Check for updates

Growth and Change

WILEY

growth and change

ORIGINAL ARTICLE OPEN ACCESS

Innovation Ecosystems in Catalonia: Exploring Location Patterns of High-Tech Firms

Keli Araujo-Rocha[1,2] | Josep-Maria Arauzo-Carod[1,2]

[1]Departament d'Economia & ECO-SOS, Universitat Rovira i Virgili, Reus, Catalonia, Spain | [2]Universitat Rovira i Virgili, Institut Universitari de Recerca en Sostenibilitat, Canvi Climàtic i Transició Energètica, IU-RESCAT, Vila-seca, Catalonia, Spain

Correspondence: Keli Araujo-Rocha (keli.dearaujo@urv.cat)

Received: 20 August 2025 | **Revised:** 17 March 2026 | **Accepted:** 28 March 2026

Keywords: clusters | firm location | high-tech industries | municipalities

ABSTRACT

This paper analyses high-tech firms' location determinants in Catalonia, Spain, using 2010–2019 firm data, and spatial models to assess spillover and industry-specific factor effects. Results show that high-tech firms, especially in services, are clustered in busy, wealthy cities with strong innovation hubs, while non-high-tech firms prefer lower-density and lower-cost areas. Income levels and nearby high-tech activity influence firm location, highlighting the inter-municipal dynamics. Labour availability, universities, and innovation hubs also play relevant roles, though effects vary by sector. This paper contributes to firm location literature by integrating innovation ecosystem components (e.g., universities, incubators, and technology parks) into a spatial econometric framework that captures inter-municipal spillovers. These findings offer new insights into the literature on firm location choices and provide policymakers tools to promote innovation and regional balance.

JEL Classification: O30, R12, R30

1 | Introduction

In regional economics, considerable attention has been devoted to the spatial distribution of industries and the factors influencing firm location. High-tech firm entries, in particular, shed light on the innovation geography, as these firms tend to concentrate in areas with favourable economic and technological conditions (Arauzo-Carod et al. 2024, 2010; Jofre-Monseny 2008). Analysing the location choices of high-tech firms is therefore essential for understand spatial concentration and the clustering of technology-oriented industries.

Although many studies highlight the strategic importance of high-tech clusters for regional growth (Segarra-Blasco et al. 2018), questions remain about the spatial factors driving their formation. Previous research shows that high-tech industries display distinct locational behaviours compared to non-tech sectors, emphasising the relevance of infrastructure, agglomeration economies, policy interventions, and knowledge spillovers in shaping firm location decisions (Behrens 2016; Jofre-Monseny et al. 2014; Pe'er and Keil 2013; Arauzo-Carod and Manjón-Antolín 2012; Zhang et al. 2013). However, much of this literature examines these drivers separately or relies on descriptive spatial tools without explicitly modelling inter-municipal spillovers. This paper addresses this gap by incorporating these elements into a spatial framework that captures cross-municipality spillovers and their joint influence on high-tech firm location.

This paper focuses on Catalonia, a dynamic NUTS-2 region in Northeast Spain and one of country's leading innovation hubs. According to the Tech Hubs Overview 2024 (Mobile World Capital Barcelona Barcelona City Council's International Economic Promotion and ACCIÓ Catalonia Trade & Investment 2024), Catalonia recorded the fastest growth in digital hubs in Spain, reaching 140 hubs in 2023 and generating over €2.5 billion in economic activity and more than 26,000 jobs. This rapid technological expansion, supported by strong infrastructure and public policies, makes Catalonia an ideal case for

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2026 The Author(s). *Growth and Change* published by Wiley Periodicals LLC.

investigating how innovation ecosystems influence firm entry patterns.

Catalonia has implemented several initiatives to strengthen competitiveness and attract skilled workers, including the Catalonia Digital Innovation Hub (G and eneralitat de Catalunya 2022). Despite this progress, the factors shaping high-tech firm location choices remain insufficiently explored. This paper therefore analyses how spatial spillovers, local economic conditions, and industry-specific characteristics drive high-tech firm entry.

The geographical concentration of high-tech firms is influenced by both local advantages and broader regional dynamics. Firms respond not only to conditions within a municipality but also by nearby areas, as spatial spillovers affect industrial performance and attractiveness. This paper examines these effects by comparing high-tech and non-high-tech firm entries and analysing the mechanisms behind technological clustering in Catalonia. Expanding knowledge on this topic contributes to the literature on regional economic development, spatial economics, and innovation-driven growth (Galaso and Kovářík 2021; Medina et al. 2020). By exploring innovation ecosystems, the paper identifies the spatial determinants shaping high-tech firm location and their implications for resource allocation, investment attraction, and talent retention. It integrates spatial and industry-specific perspectives within a unified analytical framework and provides evidence for targeted policymaking, fostering regional innovation and balanced economic development. Ultimately, it offers policy insights to support less developed areas, promote sustainable technologies, and strengthen competitiveness through well-functioning innovation clusters.

High-technology firms are typically more likely to locate in urbanised core areas that offer access to infrastructure, skilled labour and innovation networks (Cao et al. 2018; Carlino and Kerr 2015). Innovative clusters further enhance growth opportunities (Doloreux and Shearmur 2023; Tu et al. 2023; Cheng et al. 2011). Universities (Thomas et al. 2021; Audretsch and Lehmann 2005), technology parks (Segarra-Blasco et al. 2018; Squicciarini 2008; Phan et al. 2005) and business incubators (Ratinho and Henriques 2010; Aernoudt 2004) also contribute to favourable innovation environments by fostering knowledge spillovers, research collaboration, and entrepreneurial support (Clarysse et al. 2005; Colombo and Delmastro 2002). Building on this literature, this paper integrates these elements within a spatial-econometric framework that explicitly captures cross-municipal spillovers in firm location decisions.

To provide empirical evidence, this paper employs firm-level data from the Mercantile Register and apply count data models and spatial econometric techniques to analyse firm location determinants across Catalan municipalities from 2010 to 2019. It is guided by the following research question: "How do spatial asymmetries, industry-specific characteristics, and local economic conditions influence high-tech firm location choices in Catalonia?".

