Innovation Ecosystems in Catalonia:
Exploring location patterns of high-tech firms

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Abstract

This paper investigates the determinants of high-technology and non-high-technology firm location choices in Catalonia, Spain, emphasizing the role of spatial spillovers and industry-specific dynamics. The analysis examines firm entries across high-tech manufacturing, knowledge-intensive services, and non-high-tech sectors by employing spatial econometric models and count data techniques in Catalan municipalities between 2010 and 2019. Results highlight the importance of population density, income levels, and proximity to urban hubs for high-tech sectors as main determinants of location decisions, while non-high-tech firms exhibit a preference for less urbanized regions. Spatial spillovers of income and labor market conditions significantly influence high-tech firm entries, underscoring the interconnected nature of regional economies. The findings reveal sector-specific location patterns and contributes to the literature on industrial location, offering practical recommendations for enhancing Catalonia's role as a hub for technological innovation and economic growth and providing actionable insights for policymakers.

Keywords: high-tech industries, clusters, firm location, municipalities
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1. Introduction

The spatial distribution of industries and the factors influencing their performance have been central topics in regional economics. Understanding what drives firm location patterns and performance is critical for policymakers aiming to reduce regional disparities, promote innovation, and foster economic development.

Location patterns of new firms are fundamental in helping to elucidate the spatial and specific characteristics of each sector (Arauzo-Carod et al., 2024, 2010; and Jofre-Monseny, 2008), so comprehending the variables influencing new enterprises' site decisions is a crucial first step toward understanding the current ongoing debate regarding the intricate patterns and varying levels of clustering of intra-national high-technology firms.

Although many authors examining firm location patterns acknowledge the significance of high-tech firm concentration and strategies for regional economic development, it is necessary to critically assess the specific role played by these kinds of clusters. In this sense, several scholars, such as Behrens (2016), Jofre-Monseny et al. (2014), Pe'er and Keil (2013), Arauzo-Carod and Manjón-Antolín (2012), Viladecans-Marsal and Arauzo-Carod, (2012), Hervas-Oliver (2012), Ellison et al. (2010), and many others have carried out in-depth analyses shedding light on this topic, in order to assess how firms belonging to high-tech industries agglomerate differently than those without that technological dimension.

In terms of empirical papers analysing the location determinants of entering firms, there are two streams of literature depending on where the focus is: the firm or the territory. As for the papers focusing on firms taking the entry decision, they normally use conditional logit models (see Arauzo-Carod et al., 2010, for a review), whilst papers focusing on chosen areas normally use count data models (see also Arauzo-Carod et al., 2010) and, more recently, Geographical Weighted Regression approaches (Arauzo-Carod et al., 2024; Tyas et al., 2023; Fotheringham, 2023; Comber et al., 2022; Xiong et al., 2021; Liu et al., 2018; Fotheringham et al., 1998) or other spatial methods, such as Geographically Weighted Multivariate Poisson Inverse Gaussian Regression (Mardalena et al., 2022), Geographically and Temporally Weighted Bivariate Poisson Inverse Gaussian Regression Model (Sari et al., 2021), and Geographically and Temporally Weighted Regression Model with Gaussian Kernel Weighted Function and Bisquare Kernel Weighted Function (Harianto et al., 2021).

This paper focuses on Catalonia, an autonomous region (i.e., NUTS 2 region) in Northeast Spain, a highly diverse and economically dynamic area, to investigate how spatial and industry-specific determinants influence industrial entries. That choice is motivated by the fact that Spain has invested heavily in research and technology over the past 20 years, but without generating a prosperous technological ecosystem except for Catalonia, which concentrates the highest number of high-tech firms among Spanish regions.

According to a report drawn up jointly by the Mobile World Capital Barcelona, Barcelona City Council's International Economic Promotion and ACCIÓ Catalonia Trade & Investment – the business competitiveness agency of the Generalitat de Catalonia – called "Tech Hubs Overview 2024", Catalonia has the most significant growth in the number of tech hubs recently in Spain (total of 140 digital hubs in 2023), generating an economic value of over 2.5 billion euros and creating more than 26,000 jobs, with a considerable increase expected over the next three years. This rapid expansion reflects Catalonia's robust infrastructure, strong government support, and strategic focus on competitiveness and innovation, establishing the region as an ideal environment for technology-intensive industries. Against this backdrop, analysing the location patterns of firms provides a critical opportunity to understand the spatial determinants of industry concentration, shedding light on the factors driving economic growth and innovation in this dynamic region.

By focusing on Catalonia, this research not only addresses a region of growing economic and technological significance but also contributes to understanding how infrastructure and innovation interact to shape the geography of technology-driven industries. Furthermore, Catalonia is currently developing strategies to gather funds and coordinated actions focused on increasing its economic impact and talent attraction such as the Digital Innovation Hub of Catalonia, which aims to promote the technological transformation of small and medium-sized enterprises, technological start-ups and public organizations (Generalitat de Catalunya, 2022). This information demonstrates the potential for innovation in the region, which requires a more in-depth study precisely to identify the determinants of the entry of high-tech firms in this area, which is what this study sets out to do.

It is precisely because it has become a technological centre with exponential growth that the need arises to comprehend the pivotal factors that shape the geographical location of high-tech firms in Catalonia and to understand the mechanisms underlying these clustering processes. This includes a nuanced examination of the role of spatial spillovers in shaping industrial performance and the specific determinants of entries across high-tech and non-high-tech industries. Spatial spillovers represent the influence of neighboring regions' characteristics – such as population density, income, and firm size – on a region's industrial outcomes. Industry-specific factors reveal how firm size, competition, and proximity affect different sectors.

Starting from the research question "How do spatial factors, industry-specific characteristics, and regional economic conditions influence firm location choices in Catalonia?", this paper analyses a dataset of firms in all Catalan municipalities by employing econometric models with spatial lags. The results provide new insights into the interplay between geography and industry structure, offering valuable recommendations for regional economic policy. This will be achieved through a meticulous analysis and thorough examination of the geographical firm entries in Catalonia's municipalities specifically between 2010 and 2019. By delving into this period, an in-depth understanding of the dynamics and trends of high-technology firm clustering within Catalonia can be unveiled.

