the Breusch-Pagan test. These tests help us to test whether the error variance of the model is correlated with the relationship between the independent variables, and thus determine whether a correction for heteroscedasticity needs to be introduced in the model. Based on the results of White's test and Breusch-

Pagan test (the results are placed in the Appendix), we re-analysed the data using robust statistical methods. The results of the analysis are presented below:

Table 5: Robust Analysis for Manufacturing

Employment_M	0.0000143***
	(0.00000327)
Entryrate	96.45122***
	(15.69051)
Totalpop	0.00000823**
	(0.00000379)
Input	0.0006411***
	(0.0001668)
Output	-0.0001175***
	(0.0000364)
Labor	-1.517899***
	(0.4046355)
A19	-5.41E-07
	(0.00000429)
A20_39	-0.0000243***
	(0.00000807)
A60	-9.05E-06
	(0.00000614)
Density	-0.0002246***
	(0.0000254)
Education	-1.82E-06
	(0.00000131)
Immigration	-0.0000161
	(0.0000124)
_cons	1.421208***
	(0.151962)

Notes: Standard errors are reported in parentheses. The dependent variable is the log employment in new manufacturing firms by city.

$*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

The results reported in Table 5 confirm the robustness of our conclusions. The estimated coefficients remain statistically significant and their magnitudes are consistent with those of the baseline model. In addition, the robust standard errors provide more reliable inferences by accounting for the presence of heteroscedasticity in the data.

Conclusion

The first attempt in this study is to explore spatial clusters in all industries in Spain, focusing on the factors that influence the phenomenon of manufacturing clusters. Most studies on Spain focus on the impact of the external economy (Becattini et al., 2002) and the emphasis is not on start-ups. This paper builds on previous articles that have studied other countries and explores for the first time whether the Marshall Agglomeration advantage also plays a role in the clustering of manufacturing start-ups in Spain. The low rate of entrepreneurship in Spain in the last three years may be due to the influence of Covid-19.

Regarding the distribution of manufacturing start-ups, our first finding is related to local industrial conditions. In order to facilitate the formation of new firms in a given location, a key variable is the presence of a large number of existing firms in the same industry within the area (Zheng & Zhao, 2017). More importantly, our results seem to support a significant meshing effect in manufacturing. More manufacturing entrepreneurship is likely to emerge where there is a concentration of upstream firms and a large potential labor force.

Our second finding relates to city characteristics. Specifically, levels of manufacturing entrepreneurship tend to be higher in cities with larger populations, smaller middle-aged populations, and lower population densities. Of course, the specific underlying causal mechanisms linking urban attributes to entrepreneurship require more future research.

As with all research, this study has its limitations. Firstly, the biggest limitation comes from the collection of variables for the sample. Due to the limitations of some databases, we were unable to obtain data on all possible variables. Therefore, future research is urgently needed regarding other cultural advantages, natural resources and other characteristics. In any case, the text already contains the most important explanatory variables. In addition, the research sector set out in this paper has its limitations. For the time being, we have focused only on manufacturing firms in Spain, but in reality there may be other sectors or even a more detailed classification of research manufacturing that could be studied. Therefore, future research could take advantage of more spatial and temporal variation to complement the literature on entrepreneurship in the Spanish context.

In terms of theoretical significance, this study adds to our overall knowledge of spatial clustering of start-ups in Spain. This study's analysis of the spatial clustering of start-ups across all sectors in Spain has the potential to be able to assist other researchers investigating related areas. On this basis, some of the limitations of this study could allow for future research to be added, while providing certain research sources for more detailed future studies. Future research could combine the methodologies and findings in this paper to explore whether similar conclusions could be drawn in other, different sectors.

In terms of management implications, the influencing factors presented in the study can provide a tool for relevant academics, policy makers and business leaders that can be applied to manage and decide on the location of industry start-ups, and also to develop local innovation and entrepreneurship policies based on the findings of this study.

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Appendices

I. Correlation coefficient of independent variables

	ln_Emp~t	Employ~M	Entryr~e	Totalpop	Input	Output	Labor	A19	A20_39	A40_59	A60	Density	Educat~n	Immigr~n
ln_Employm~t	1.0000													
Employment_M	0.6288	1.0000												
Entryrate	0.5244	0.1217	1.0000											
Totalpop	0.6110	0.9289	0.0889	1.0000										
Input	0.4938	0.8403	0.0236	0.9488	1.0000									
Output	0.5015	0.8684	0.0216	0.9518	0.9922	1.0000								
Labor	-0.0046	0.0993	0.3023	-0.1269	-0.1391	-0.1186	1.0000							
A19	0.6104	0.9287	0.0935	0.9979	0.9454	0.9477	-0.1172	1.0000						
A20_39	0.5952	0.9200	0.0912	0.9984	0.9541	0.9542	-0.1330	0.9982	1.0000					
A40_59	0.6098	0.9227	0.0904	0.9997	0.9511	0.9529	-0.1303	0.9970	0.9983	1.0000				
A60	0.6234	0.9382	0.0805	0.9956	0.9360	0.9438	-0.1235	0.9890	0.9893	0.9948	1.0000			
Density	-0.1015	0.1498	0.0685	0.1522	0.1682	0.1695	-0.0837	0.1559	0.1574	0.1519	0.1433	1.0000		
Education	0.5662	0.9324	0.0440	0.9881	0.9676	0.9731	-0.1015	0.9831	0.9860	0.9872	0.9872	0.1673	1.0000	
Immigration	0.5549	0.9210	0.0663	0.9742	0.9497	0.9551	-0.1122	0.9727	0.9755	0.9729	0.9679	0.1749	0.9704	1.0000

II. Heterogeneity test

```
White's test
H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

   chi2(52) =  51.00
Prob > chi2 = 0.5132

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	51.00	52	0.5132
Skewness	4.17	12	0.9801
Kurtosis	1.15	1	0.2845
Total	56.32	65	0.7700

```
Breusch–Pagan/Cook–Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of ressq

H0: Constant variance

    chi2(1) =  34.18
Prob > chi2 = 0.0000
```