Beyond addressing the central research question, this paper provides a more comprehensive understanding of the factors shaping the spatial configuration of high-tech firms across Catalonia. In particular, the analysis explores the role of location-specific advantages (such as skilled labour, R&D infrastructure, and agglomeration economies) in explaining the concentration of high-tech firms, especially around Barcelona, as well as how knowledge-intensive local characteristics influence high-tech firm entry (Maddah et al. 2023; Méndez-Ortega and Arauzo-Carod 2020).

Our findings suggest that high-tech firms are predominantly attracted to dense urban environments, whereas non-high-tech firms exhibit a more balanced spatial distribution. While most high-tech firms concentrate in the Barcelona metropolitan area, smaller innovative hubs also attract such firms. Spatial spillovers significantly influence these patterns, providing policy insights for fostering innovation clusters and promoting balanced regional development.

The paper structure is as follows: Section 2 reviews the literature on innovation ecosystems and firm location. Section 3 describes the dataset and empirical strategy. Section 4 presents the results, and Section 5 concludes with policy implications.

2 | Literature Review

The term "agglomeration economies" (Marshall 1890) addresses the benefits arising from industry clustering, primarily encapsulated in the positive externalities of agglomeration, acting as a catalyst for economic growth, and has evolved a great deal over time with Weber (1909), Schumpeter (1934), and Krugman (1991) contributions about firm clustering and the consequent decreased transaction costs, heightened flexibility and optimal information flows.

Duranton and Puga (2004) classify urban agglomeration economies into three key mechanisms: sharing (infrastructure, suppliers, and skilled labour), matching (better alignment between firms, workers, and partners), and learning (facilitating innovation and knowledge diffusion). Several authors have increasingly associated agglomeration economies with innovation-oriented structures, including Jacobs (1969), Glaeser et al. (1992) (indirectly) and Nylund and Cohen (2017) (directly), who have linked agglomeration dynamics to urban ecosystems and the associated economic and innovation benefits. More recently, Bhardwaj (2019) highlights the role of technology-integrated platforms in facilitating knowledge exchange and innovation in high-tech firms, while Ferdinand and Meyer (2017) define innovation ecosystems as interconnected social, economic and material networks through which actors collaborate, share resources and coordinate innovation efforts. Although location literature has recognised the role played by agglomeration economies (see, among others, Duranton and Puga 2004), only a few studies have explicitly analysed their interaction with innovation systems and cross-municipality spillovers, a gap that this paper tries to bridge.

In this context, high-technology firm[1] clusters emerge as a key intermediary, translating agglomeration advantages into structured innovation dynamics. High-tech clusters function as innovation ecosystems by combining labour market pooling, knowledge spillovers, entrepreneurial activity, and smart

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

specialisation, thereby increasing productivity and regional growth (Gordon and Kourtit 2020). These clusters promote both competition and cooperation, driving local economic growth, higher wages, and job creation. Innovation ecosystems are often geographically concentrated clusters of interconnected firms and institutions within specific industries or research fields (Yashiro 2023). A key element is collaboration in innovation (Granstrand and Holgersson 2020), typically coordinated and funded by government agencies trying to improve firms' productivity already located in the area and attract new firms. Innovation ecosystem knowledge spillovers are crucial for regional economic development (Huber 2012) and for the efficient development of industrial structures and firm entries within technological clusters (Xu et al. 2022; Arauzo-Carod 2021).

From a conceptual point of view, innovation ecosystems are universally understood as dynamic and evolving configurations of actors, activities, artifacts, and institutional arrangements, linked by both complementary and competitive relationships that affect innovative performance (Granstrand and Holgersson 2020). They also encompass loosely connected networks of firms and organisations that jointly develop capabilities together and share technological knowledge around common domains through collaborative and co-evolutionary processes (Nambisan and Baron 2013). Recent studies further emphasise their multilevel nature, highlighting how firms, universities, intermediaries, and public institutions collectively create, exchange, and apply ideas and technologies, reinforcing the ecosystem's capacity for continuous innovation (Spinazzola et al. 2025; Serrano-Ruiz et al. 2025; Secundo et al. 2025).

Taken together, high-technology clusters represent the spatial manifestation of innovation ecosystems, in which agglomeration economies provide the underlying externalities while ecosystem coordination mechanisms turn proximity into sustained innovation. This interaction plays a decisive role in firm location decisions and supports regional competitiveness strategies. While agglomeration effects provide fertile ground through knowledge flows, skilled labour, and shared suppliers (Duranton and Puga 2004; Rosenthal and Strange 2004), innovation ecosystems organise these resources into collaborative frameworks that foster technological development and regional growth (Yashiro 2023; Granstrand and Holgersson 2020). These ecosystems often take the form of high-technology clusters, where spatial proximity enables firms to leverage both competitive and cooperative advantages, driving higher innovation output and efficiency (Gordon and Kourtit 2020). Identifying the factors that attract high-tech firms to specific locations is therefore a key task for policymakers, who must consider infrastructure, skilled labour availability, market connections, and institutional strength (Asheim et al. 2011; Feldman and Kogler 2010) when designing strategies to support innovation-driven development (Audretsch and Belitski 2017; Faggio et al. 2017).

Based on previous literature, it is possible to infer two hypotheses:

Hypothesis 1. *The high-tech firms' concentration across Catalonia—particularly in and around Barcelona—is driven by location-specific advantages such as a skilled workforce, R&D infrastructure, and agglomeration economies.*

Hypothesis 2. *While common location factors affect all industries, knowledge-intensive local characteristics have a stronger effect on high-tech firm entry.*

These hypotheses are grounded in the role of agglomeration economies (Maddah et al. 2023; Méndez-Ortega and Arauzo-Carod 2020) in terms of the way in which firms in knowledge-intensive industries benefit from spatial proximity to skilled workforce and research institutions. Concretely, literature provides extensive evidence of this clustering pattern in urban cores (Arauzo-Carod 2021), where knowledge spillovers and network opportunities are strongest. Conversely, evidence from location analyses indicates that non-high-tech firms tend to respond more strongly to cost-related factors, such as land prices, leading them to locate in less dense and more affordable areas in view of their lower requirements of proximity to core areas where knowledge is generated (Asheim et al. 2011; Feldman and Kogler 2010).