Through a comprehensive analysis and examination of the intricate interconnections and networking activities between these firms, this paper will shed light on the underlying patterns that have driven the development of technological clusters within this region. By expanding our knowledge in this domain, we can contribute to the broader discourse surrounding the spatial distribution of high-technology firms, ultimately fuelling advancements in regional economic development strategies and fostering innovation within Catalonia (Galaso and Kovářík, 2021; Medina et al., 2020).

For all, this paper seeks to address this need for in-depth information and knowledge about a mature economy like Catalonia, by offering new empirical perspectives on the factors that determine high-tech firms' locational preferences, analysing the data entering firms from Sistema de Análisis de Balances Ibéricos (SABI) using Count Data Models and spatial econometrics. This will be used to investigate the determinants that drive the clustering of these firms, focusing on the role of spatial spillovers and sector-specific characteristics, shedding light on their concentration patterns and contributing to a more comprehensive understanding of regional economic dynamics.

In summary, investigating these innovation ecosystems can help identify the determinants of high-technology firms' locational preferences to make it possible to optimize resource allocation, attract investments and skilled professionals. It emphasizes the advantages of focusing on tactics to support competitiveness, boost local economies, and accomplish sustainability objectives. The ultimate goal of the research is to provide evidence for evidence-based policymaking that will help regional innovation and sustained economic growth. The research seeks to identify and compare the role of spatial determinants in shaping industrial entries, analysing the performance across high-tech and non-high-tech industries, and integrate spatial and industry-specific analyses into a unified framework. After all, regions with well-functioning innovation clusters often become more targeted on a global scale.

Nevertheless, this work ultimately aims to provide actionable recommendations for regional and industrial policy for promoting balanced economic development practices. It suggests that such knowledge can guide interventions in regions needing support, encourage environmentally friendly technologies, and inform evidence-based policymaking.

This paper is based on the premise that high-technology firms are more likely to locate in urbanized areas that provide access to infrastructure, skilled labor and innovation networks (Carlino and Kerr, 2015). Due to the growth potential of high-tech firms and the competition for these spaces for the creation of new firms, the economic development of firms in the sector is greater when they are part of an innovation cluster (Doloreux and Shearmur, 2023; Tu et al., 2023; Raimbault, 2022; and Van Aswegen and Retief, 2020). Besides that, we assume that universities (Audretsch and Lehmann, 2005; Etzkowitz and Leydesdorff, 2000), technological parks (Squicciarini, 2008; Phan et al., 2005), and business incubators (Ratinho and Henriques, 2010; Aernoudt, 2004) play a crucial role in fostering innovation ecosystems and driving the agglomeration of high-tech firms by facilitating knowledge spillovers, research collaboration, and entrepreneurial support (Clarysse et al., 2005; Colombo and Delmastro, 2002).

The hypothesis raised is that the concentration of high-technological activities in and around Barcelona is explained in terms of its location as a point of international interest throughout its history and has favoured its growth to become the great metropolis it is today (Maddah et al., 2023 and Méndez-Ortega et al., 2020). Our results suggest that high-tech firms in Catalonia are predominantly attracted to urban areas with high population density, income levels, and proximity to provincial capitals, while non-high-tech firms favor less urbanized regions. Spatial spillovers play a crucial role, particularly for high-tech sectors, as neighboring regions' characteristics - such as income and labor market conditions - enhance their attractiveness. Additionally, the presence of large anchor firms fosters high-tech manufacturing clusters but deters non-high-tech entries, highlighting the interplay between agglomeration economies and resource competition. These findings provide valuable insights into the dynamics of firm location patterns, offering actionable recommendations for fostering innovation clusters, balancing regional development, and promoting sustainable economic growth.

The remainder of the paper is structured as follows. Second section discusses recent literature focusing on innovation ecosystems with a special focus on Catalonia. Third section presents the data set to be used and describes the results of the survey and the empirical strategy. Fourth section discusses main results. Fifth section concludes and provides directions for future research.

2. Literature review

The term agglomeration economies[1] originated from Marshall's theories (1890) addresses the concept of industry clustering's benefits, primarily encapsulated in the positive externalities of agglomeration, acting as a catalyst for economic growth, has evolved a lot over time with the contributions of Weber (1909), Schumpeter (1961), and Krugman (1991) about the firms clustering together results in decreased transaction costs, heightened flexibility, and optimal information flow. According to Puga (2010), this can be studied from three distinct perspectives: the excessive number of nearby firms, the number of wages and rents, and systematic variations in productivity as a result of local increasing returns.

Duranton and Puga (2004) classify urban agglomeration economies into three key mechanisms: sharing (infrastructure, suppliers, and skilled labor), matching (better alignment between firms, workers, and partners), and learning (facilitating innovation and knowledge diffusion). Some authors, like Jacobs (1969), Glaeser et al. (1992) – indirectly – and Nylund and Cohen (2017) in a direct way, connect the themes of agglomeration economies and innovation ecosystems[2] through studies on urban

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[1] Agglomeration economies: a consequence of adding up the individual external effects of the interaction of firms located in the same geographical environment (Jofre-Monseny, 2008). It could be defined as the benefits that derive from the spatial concentration of jobs and firms as well (Coll-Martínez, 2019). According this definition, agglomeration economies are subdivided into localization economies (Marshall, 1890) and urbanization economies (Jacobs, 1961 and 1969).

[2] Innovation ecosystems: A network of businesses, research institutions, government agencies, and investors collaborating to drive research, development, and commercialization of new technologies, focusing on shared priorities like industrial competitiveness and climate change mitigation (Yashiro, 2023).

ecosystems and the economic and innovation benefits accrued. Bhardwaj (2019) highlights the role of technology-integrated platforms in facilitating knowledge exchange and innovation in high-tech firms. Ferdinand and Meyer (2017) define innovation ecosystems as interconnected social, economic, and material networks where actors collaborate, share resources, and coordinate innovation efforts.

High-tech firms[3] clusters function as innovation ecosystems, offering benefits such as labor market pooling, knowledge spillovers, enhanced entrepreneurship, smart specialization, and increased productivity (Gordon and Kourtit, 2020). These clusters foster both competition and cooperation, driving local economic growth, higher wages, and job creation. Innovation ecosystems often take the form of geographically concentrated clusters of interconnected firms and institutions within specific industries or research fields (Yashiro, 2023). A key element is innovation collaboration (Granstrand and Holgersson, 2020), typically coordinated and funded by government agencies.