Furthermore, prior research suggests that knowledge-intensive industries are more dependent on localised innovation assets than other sectors, but this also depends on local specialisation. The literature on differentiated knowledge bases (Asheim et al. 2011) and knowledge spillovers (Andersson and Hellerstedt 2009; Audretsch and Lehmann 2005) highlights that high-tech firms rely more heavily on proximity to universities, research institutions, and specialised labour markets, although that proximity is shaped by availability and quality of local transport infrastructures. Empirical evidence from high-tech clusters (Wei et al. 2016; Arbia et al. 2012; Moriset 2003) confirms that these firms tend to respond more strongly to innovation-related local attributes, whereas non-high-tech firms tend to be more sensitive to cost and market-access factors (Feldman and Kogler 2010; Rosenthal et al. 2003).

3 | Data and Methods

3.1 | High-Technology Industries

Defining the high-tech sector is challenging because many emerging technologies transcend conventional sectorial boundaries. Therefore, this paper focuses on sectors relying heavily on scientific and technological advances identified by the National Science Foundation, and those leveraging research outcomes for industrial applications (Bessant 2003). Accordingly, this paper departs from a sectoral approach to identify technological intensity, using the Statistical Classification of Economic Activities (NACE). This categorisation assesses the manufacturing industries' technological intensity (see Table 1) by measuring R&D expenditure relative to value-added, classifying them as high, medium, or low technology based on their scores. Services are similarly categorised based on the highly skilled personnel. Therefore, it explores high-tech sectors including both high-tech manufacturing and knowledge-intensive services (Eurostat 2013).

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

3.2 | Study Area

Located along Europe's western Mediterranean coast, Catalonia is an autonomous Spanish community in the Northeastern Iberian Peninsula. It includes 947 municipalities within 42 counties, covers 32,108.2 km^2 and has a population nearing 8 million (2024). This paper empirically examines the factors influencing high-tech firm entry in Catalonia, considering its innovation ecosystem and growth potential.

3.3 | Data

This paper uses *Sistema de Análisis de Balances Ibéricos* (henceforth SABI) as the main data source regarding the dependent variable (i.e., number of firm entries at municipal level). SABI was compiled by INFORMA D&B and Bureau Van Dijk, with data from the Spanish Mercantile Register. SABI provides firm-level information including location, number of employees, legal status, and sales. Although SABI supplies firm data at the 4-digit NACE level, a 3-digit level is preferred to focus on a limited number of industries. We consider entries between 2010 and 2019 to avoid COVID-19 related bias. For comparative purposes, we consider all entries (i.e., including those belonging to non-high-tech industries). As for the independent variables, these are obtained from the Catalan Statistical Institute (IDESCAT).

Table 2 illustrates that, between 2010 and 2019, high-tech firm formation in Catalonia was overwhelmingly driven by knowledge-intensive services, which accounted for 92%–97% of high-tech entries. High-tech manufacturing remained a small share, at just 3%–8%. High-tech firms overall represented 5%–6% of all new entries each year, while non-high-tech firms consistently dominated, with 94%–95%. Notably, non-high-tech firm entries peaked in 2016 but saw a marked decline by 2019. A similar drop was observed in knowledge-intensive services, following years of robust growth, signalling a broader slowdown in firm creation toward the decade's end.

Figure 1 compares the spatial patterns of firm entries across Catalonia's high-tech manufacturing, knowledge-intensive services, and non-high-tech sectors between 2010 and 2019. The maps highlight a marked increase in entries for knowledge-intensive services, especially around the Barcelona metropolitan area. High-tech manufacturing remains relatively limited and clustered, with only minor changes over time. In contrast, non-high-tech firms, while more widely distributed, exhibit a slight decline in more peripheral municipalities. These trends

TABLE 1 | High-technology industries.

NACE rev. 2 3-Digit level	High-technology sectors	
210	Manufacture of basic pharmaceutical products and pharmaceutical preparations	Manufacturing sectors
260	Manufacture of computer, electronic and optical products	
590	Motion picture, video and television programme production, sound recording and music publishing activities	Knowledge-intensive services
600	Programming and broadcasting activities	
610	Telecommunications	
620	Computer programming, consultancy and related activitie	
630	Information service activities	
720	Scientific research and development	

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

TABLE 2 | Firm entries by year.

Industry	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
HT manufacturing (a)	31	23	23	24	24	18	28	14	13	13
% In all HT	8%	5%	5%	5%	5%	4%	5%	3%	3%	5%
Knowledge-intensive services (b)	343	405	433	413	427	420	495	431	390	251
% In all HT	92%	95%	95%	95%	95%	96%	95%	97%	97%	95%
HT total ($a + b$)	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 (c)	7460	7655	8315	8345	8130	8751	10,146	8068	6782	5068
% In all the economy	95%	95%	95%	95%	95%	95%	95%	95%	94%	95%
All industries ($a + b + c$)	7834	8083	8771	8782	8581	9189	10,669	8513	7185	5332

Source: Compiled by authors.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