Innovation ecosystem knowledge spillovers are crucial for regional economic development (Huber, 2012), with Xu et al. (2022) examining their role in driving efficient industrial structures within technological clusters. These studies build on foundational research on knowledge spillovers (Arrow, 1962) and externalities (Glaeser et al., 1992). For firms, technological leadership benefits depend on location, ecosystem uncertainty, and the technology life cycle, while vertical integration's effectiveness in managing uncertainty is shaped by the technology life cycle's strategic impact (Adner and Kapoor, 2010). Raines et al. (2001) highlight the policy relevance of clusters, viewing them as both an analytical tool for economic development and a framework for regional policy interventions. A prevailing perspective sees innovation as driven by clusters of interconnected firms embedded in local economies through production linkages and communication flows (Hart, 2000). Since industrial clustering varies by region and national context (Palacios, 2005), the focus is on identifying factors that drive high-tech firm agglomeration.

The interconnection between agglomeration economies, innovation ecosystems, and high-technology clusters plays a crucial role in shaping regional economic development and firm location decisions. Agglomeration economies – driven by knowledge spillovers, labor market pooling, and input sharing – create environments that attract and sustain high-tech firms (Duranton and Puga, 2004; Rosenthal and Strange, 2004). At the same time, innovation ecosystems function as collaborative networks where firms, research institutions, and government agencies interact to promote technological advancement and economic growth (Granstrand and Holgersson, 2020; Yashiro, 2023). These ecosystems often take the form of high-technology clusters, where firms benefit from spatial proximity to industry peers, facilitating both competition and cooperation that enhance innovation and productivity (Gordon and Kourtit, 2020). Realizing the location preferences of high-tech firms is critical for policymakers, as firm agglomeration patterns

[3] High-tech firms: High-technology firms are innovation-driven, knowledge-based firms that focus on developing and commercializing new technologies. Their strategies emphasize both the creation of technological knowledge (e.g., patents and inventions) and the exploitation of innovation, which involves refining products, expanding markets, and optimizing organizational structures. Successfully integrating both stages enhance their adaptability and competitiveness (Zakrzewska-Bielawska, 2016).

are influenced by factors such as infrastructure, talent availability, market access, and institutional support (Feldman and Kogler, 2010; Asheim et al., 2011). Since high-tech industries tend to cluster in specific regions, identifying the key determinants behind these location choices can provide insights for fostering economic growth and enhancing regional innovation capacity (Audretsch and Belitski, 2017; Faggio et al., 2017).

3. Data and methods

3.1 High-technology industries

As the challenge of defining the high-tech sector stems from the fact that many emerging technologies transcend the conventional boundaries of the sector, it can be seen that it encompasses sectors that rely heavily on scientific and technological advances, as identified by the National Science Foundation, and those that heavily leverage research outcomes for industrial applications, as outlined by Bessant (2003). Moreover, there is a broad consensus to incorporate industries and products demonstrating elevated levels of research and development (R&D) intensity compared to their counterparts, as defined by Eurostat (2013).

This paper is focused on the primary method employed for assessing technological intensity: the sectoral approach[4], which is based on the Statistical Classification of Economic Activities (NACE). This categorization assesses the technological intensity of sectors by measuring R&D (research and development) expenditure relative to value-added, categorizing them as high, medium, or low technology based on their scores. Services are similarly categorized based on the presence of highly skilled personnel. The aggregate of high-tech sectors includes both high-tech manufacturing and knowledge-intensive services, according to Eurostat (2013).

Table 1. High-technology Firms

<table>
<tr><th>NACE Rev. 2
3-digit level</th><th colspan="2">High-technology sectors</th></tr>
<tr><td>210</td><td>Manufacture of basic pharmaceutical products and pharmaceutical preparations</td><td rowspan="2">Manufacturing Sectors</td></tr>
<tr><td>260</td><td>Manufacture of computer, electronic and optical products</td></tr>
<tr><td>590 to 630</td><td>Motion picture, video and television programme production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities</td><td rowspan="2">Knowledge-Intensive Services</td></tr>
<tr><td>720</td><td>Scientific research and development</td></tr>
</table>

Source: Eurostat - Statistics Explained: Glossary: High-tech classification of manufacturing industries by NACE Rev.2.

[4] The sectoral approach relies on the Statistical Classification of Economic Activities (NACE Rev.2). This system assesses the technological intensity of sectors by considering R&D expenditure/value added and categorizes them as high, medium, or low technology based on their scores. Additionally, services are classified based on their knowledge-intensive services (KIS), determined by the number of highly qualified personnel. The high-tech sector encompasses the combined totals of high-tech manufacturing and high-tech knowledge-intensive services (Eurostat, 2013).

Furthermore, high-tech enterprises exhibit traits such as short product and process life cycles, swift adoption of innovations, growing need for skilled personnel, and close collaboration between businesses and research centers at both national and international levels (Zakrzewska-Bielawska, 2016). To analyse that, this paper selected participants based on the criteria that the enterprises are operating in a field recognized as high technology according to the OECD classification (2013) and the sectoral approach of NACE (Rev.2., 2012).

3.2 Study area

Catalonia is a European region located along the western Mediterranean coast, comprising 947 municipalities organized into 42 counties. It has the status of an autonomous community in Spain, in the north-eastern part of the Iberian Peninsula. Catalonia covers an area of 32,108.2 km^2 and has a population of around 8 million people in 2024 (Catalan Statistical Institute - IDESCAT).

This paper is designed with the specific purpose of exploring and analysing the factors determining the entry of high-technology firms into Catalonia. The region's recognized innovative ecosystem profile and its promising development prospects underscore the importance of this investigation. The aim is to carry out an empirical study of the location patterns of high-tech firms across the diverse municipalities comprising Catalonia.

3.3 Data

This paper uses Sistema de Análisis de Balances Ibéricos (henceforth SABI) as the main data source. SABI was compiled by INFORMA D&B and Bureau Van Dijk, with data from the Spanish Mercantile Register. Data from SABI includes detailed information at the firm level such as location, number of employees, legal status, and sales, among others. Data is provided at a 4-digit NACE level, although a 3-digit level is preferred to focus on a limited number of industries. Specifically, will be analysed the location entries between 2010 and 2019 for the high-technology industries described in Table 1. For comparative purposes, we will consider all entries as well, including those not belonging to previous industries, in this case, all entries from non-high-tech industries.

Table 2. Firms entries by year

HT entries	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Manufacturing	31	23	23	24	24	18	28	14	13	13
% in all the HT	8%	5%	5%	5%	5%	4%	5%	3%	3%	5%
Knowledge-Intensive Services	343	405	433	413	427	420	495	431	390	251
% in all the HT	92%	95%	95%	95%	95%	96%	95%	97%	97%	95%
HT Total	**374**	**428**	**456**	**437**	**451**	**438**	**523**	**445**	**403**	**264**
% in all the economy	**5%**	**5%**	**5%**	**5%**	**5%**	**5%**	**5%**	**5%**	**6%**	**5%**
Non-HT	7460	7655	8315	8345	8130	8751	10146	8068	6782	5068
% in all the economy	95%	95%	95%	95%	95%	95%	95%	95%	94%	95%
All industries	7834	8083	8771	8782	8581	9189	10669	8513	7185	5332
	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source: Own elaboration.

Table 2 illustrates the 2010-2019 period showing a pattern that suggests that the trend toward high-tech firms' new entries will continue at a rate of five percent compared to the general panorama of firms' entries, with a slight increase in 2018. Among the entries of high-tech firms, we can see that the absolute majority are among the knowledge-intensive services.

3.4 Econometric methods

Model Specification

We assume that location choices of new firms at local level are affected by various factors. These include the median household income (Carlino and Kerr, 2015; Overman, 2006; Hanson, 2004; Redding and Venables, 2003; and Duranton and Puga, 2003), distance from the capital and the seaside (Hanson, 2004; and Redding and Venables, 2003), education (Faggio et al., 2017; and Moretti, 2012), unemployment rate (Moretti, 2012; Arauzo-Carod et al., 2010; and Hanson, 2004), and population density (Faggio et al., 2017; Carlino and Kerr, 2015; Arauzo-Carod et al., 2010; and Rosenthal and Strange, 2003). Addressing Moran's global index to analyse the correlation of spatial distribution and the degree of clustering and dispersion of the same variable in different areas. The stronger the spatial correlation, the more concentrated the distribution (Tu et al., 2023).

To examine the factors driving high-tech firms' location decisions and their connection to high-tech specialization, we modelled the number of new firms as a function of distinct local characteristics:

$$Firm\ entries_{it} = \beta_0 + \beta_1\ ht\_firms + \beta_2\ estden + \beta_3\ large + \beta_4\ pden + \beta_5\ inc\_hab + \beta_6\ une + \beta_7\ dist\_cpro + \beta_8\ univ + \beta_9\ t\_parks + \beta_{10}\ incub$$

The dependent variable (Y) measures firm entries (*Firm entries*), while independent variables (X) include: Concentration of high-tech existing firms (*ht_firms*) and establishment density (*estden*): captures market concentration, as well as proportion of large firms (*large*), which indicates the presence of large, resource-rich firms (with over than 251 employees); Population density (*pden*): a proxy for urbanization; The median household income per inhabitant (*inc_hab*): reflecting local purchasing power; Unemployment rate (*une*): indicator of labor market dynamics; Distance to province center (*dist_cpro*): measures proximity to urban hubs; Universities (*univ*), Technological parks (*t_parks*) and Business incubators (*incub*): highlight the incentive for entrepreneurship and innovation.

The empirical strategy consists in estimating three different models that share the same set of explanatory variables with different dependent variables ($Firm\ entries_{it}$): non-high-technology firms (NON_HT), high-tech manufacturing firms (HT_MAN) and high-tech knowledge-intensive services (HT_KIS). This strategy allows us to compare the location determinants of the group of firms considered.

Panel data will be used to provide evidence on high-technology firms' location determinants. Panel regressions offer several advantages in empirical analysis. First, they mitigate bias in parameter estimates commonly found in cross-sectional studies by controlling for unobserved time-invariant characteristics within geographical units, thereby enhancing the accuracy of estimations (Hsiao, 2007). Second, panel data models help address potential endogeneity concerns by capturing temporal dynamics and reducing omitted variable bias, leading to more reliable causal inferences (Wooldridge, 2010). These advantages make panel regressions particularly suitable for studying firm location choices and spatial economic dynamics over time (Arauzo-Carod et al., 2024).

Most recent contributions that analyse firms' location factors, and that focus on the characteristics of sites potentially selected by new firms, rely on Count Data Models (CDM) (see Arauzo-Carod et al., 2010, for an extensive review of the empirical literature). Given the extensive family of CDM, selecting the most appropriate specification requires a systematic approach. To discriminate among alternative CDM specifications, we first estimated a baseline model and then selected the best-fitting model based on key goodness-of-fit statistics, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Cameron and Trivedi, 2013). This approach ensures that the chosen model appropriately captures the underlying distribution of the dependent variable while addressing issues such as overdispersion and excess zeros, which are common in count data applications (Hilbe, 2011). Since the number of firm entries in a region is represented by a nonnegative integer (count variable), more specialized estimation techniques are required than ordinary least squares (OLS), making alternative methods better suited for accurate analysis (Long, 1997).

Model Selection

Count Data Models (CDMs) are frequently employed in analysing spatial phenomena regarding the number of occurrences of an event within an area in a fixed period (Mendez-Ortega et al., 2023). These models include the Poisson Model (PM), the Negative Binomial Model (NBM), the Zero-Inflated Poisson Model (ZIPM), and the Zero-Inflated Negative Binomial Model (ZINBM). To determine the most suitable model, we evaluate them using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Cameron and Trivedi, 2013). These metrics ensure that the selected model balances goodness-of-fit with parsimony.

Neighboring impacts are significant in firm location decisions, and failing to account for spatial dependence can lead to biased results. Spatial econometric methods help address these interdependencies, as firm locations are influenced by both local and neighboring characteristics (Anselin, 1988; Arauzo-Carod et al., 2024). To capture these effects, spatial lag variables are included in the model, reflecting the average attributes of surrounding municipalities. This approach allows measurement of spillover effects, such as how population density, income levels, and firm sizes in neighboring areas impact high-tech firm entry rates.