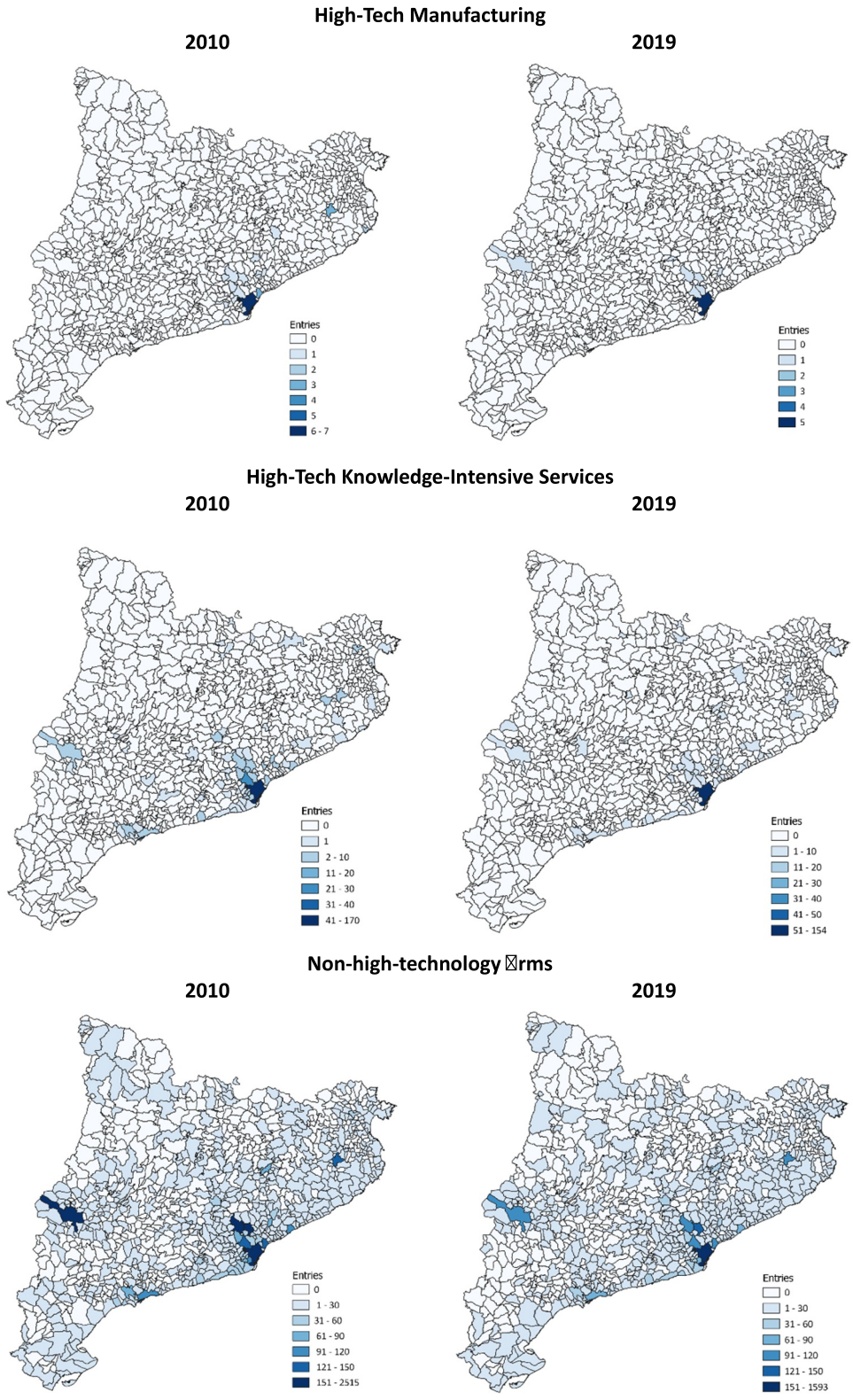


FIGURE 1 | Firm entries at the industry level (2010 vs. 2019). *Source:* compiled by authors.

point to the strengthening role of urban hubs in attracting high-tech firms and reveal persistent spatial imbalances in firm dynamics.

High-tech manufacturing firm entries show moderate clustering, primarily in industrial areas, especially around Barcelona and key transportation corridors. These firms' location choices are closely tied to infrastructure, particularly highways, industrial parks, and proximity to supplier networks and skilled labour markets. Compared to knowledge-intensive services, clustering is less intense, suggesting a wider spatial footprint typical of the manufacturing sector's diversity.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

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

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 urban clusters' presence suggests competition and potential spillover benefits from high-tech industries.

3.4 | Econometric Methods

In terms of empirical papers analysing the location determinants of entering firms, there are two streams of literature depending on the unit of analysis: firm or territory. As for the papers focussing on firms taking the entry decision, they normally use conditional logit models (see Arauzo-Carod et al. 2010, for a review), whilst papers focussing on the characteristics of chosen areas normally use count data models (see also Arauzo-Carod et al. 2010) and, more recently, Geographical Weighted Regression (GWR) approaches (Arauzo-Carod et al. 2024; Tyas et al. 2023; Fotheringham 2023; 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 and Sumarminingsih 2021). This paper aligns with the territory-based stream, applying count data models and incorporating a spatial dimension to capture how nearby areas may influence each other's activity.

The empirical literature highlights that new firms' location choices at the local level depend on various determinants, such as median household income (Carlino and Kerr 2015; Hanson 2005; Redding and Venables 2003; Duranton and Puga 2004), proximity to the capital and the coast (Hanson 2005; Redding and Venables 2003), education (Faggio et al. 2017; Moretti 2012), unemployment (Moretti 2012; Arauzo-Carod et al. 2010; Hanson 2005), and population density (Faggio et al. 2017; Carlino and Kerr 2015; Arauzo-Carod et al. 2010; Rosenthal et al. 2003). Regarding the innovation ecosystems core dimensions, firm entries clearly could demonstrate the environment vitality and entrepreneurial dynamics (Granstrand and Holgersson 2020; Nambisan and Baron 2013), as well as the presence of high-technology firms, establishment density and the share of large firms, proxying the existing industrial structure, critical mass and the capacity of the ecosystem (Oghazi et al. 2022). Population density and median household income per inhabitant capture urbanisation economies, market potential, and local absorptive capacity, while the unemployment rate reflects labour market conditions influencing firm entry and resource availability (Nan and Huang 2025; Paasi et al. 2023). Distance to the provincial capital measures access to institutional thickness, governance structures, and advanced services typically concentrated in major urban cores, which are central to ecosystem coordination and performance (Serrano-Ruiz et al. 2025; Barile et al. 2022). Finally, dummies for universities, technology parks, and business incubators capture the presence of key knowledge producers and intermediaries that facilitate knowledge creation, diffusion, collaboration, and entrepreneurial support, serving as core infrastructural components of innovation ecosystems (Secundo et al. 2025; Serrano-Ruiz et al. 2025; Nambisan and Baron 2013). So, to explore the drivers behind high-tech firms' location decisions and their connection to specialisation, we model firm entries based on these local features:

$$\begin{aligned}\text{Firm entries}_{it} = {} & \beta_0 + \beta_1\ \text{HIGHTECH} + \beta_2\ \text{ESTDEN} \\ & + \beta_3\ \text{LARGE} + \beta_4\ \text{POPDEN} + \beta_5\ \text{INCOME} \\ & + \beta_6\ \text{UNEMPLOYMENT} + \beta_7\ \text{DISTANCE} \\ & + \beta_8\ \text{UNIVERSITY} + \beta_9\ \text{TECHPARKS} \\ & + \beta_{10}\ \text{INCUBATOR}.\end{aligned}$$

The dependent variable (Y) measures firm entries (*Firm entries*), while independent variables (X) include: high-tech firms existence (*HIGHTECH*); establishment density (*ESTDEN*); large firms proportion (*LARGE*), which measures firms share with over 251 employees; population density (*POPDEN*), that proxies urbanisation; median household income per inhabitant (*INCOME*), proxying local purchasing power; unemployment rate (*UNEMPLOYMENT*), proxying labour market dynamics; distance to province capital (*DISTANCE*), measuring connection with institutions and high-level services provided at the main urban cores; and dummies for universities (*UNIVERSITY*), technology parks (*TECHPARKS*) and business incubators (*INCUBATOR*), showing knowledge-related services required by high-tech firms and serving as well as a proxy for the idea, spatial configuration and performance of innovation ecosystems.