To model spatial dependence, we employ a spatial weights matrix (W), which defines the spatial structure of relationships between municipalities. The construction of Spatial Weights Matrix (SWM) is the key to spatial econometric models (Zhu et al., 2022), since SWMs are intended to capture the interactions among spatial units (Kostov, 2010). For this study, we use an inverse distance matrix, where weights decrease as the geographical distance between municipalities increases.

Before estimating the models, we test for spatial dependence using Moran's I statistic, which quantifies the degree of spatial autocorrelation. A significant Moran's I value would indicate that firm entries are not randomly distributed but instead exhibit clustering or dispersion patterns (Tu et al., 2023; Fotheringham et al., 1998).

Given the count nature of the dependent variable and the inclusion of spatial lags, the estimation strategy is designed to ensure a comprehensive analysis of the determinants of firm entries while capturing spatial dependencies. For this, baseline models are estimated using Poisson and Negative Binomial Models. These models do not include spatial terms and serve as a foundation for understanding the primary relationships between the explanatory variables and firm entries. Then, spatial lag models are employed to account for spatial dependencies. Specifically, spatially lagged Poisson Models (SLPM) and spatially lagged Negative Binomial Models (SLNBM) are estimated to examine how firm entries in neighboring regions influence those in a given region. And, finally, a model comparison is conducted to determine the best-fit model.

To ensure the reliability and validity of the results, a series of robustness checks were conducted. First, alternative spatial weights matrices were employed. The analysis was repeated using different definitions of spatial relationships, specifically contiguity-based and k-nearest neighbor spatial weights matrices. This approach was designed to verify whether the findings remained consistent across various specifications of spatial dependence, ensuring that the choice of spatial weights did not unduly influence the results. Second, zero-inflated models were tested to account for the potential overrepresentation of zero firm entries in the dataset. Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) models were employed to address regions with no firm entries during the study period. These models provided a more nuanced understanding of the distribution of firm entries by accommodating the unique characteristics of zero-heavy data. Finally, this analysis was performed to identify sector-specific patterns and separate estimations were conducted for high-tech manufacturing, high-tech knowledge-intensive services, and non-high-tech firms. This approach allowed for a deeper examination of the unique dynamics influencing each group of firms and ensured that the results accurately reflected the characteristics of these distinct sectors.

4. Results

This paper highlights the influence of spatial factors on firm location patterns in Catalonia, emphasizing the interaction between geography, regional spillovers, and sectoral dynamics. The findings provide valuable insights for fostering innovation, reducing regional disparities, and promoting sustainable economic growth.

The model involves negative binomial regressions that accounts for overdispersion in the data, with the baseline estimation in Table 3 without spatial lags, Table 4 extended estimation with spatial lags, Table 5 with sector-level results without spatial lags and Table 6 with sector-level results with spatial lags:

Table 3. Baseline Estimation			
Variable	**HT_MAN**	**HT_KIS**	**NON_HT**
ht_firms	-.0015	-.0007***	-.0003***
	(0.0008)	(.0002)	(.0000)
pden	.0002**	.0002***	-.0001***
	(0.0001)	(.0000)	(.0000)
inc_hab	.0002***	.0001***	-.0000***
	(0.0001)	(8.51e-06)	(4.33e-06)
une	.0000***	.0000***	5.22e-06***
	(0.0000)	(1.87e-06)	(6.20e-07)
dist_cpro	-.0148*	-.0105***	-.0182***
	(0.0069)	(.0026)	(.0017)
estden	.0000	.0002	.0023***
	(0.0000)	(.0001)	(.0002)
pct_est_large	.0220**	.0059	-.0032**
	(0.0069)	(.0037)	(.0011)
univ	-.3803	.4451	-1.5297*
	(0.7612)	(.4795)	(.6680)
t_parks	.9304	.6789	-1.3174**
	(0.5086)	(.3574)	(.4474)
incub	.6144*	1.2547***	.9095***
	(0.2976)	(.1638)	(.1819)
_cons	-6.5665***	-3.8856***	1.3542***
	(0.5185)	(.1680)	(.1228)
/lnalpha	.3639	-.0221	.6380***
	(0.2963)	(.1271)	(.0503)
alpha	1.4389	.9782	1.8928
	.4264	.1243	.0951
N	9452	9452	9452

The dependent variable is the number of entries.
**** Significance at 1%. ** Significance at 5%. * Significance at 10%.*

Table 4. Extended Estimation with Spatial Lags			
Variable	**HT_MAN**	**HT_KIS**	**NON_HT**
ht_firms	-.0014	-.0007***	-.0020***
	(.0008)	(.0002)	(.0000)
wht_firms	.0063	-.0013	-.0014**
	(.0056)	(.0019)	(.0005)
pden	.0000	.0001**	-.0001**
	(.0001)	(.0000)	(.0000)
wpden	.0002	-.0000	-.0000
	(.0001)	(.0001)	(.0001)
inc_hab	.0001**	.0001***	.0000***
	(.0000)	(9.72e-06)	(5.15e-06)
winc_hab	.0001***	.0001***	-.0001***
	(.0000)	(.0000)	(6.54e-06)
une	.0000	.0000***	1.93e-06**

	(.0000)	(2.36e-06)	(6.93e-07)
wune	.0002**	.0001***	.0000***
	(.0001)	(.0000)	(5.22e-06)
estden	.0000	.0001	.0023***
	(.0000)	(.0001)	(.0002)
westden	-.0006**	-.0000	.0004**
	(.0002)	(.0001)	(.0001)
pct_est_large	.0209**	.0060	-.0024*
	(.0070)	(.0035)	(.0012)
wlarge	.01798	-.0097	-.0143***
	(.0164)	(.0073)	(.0023)
dist_cpro	-.0012	-.0060*	-.0200***
	(.0074)	(.0026)	(.0019)
univ	.1892	.6448	-2.7508***
	(.6803)	(.4325)	(.6592)
t_parks	.9320*	.7036*	-1.9791***
	(.4699)	(.3132)	(.4249)
incub	.6659*	1.3874***	.8521***
	(.2858)	(.1461)	(.1859)
cons	-7.8461***	-4.4394***	1.5491***
	(.6099)	(.1916)	(.1411)
/lnalpha	-.1799	-.2980*	.6226***
	(.3615)	(.1426)	(.0517)
alpha	.8354	.7423	1.8638
	(.3020)	(.1059)	(.0964)
N	9452	9452	9452

The dependent variable is the number of entries.
**** Significance at 1%.   ** Significance at 5%.   * Significance at 10%.*

Table 5. Baseline Estimation of Disaggregated Sectors

Variable	COD_210	COD_260	COD_590	COD_600	COD_610	COD_620	COD_630	COD_720
ht_firms	-.0016	-.0014	-.0003	-.0008	-.0012*	-.0009***	-.0009	.0001
	(.0021)	(.0009)	(.0004)	(.0015)	(.0006)	(.0002)	(.0005	(.0006)
pden	.0001*	.0002*	.0002**	.0001	.0001*	.0001**	.0001	.0001*
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
inc_hab	.0002***	.0002***	.0001***	.0002*	.0002***	.0001***	.0001***	.0002***
	(.0001)	(.0000)	(.0000)	(.0001)	(.0000)	(.0000)	(.0000)	(.0000)
une	.0000	.0000**	.0000**	.0001*	.0000**	.0000***	.0000***	.0000*
	(.0000)	(.0000)	(4.51e-06)	(.0000)	(7.29e-06)	(2.32e-06)	(7.00e-06)	(8.11e-06)
dist_cpro	-.0470*	-.0109	-.01430*	-.0120	.0016	-.0083**	-.0085	-.0353***
	(.0208)	(.0075)	(.0060)	(.0169)	(.0048)	(.0031)	(.0072)	(.0094)
estden	.0000	.0003*	.0003**	.0003	.0005***	.0007***	.0004**	.0002
	(.0001)	(.0001)	(.0001)	(.0002)	(.0001)	(.0001)	(.0001)	(.0001)
pct_est_large	.0162	.0244**	.0163*	.0213	.0047	.0101*	.0157	.0186*
	(.0132)	(.0079)	(.0070)	(.0176)	(.0082)	(.0045)	(.0089)	(.0084)
_cons	-8.2450***	-6.8064***	-5.9853***	-8.3822***	-6.4177***	-4.3860***	-6.6592***	-6.0383***
	(1.1834)	(.5677)	(.4096)	(1.2381)	(.3995)	(.2083)	(.5243)	(.5503)
/lnalpha	-14.2208	.9018***	.5321*	1.5846***	.8348***	.4429***	.9573***	.7802**
	(790.9073)	(.2451)	(.2239)	(.4777)	(.1969)	(.1151)	(.2394)	(.2615)
alpha	6.68e-07	2.4640	1.7025	4.8775	2.3043	1.5571	2.6047	2.1819
	(.0005)	(.6039)	(.3812)	(2.3299)	(.4537)	(.1792)	(.6236)	(.5706)
N	9452	9452	9452	9452	9452	9452	9452	9452

*The dependent variable is the number of entries. *** Significance at 1%. ** Significance at 5%. * Significance at 10%.*

Table 6. Extended Estimation with Spatial Lags of Disaggregated Sectors

Variable	COD_210	COD_260	COD_590	COD_600	COD_610	COD_620	COD_630	COD_720
ht_firms	-.001802	-.001428	-.000330	-.001436	-.001152	-.000891***	-.001180*	2.19e-06
	(.002032)	(.000891)	(.000357)	(.001406)	(.000602)	(.000190)	(.000553)	(.000624)
wht_firms	.003001	.008008	-.002892	-.045222	-.001313	-.000929	.019798*	-.004315
	(.0129)	(.0063)	(.0049)	(.0318)	(.0057)	(.0024)	(.0091)	(.0053)

pden	.0001	.0000	.0001	-.0000	.0002*	.0001*	.0001	.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
wpden	-1.01e-06	.0001	-.0001	.0002	-.0003	-.0001	-.0001	-.0000
	(.0002)	(.0001)	(.0001)	(.0002)	(.0002)	(.0001)	(.0002)	(.0001)
inc_hab	.0001	.0001**	.0001***	.0001	.0002***	.0001***	.0001***	.0001**
	(.0001)	(.0000)	(.0000)	(.0001)	(.0000)	(.0000)	(.0000)	(.0000)
winc_hab	.0002*	.0001***	.0001**	.0000	.0000	.0001**	.0001	.0001***
	(.0001)	(.0000)	(.0000)	(.0001)	(.0000)	(.0000)	(.0000)	(.0000)
une	.0001	.0000	.0000	.0001**	.0000	8.76e-06**	.0000**	.0000
	(.0000)	(.0000)	(5.71e-06)	(.0000)	(9.03e-06)	(2.99e-06)	(.0000)	(9.20e-06)
wune	.0000	.0003**	.0001	-.0002	.0001	.0001***	-.0001	.0001
	(.0001)	(.0001)	(.0001)	(.0002)	(.0001)	(.0000)	(.0001)	(.0001)
estden	.0000	.0002	.0002*	.0000	.0004***	.0006***	.0004**	.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
westden	-.0002	-.0007**	.0001	.0016	.0000	-.0000	-.0005	.0001
	(.0004)	(.0002)	(.0002)	(.0011)	(.0002)	(.0001)	(.0003)	(.0002)
pct_est_large	.0161	.0261**	.0162*	.0307*	.0070	.0096*	.0138	.0165
	(.0150)	(.0081)	(.0073)	(.0120)	(.0083)	(.0045)	(.0095)	(.0092)
wlarge	.0310	.0003	-.0217	-.0048	-.0253	-.0015	.0123	-.0358
	(.0311)	(.0191)	(.0162)	(.0362)	(.0184)	(.0094)	(.0208)	(.0207)
dist_cpro	-.0404	.0001	-.0099	-.0261	.0022	-.0042	-.0076	-.0299**
	(.0244)	(.0082)	(.0063)	(.0170)	(.0052)	(.0033)	(.0078)	(.0104)
cons	-9.8558***	-8.0374***	-6.5773***	-7.8336***	-6.6905***	-4.8549***	-6.9202***	-6.7943***
	(1.5844)	(.6650)	(.4549)	(1.1129)	(.4543)	(.2417)	(.5730)	(.6013)
/lnalpha	-14.8075	.6144*	.3515	.3453	.7634***	.3286**	.8758***	.5119
	(928.531)	(.2832)	(.2526)	(1.1277)	(.2059)	(.1194)	(.2489)	(.3194)
alpha	3.72e-07	1.8485	1.4211	1.4124	2.1455	1.3891	2.4009	1.6685
	(.0004)	(.5235)	(.3590)	(1.5927)	(.4417)	(.1659)	(.5975)	(.5328)
N	9452	9452	9452	9452	9452	9452	9452	9452