Figure 2 shows clear spatial patterns across Catalonia from 2010 to 2018. Population density and income per inhabitant remain highly concentrated in urban areas, particularly around Barcelona, reinforcing the metropolitan region's role as an economic and innovation hub. Unemployment rates vary across municipalities, with higher rates in persistent pockets, especially in less urbanised areas. Establishment density and the large firms' presence also cluster strongly near major urban centres, indicating localised economic concentration. High-tech firms are primarily clustered in and around Barcelona, with little spread into rural or peripheral zones, reflecting strong spatial imbalances in innovation activity. Taken together, the maps indicate a persistent urban-rural split across Catalonia's core economic and innovation drivers.

The empirical strategy consists of estimating three different models that share the same set of explanatory variables with different dependent variables (Firm entries): high-tech manufacturing firms (HT_MAN), high-tech knowledge-intensive

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

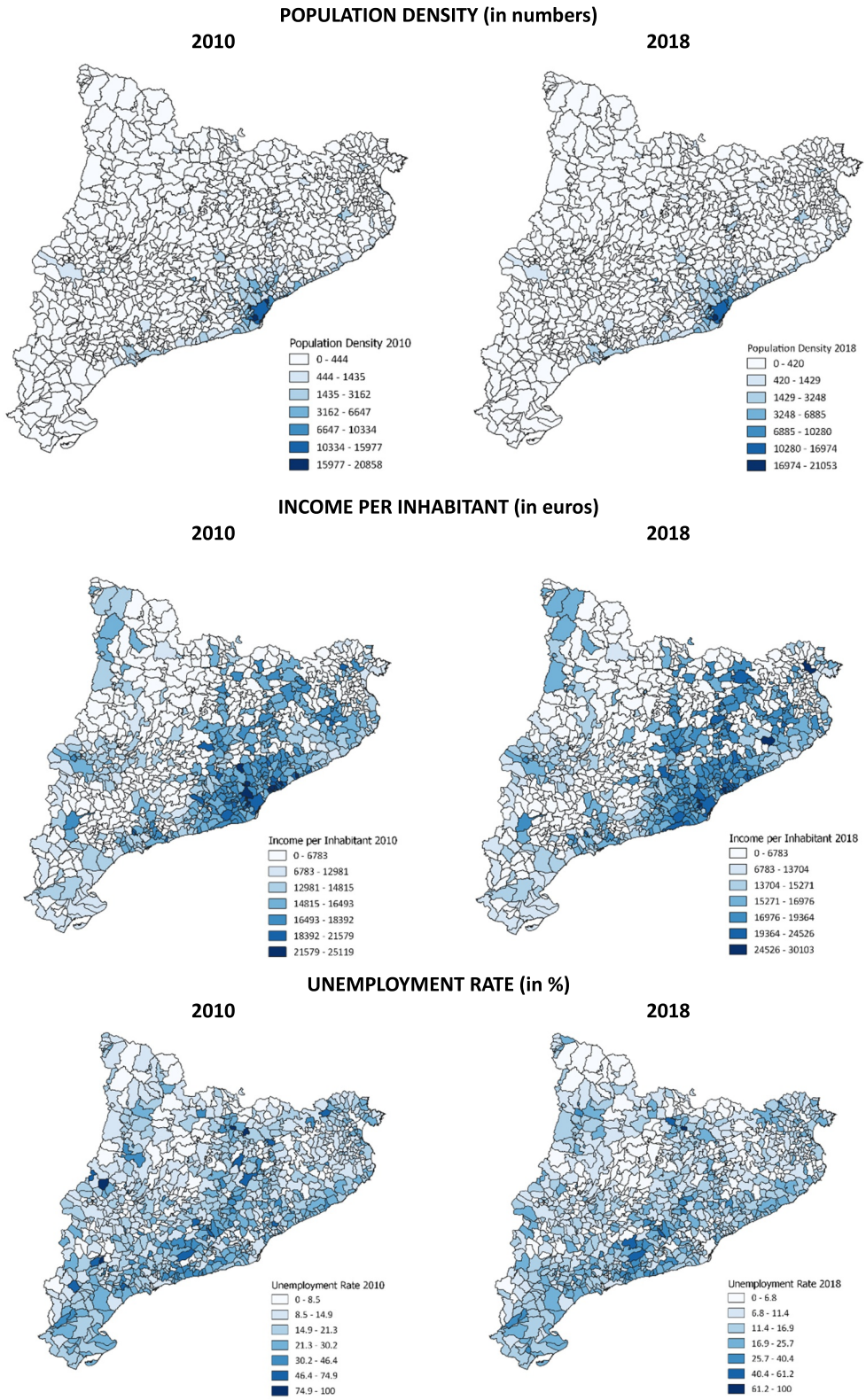


FIGURE 2 | Explanatory Variables (2010 vs. 2018). *Source:* compiled by authors.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