*The dependent variable is the number of entries. *** Significance at 1%. ** Significance at 5%. * Significance at 10%.*

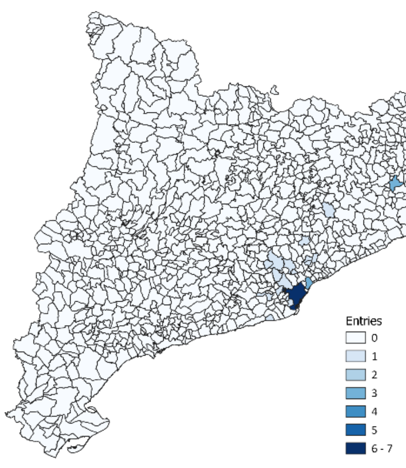
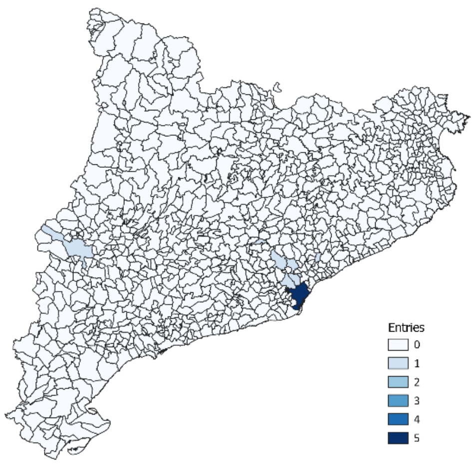
4.1 Determinants of Firm Entries in High-Tech and Non-High-Tech Sectors

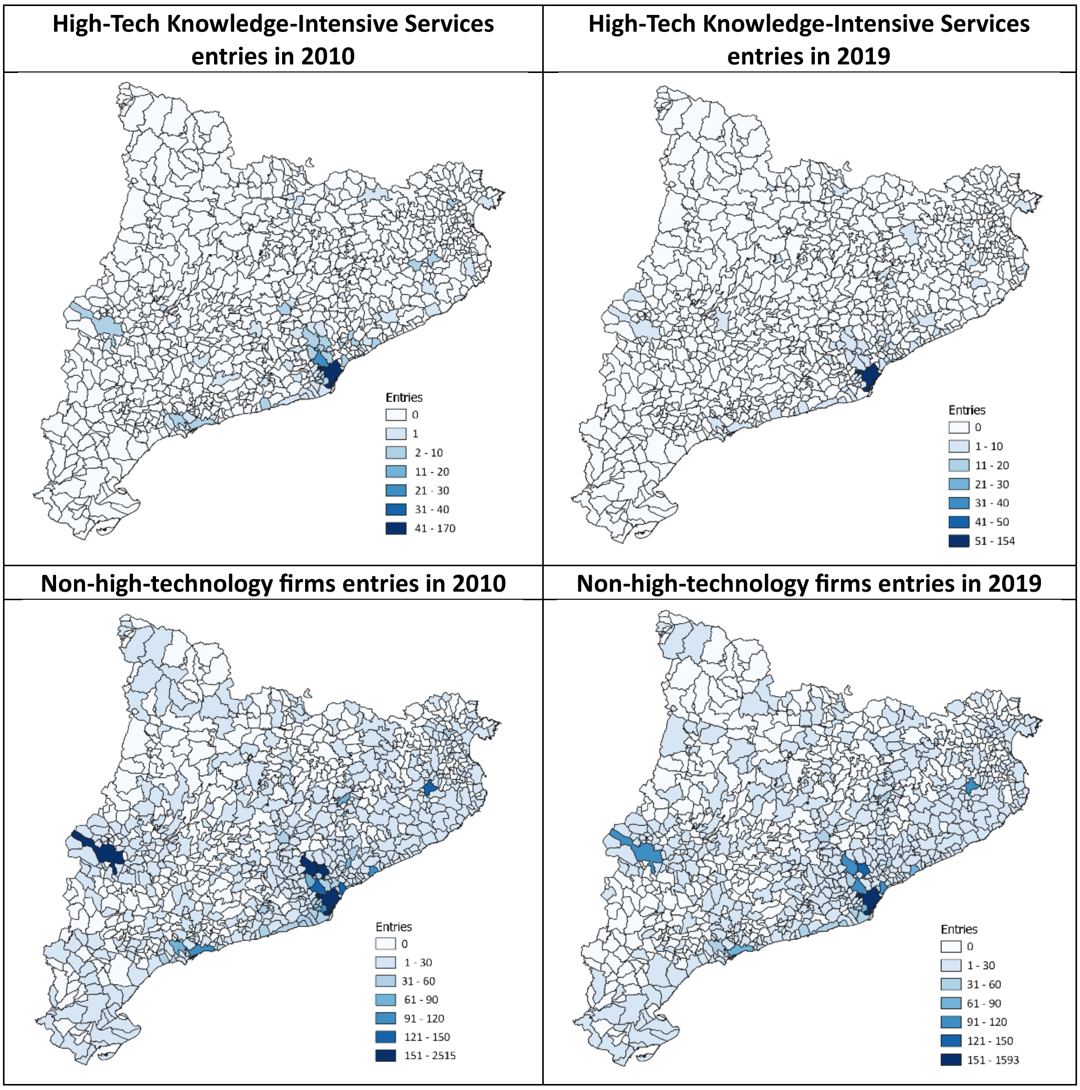
The analysis reveals significant differences in the determinants of firm entries across high-tech manufacturing (HT_MAN), high-tech knowledge-intensive services (HT_KIS), and non-high-tech (NON_HT) sectors.