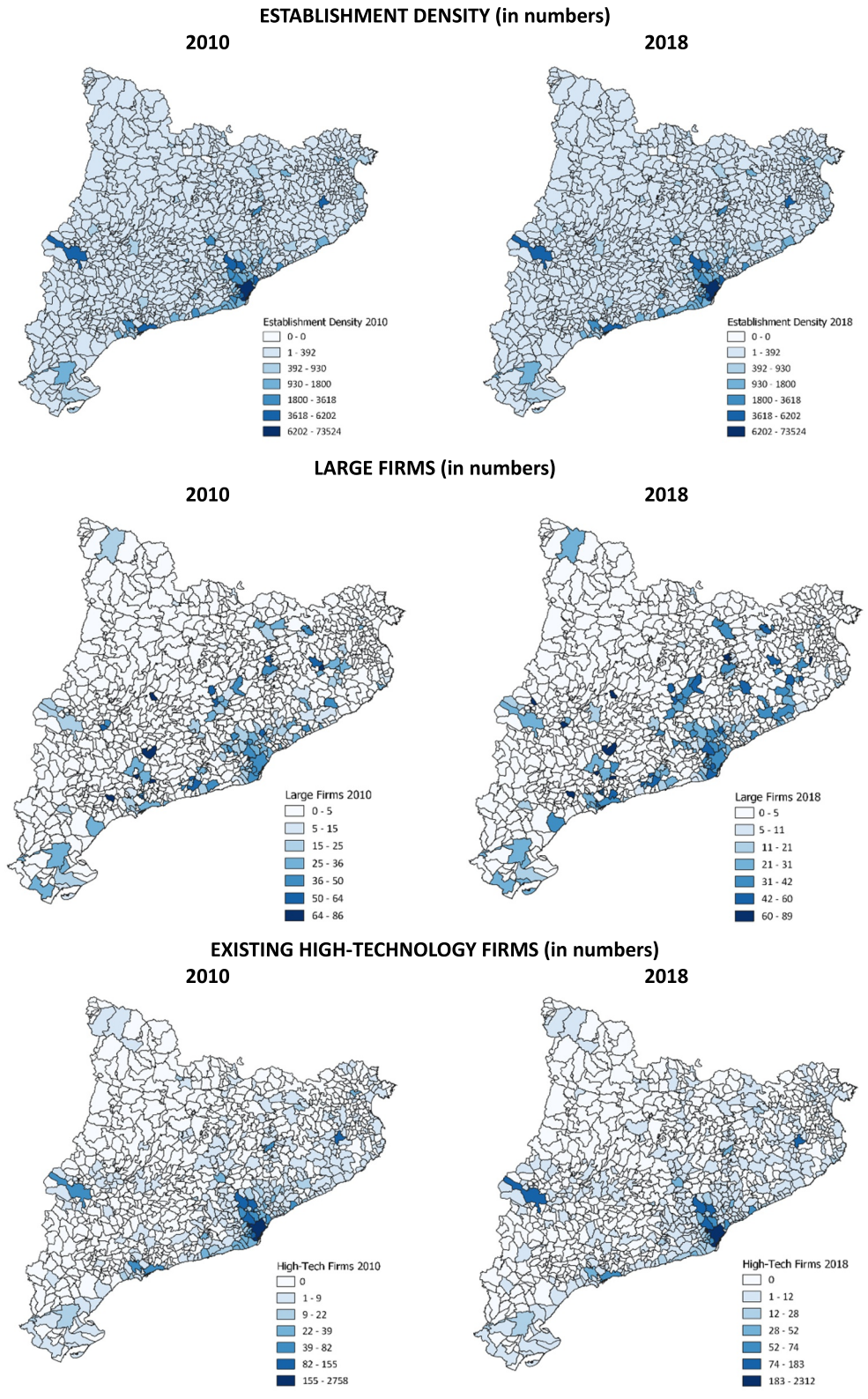


FIGURE 2 | (Continued)

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

services (HT_KIS) and non-high-technology firms (NON_HT). This strategy allows us to compare the firms' location determinants considered.

Panel data are 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, consequently enhancing the estimation's accuracy (Hsiao 2007). Second, they help address potential endogeneity concerns by capturing temporal dynamics and reducing omitted-variable bias, leading to more reliable causal inferences (Wooldridge 2002). 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 characteristics of sites potentially selected by new firms, rely on Count Data Models (CDM) (see Arauzo-Carod et al. 2010, for an empirical literature review). Given the extensive family of CDM, selecting the most appropriate specification requires a systematic approach.

3.4.1 | Model Selection

Count Data Models (CDMs) are commonly used to examine spatial patterns of event frequencies within a given area and time period (Méndez-Ortega et al. 2024). The analysis considers four models: Poisson (PM), Negative Binomial (NBM), Zero-Inflated Poisson (ZIPM), and Zero-Inflated Negative Binomial (ZINBM). We rely on AIC and BIC (Cameron and Trivedi 2013) to identify the model that offers both a good fit and minimal complexity. This strategy ensures that the chosen model appropriately captures the dependent variable underlying distribution while addressing issues such as overdispersion and excess zeros (Liviano and Arauzo-Carod 2013), which are common in count data applications (Hilbe 2011). Since the firm entries number in an area is represented by a nonnegative integer (count variable), more specialised estimation techniques are required than ordinary least squares (OLS), making alternative methods better suited for accurate analysis (Long 1997).

Neighbouring impacts are significant in firm location decisions, and failing to account for spatial dependence can lead to biased results. Spatial econometric methods address these interdependencies, as firm locations depend on both local and neighbouring characteristics. To capture these effects, spatial lag variables are included, reflecting the surrounding municipalities' average attributes. This approach measures spillovers, such as how population density, income levels, and firm sizes in neighbouring areas impact high-tech firm entry.

To model spatial dependence, we employ a spatial weights matrix (W) that defines the spatial structure of relationships between municipalities. The construction of a Spatial Weights Matrix (SWM) is key to spatial econometric models (Zhu et al. 2022), as SWMs are intended to capture interactions among spatial units (Kostov 2010). In this paper, we use an inverse-distance matrix, where weights decrease as the geographical distance between municipalities increases. Before estimating the models, we tested for spatial dependence using Moran's I statistic to identify the spatial autocorrelation degree for independent variables (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. Then, spatial lag models are employed to account for spatial dependencies.

To ensure the results reliability and validity, 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 queen contiguity-based and k-nearest, on six neighbours' spatial weights matrices. This approach verifies whether findings remain consistent across spatial specifications, ensuring that results are not driven by spatial weights choice. Second, zero-inflated models were tested to account for the potential overrepresentation of zero firm entries in the dataset. 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 allowed examination of sector-specific dynamics and ensured results reflected the characteristics of each group. All these robustness checks are available upon request.

4 | Results

Results for negative binomial estimations are shown in Table 3 (baseline estimation), Table 4 (with spatial lags), Table 5 (estimation at 3-digit level) and Table 6 (with spatial lags). Our strategy focuses on standard location determinants, such as agglomeration economics, as well as local characteristics related to the high-tech activities' nature, including the existence of business incubators, universities and technology parks.