The location of high-tech manufacturing (HT_MAN) and high-tech knowledge-intensive services (HT_KIS) firms is influenced by distinct spatial and economic factors. Intra-sectoral competition limits firm entries, with significant competitive spillovers in services but minimal in manufacturing. Urban areas attract high-tech firms due to high population density, though neighboring regions' density has little effect. Higher income levels and regional income spillovers foster firm agglomeration, while local and regional unemployment positively influence entries by expanding the skilled labor pool. Proximity to provincial capitals is particularly important for manufacturing, emphasizing the role of urban infrastructure. Large establishments support high-tech manufacturing clusters, while universities and technological parks drive firm entries, especially in knowledge-intensive services. Business incubators universally enhance entrepreneurship and innovation across sectors.

The location of non-high-tech firms (NON_HT) follows dynamics that contrast with high-tech sectors. High-tech firms in neighboring regions create competitive pressure, discouraging non-high-tech entries. These firms prefer less dense areas, as population density negatively influences their location choices, with minimal spillover effects. Higher local and regional income levels deter non-high-tech firms, as they tend to concentrate in less affluent markets. While local unemployment attracts firm entries due to labor availability, regional spillovers are weaker. Proximity to provincial capitals plays a role but is less influential than for high-tech firms. Establishment density supports non-high-tech agglomeration, extending across regional boundaries, but large establishments create resource competition, negatively affecting entries. Universities and technological parks further discourage non-high-tech firms, as these institutions mainly benefit high-tech sectors. However, business incubators have a positive impact, fostering entrepreneurship and firm growth in non-high-tech industries.

Figure 1. Firm entries by each sector (2010 versus 2019)

High-Tech Manufacturing entries in 2010	High-Tech Manufacturing entries in 2019
	



Source: Own elaboration.

High-tech manufacturing firm entries show moderate clustering, primarily in industrial regions, especially around Barcelona and key transportation corridors. Their location patterns suggest sensitivity to infrastructure, such as highways and industrial parks, as well as proximity to suppliers and skilled labor pools. Compared to high-tech knowledge-intensive services, clustering is less pronounced, reflecting the broader geographic distribution and diverse nature of manufacturing industries.

The 2019 map of high-tech knowledge-intensive services firm entries reveals strong clustering, mainly around Barcelona and Tarragona, with smaller clusters in Girona and Lleida. This pattern suggests that these firms thrive in urban centers with regional connectivity, benefiting from skilled labor availability, proximity to research institutions, and infrastructure essential for innovation-driven industries.

On the other hand, non-high-tech firm entries are more dispersed across Catalonia, including rural and semi-urban areas, forming smaller, scattered clusters. This distribution reflects their reliance on cost advantages and local markets, with less dependence on urban innovation ecosystems. However, the presence of urban clusters suggests competition and potential spillover benefits from high-tech industries.

5. Conclusions

This paper provides a comprehensive analysis of the geographical determinants of high-tech and non-high-tech firm entries in Catalonia, revealing distinct location preferences across high-tech manufacturing, high-tech knowledge-intensive services, and non-high-tech sectors.

The findings confirm that high-tech firms cluster in urban areas with high population density, while non-high-tech firms prefer less dense regions, aligning with the well-established role of urbanization in fostering innovation and knowledge spillovers (Carlino and Kerr, 2015; Duranton and Puga, 2004). This is particularly evident in high-tech knowledge-intensive services, which thrive in innovation ecosystems supported by research institutions, skilled labor, and infrastructure (Audretsch and Belitski, 2017).

Income levels emerge as a critical driver of high-tech firm entries, both locally and through regional spillovers, reinforcing the idea that affluent regions enhance firm agglomeration through demand, infrastructure, and financing opportunities (Faggio et al., 2021; Feldman and Kogler, 2010). In contrast, non-high-tech firms avoid high-income areas, reflecting their preference for cost-competitive locations and less economically developed markets (Baldwin et al., 2003).

The results also indicate that higher unemployment rates attract firm entries across all sectors, suggesting that labor availability is a key determinant. Additionally, spatial spillovers of unemployment positively influence high-tech firm entries, emphasizing the role of regional labor pools in shaping firm location choices (Arauzo-Carod et al., 2010; Holl, 2004).

Proximity to provincial capitals is a significant determinant, especially for high-tech manufacturing, confirming the importance of urban hubs for infrastructure, connectivity, and access to resources (Scott, 2006; Fujita et al., 1999). Similarly, local establishment density fosters firm entries, particularly in knowledge-intensive services, which benefit from agglomeration economies and localized knowledge spillovers (Asheim et al., 2011; Rosenthal and Strange, 2003). However, competition from neighboring regions negatively impacts high-tech manufacturing, limiting clustering effects beyond certain thresholds.

Finally, large establishments play a dual role in firm location decisions: they support clustering in high-tech manufacturing by acting as anchors for industrial activity, yet they discourage non-high-tech firms, likely due to resource competition and crowding-out effects (Clarysse et al., 2005; Colombo and Delmastro, 2002). These findings underscore the need for targeted regional policies that consider sector-specific location determinants to enhance Catalonia's role as a hub for technological innovation and economic growth.

This study contributes to the literature on industrial location by integrating spatial econometrics with count data models to analyse firm entry determinants. By distinguishing between high-tech and non-high-tech sectors and incorporating spatial spillovers, the study provides a more nuanced understanding of the geographical dynamics of firm entries. Practically, the findings offer valuable insights for designing evidence-based policies aimed at fostering regional innovation and balanced economic development. The role of spatial spillovers highlights the need for coordinated actions across municipalities to maximize the benefits of regional synergies.

While this paper provides significant insights, it is not without limitations. First, the analysis is limited to Catalonia, and comparisons with other areas could provide a broader perspective. Second, the paper focuses on firm entries but does not explore their subsequent growth or survival. Future research could address these gaps by analysing temporal dynamics, including longitudinal data, and expanding the geographic scope of analysis.

Finally, integrating environmental and sustainability factors into the analysis could shed light on how green technologies and policies influence firm location decisions. Such research would contribute to the broader discourse on sustainable regional development and the transition to a green economy.

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