In the baseline estimation (see Table 3), we group entries by high-tech industry and, within these, differentiate between manufacturing and services. As expected, results differ between high-tech and non-high-tech, especially regarding agglomeration economies. Concerning this, whilst population density (POP-DEN) has a positive effect for high-tech industries, the effect is negative or much weaker for non-high-tech sectors, as confirmed by Carlino and Kerr (2015) and Duranton and Puga (2004), since dense areas foster knowledge spillovers and innovation dynamics essential for knowledge-intensive industries but are less relevant or even detrimental for non-high-tech firms, who try to locate away from dense and expensive areas. Likewise, the income level (*INCOME*) boosts entries for high-tech sectors, as shown by Faggio et al. (2017) and Feldman and Kogler (2010), whilst non-high-tech sectors are deterred from these areas, suggesting that these sectors do not rely on the type of inputs, services, and employment available in rich areas. Higher density of

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 3 | Firm entries determinants (panel poisson regression with fixed effects).

Variable	HT_MAN	HT_KIS	NON_HT
HIGHTECH	−0.0016	−0.0007***	−0.0002**
	(0.0008)	(0.0002)	(0.0001)
POPDEN	0.0002**	0.0002***	−0.0001***
	(0.0001)	(0.0000)	(0.0000)
INCOME	0.0002***	0.0001***	−0.0000***
	(0.0000)	(8.47e-06)	(4.42e-06)
UNEMPLOYMENT	0.0000***	0.0000***	5.37e-06***
	(0.0000)	(2.91e-06)	(1.52e-06)
ESTDEN	0.0000	−3.31e-06	0.0001**
	(0.0000)	(0.0002)	(9.64e-06)
LARGE	0.0220**	0.0067	−0.0031**
	(0.0069)	(0.0036)	(0.0012)
UNIVERSITY	−0.3814	0.9851	6.4276***
	(0.7535)	(0.5095)	(1.0617)
TECHPARKS	0.9086	1.0357	1.3706**
	(0.5106)	(0.3265)	(0.5185)
INCUBATOR	0.6085*	1.3342***	2.0811***
	(0.2981)	(0.1506)	(0.1836)
DISTANCE	−0.0149*	−0.0105***	−0.0241***
	(0.0069)	(0.0026)	(0.0018)
Constant	−6.5604***	−3.8823***	2.114***
	(0.5177)	(0.1675)	(0.1277)
Lnalpha	0.3573	−0.0426	0.7606***
	(0.2979)	(0.1263)	(0.0495)
Alpha	1.430	0.9583	2.1395
	0.4259	0.1211	0.1059
N	9452	9452	9452

Note: Standard errors in parentheses.
The dependent variable is the number of entries.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

establishments (*ESTDEN*) attracts non-high-tech firms, whilst it has no effect for high-tech ones, as also noted by Asheim et al. (2011) and Rosenthal et al. (2003). This reflects the knowledge levels of existing establishments and differences in density between core and peripheral areas. Surprisingly, the high-tech firms' concentration (HIGHTECH) has a negative effect on all specifications that may reflect some crowding-out effects, although it is not significant for high-tech manufacturing entries (see Viladecans-Marsal and Arauzo-Carod 2012; Combes and Duranton 2006). As expected, distance to the provincial capital (DISTANCE) consistently shows a negative sign, confirming, as Fujita et al. (1999) and Scott (2006) highlight, that regardless of their knowledge profile, entering firms require some accessibility to main urban cores. Regarding the high-tech amenities hypothesised to positively influence high-tech entries, results partially show the expected effects. Specifically, incubators existence (INCUBATOR) attracts all kinds of firms, across all tech levels, as noted by Ratinho and Henriques (2010) and Phan et al. (2005). Technology parks (TECHPARKS) have a positive effect for all firms, although only significant for non-high-tech ones. Lastly, the presence of a university (UNIVERSITY) in the same municipality positively affects the entry of non-high-tech firms, while showing no statistically significant effect for high-tech firms. Jointly considered, these results suggest a discrepancy between the technological intensity of new entrants and that of the recipient areas; this is potentially explained by intensifying efforts among lagging municipalities.

These results are only partially consistent with earlier evidence showing that high-tech firms respond more strongly to agglomeration forces and knowledge-based assets than non-high-tech firms (Wei et al. 2016; Arbia et al. 2012; Moriset 2003). However, unlike these studies, which largely focus on localised concentration patterns or treat location determinants independently, our evidence highlights how multiple location forces operate simultaneously within an interconnected municipal system.

When adding spatial lags to the previous estimation (see Table 4), most results hold (which supports their robustness), and some interesting spatial issues arise. Concerning this, the previous location's negative effect of high-tech firms over non-high-tech entries still holds (although now is not significant) and is reinforced by a similar effect in neighbouring areas (*W_HIGHTECH*). The inclusion of the spatial lag of income triggers a sign reversal in the primary income variable for non-high-tech entries, suggesting a masking effect of spatial dependence. Specifically, the local income level (*INCOME*) exhibits a positive attraction on entrants when accounting for the (negative) spillover of neighbouring wealth (*W_INCOME*), except than for high-tech manufacturing entries, for which the overall effect is positive. This indicates a spatial competition framework where affluent municipalities act as "growth poles" that exhaust regional demand, thereby exerting a negative shadow effect on firm entry in proximal jurisdictions.

Instead, the population density effect remains local, with no relevant influence in nearby areas (*W_POPDEN*) although now the effect of density is positive for non-high-tech areas.

While previous studies have documented spatial clustering and localised dependence in high-tech activities (Smętkowski et al. 2021; Zhang et al. 2013; Arbia et al. 2012), they typically rely on descriptive spatial techniques or non-spatial regressions. By explicitly modelling spatial lags, our results provide direct empirical evidence that firm entry decisions depend not only on local conditions but also on neighbouring municipalities' characteristics, thereby extending this literature from spatial description to spatial causation.

Existing research has shown that universities, incubators, and science parks can stimulate entrepreneurial activity and firm creation (Antonietti et al. 2013; Audretsch and Lehmann 2005; Egeln et al. 2004; Di Gregorio and Shane 2003). Our findings nuance this literature by showing that these institutions do not operate in isolation: their effects vary by sector and are partly mediated by surrounding municipalities, suggesting that innovation infrastructures function as components of broader regional ecosystems rather than purely local assets.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 | Firm entries determinants (panel poisson regression with spatial lags).

Variable	HT_MAN	HT_KIS	NON_HT
HIGHTECH	−0.0015	−0.0007***	−0.0001
	(0.0008)	(0.0002)	(0.0001)
W_HIGHTECH	0.0067	0.0000	−0.0016***
	(0.0057)	(0.0020)	(0.0005)
POPDEN	0.0000	0.0002***	0.0001*
	(0.0001)	(0.0000)	(0.0000)
W_POPDEN	0.0002	−0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)
INCOME	0.0001**	0.0001***	0.0000***
	(0.0000)	(9.79e-06)	(5.34e-06)
W_INCOME	0.0001**	−0.0001***	−0.0001***
	(0.0000)	(0.0000)	(6.56e-06)
UNEMPLOYMENT	0.0000*	0.0000***	−8.66e-06***
	(0.0000)	(3.21e-06)	(1.66e-06)
W_UNEMPLOYMENT	−0.0002	0.0001*	−0.0000**
	(0.0001)	(0.0000)	(8.20e-06)
ESTDEN	0.0000	8.88e-06	−0.0001***
	(0.0001)	(0.0000)	(0.0000)
W_ESTDEN	−0.0005**	−0.0001	−0.0000
	(0.0002)	(0.0001)	(0.0001)
LARGE	0.0205**	0.0066	−0.0026*
	(0.0070)	(0.0035)	(0.0012)
W_LARGE	0.0131	−0.0113	−0.0104***
	(0.0172)	(0.0076)	(0.0023)
UNIVERSITY	0.0879	1.0060*	4.4898***
	(0.6870)	(0.4645)	(1.0952)
W_UNIVERSITY	−3.070	−2.9108	−4.3324*
	(3.034)	(1.5938)	(1.8057)
TECHPARKS	0.9607*	0.9373**	1.3234**
	(0.4884)	(0.3093)	(0.4904)
W_TECHPARKS	1.2747	2.324**	3.6735***
	(1.3987)	(0.9006)	(1.0794)
INCUBATOR	0.6254*	1.3849***	2.0020***
	(0.2916)	(0.1417)	(0.1758)
W_INCUBATOR	0.4387	0.1407	3.4621***
	(0.8444)	(0.4570)	(0.4639)
DISTANCE	−0.0013	−0.0055*	−0.0219***
	(0.0076)	(0.0027)	(0.0019)
Constant	−7.7528***	−4.4225***	1.7074***
	(0.6182)	(0.1944)	(0.1426)
Lnalpha	−0.1810	−0.2931*	0.6406***
	(0.3700)	(0.1405)	(0.0518)

(Continues)

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 | (Continued)

Variable	HT_MAN	HT_KIS	NON_HT
Alpha	0.8344	0.7460	1.8976
	(0.3087)	(0.1048)	(0.0982)
N	9452	9452	9452

Note: Standard errors in parentheses.
The dependent variable is the number of entries.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

TABLE 5 | Firm entries determinants of firm entries by sector at the 3-digit level (panel poisson regression with fixed effects).

Variable	COD_210	COD_260	COD_590	COD_600	COD_610	COD_620	COD_630	COD_720
HIGHTECH	−0.0018	−0.0016	−0.0003	−0.0018	−0.0014*	−0.0009***	−0.0009	−0.0001
	(0.0021)	(0.0009)	(0.0004)	(0.0014)	(0.0006)	(0.0002)	(0.0006)	(0.0006)
POPDEN	0.0001	0.0002**	0.0001***	0.0000	0.0001*	0.0002***	0.0001	0.0001*
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
INCOME	0.0002***	0.0002***	0.0002***	0.0002*	0.0001***	0.0001***	0.0001***	0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
UNEMPLOYMENTT	0.0000	0.0000**	0.0000**	0.0001**	0.0000***	0.0000***	0.0000***	0.0000
	(0.0000)	(0.0000)	(5.39e-06)	(0.0000)	(7.93e-06)	3.38e-06	(7.81e-06)	(8.80e-06)
ESTDEN	0.0000	0.0000	0.0000	7.55e-06	0.0000	9.58e-06	0.0000	−4.14e-06
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LARGE	0.0038	0.0242***	0.0116	0.0204	0.0038	0.0109**	0.0100	0.0105
	(0.0166)	(0.0073)	(0.0062)	(0.0143)	(0.0066)	(0.0040)	(0.0078)	(0.0073)
UNIVERSITY	−1.2848	−0.3147	0.3793	2.0963*	0.8534*	0.7999	0.9298	0.6312
	(1.2920)	(0.7948)	(0.5176)	(0.8204)	(0.4234)	0.5164	(0.5062)	(0.4860)
TECHPARKS	1.5649*	0.7879	1.010**	−0.7473	0.7717*	1.0117**	0.8895*	1.2442***
	(0.7728)	(0.5421)	(0.3495)	(0.8142)	(0.3214)	(0.3329)	(0.3764)	(0.3758)
INCUBATOR	0.2197	0.7346*	1.0453***	1.7055**	1.4893***	1.3233***	1.4039***	0.9571***
	(0.6775)	(0.3095)	(0.2281)	(0.5309)	(0.2048)	(0.1618)	(0.2703)	(0.2774)
DISTANCE	−0.0477*	−0.0124	−0.0139*	−0.0193	−0.0008	−0.0105***	−0.0092	−0.0285***
	(0.0224)	(0.0071)	(0.0055)	(0.0135)	(0.0041)	(0.0030)	(0.0061)	(0.0079)
Constant	−8.1210***	−6.7218***	−6.2491***	−8.4758***	−6.3336***	−4.3839***	−6.7440***	−6.4090***
	(1.2550)	(0.5435)	(0.4161)	(1.1699)	(0.3643)	(0.2007)	(0.4959)	(0.5260)
Lnalpha	−15.7648	0.4736	−0.5263	−15.8779	−0.9874	−0.0166	−0.7285	−0.9691
	(1600.92)	(0.3149)	(0.3683)	(1278.268)	(0.6391)	(0.1486)	(0.5502)	(0.5651)
Alpha	1.42e-07	1.6058	0.5908	1.27e-07	0.3725	0.9835	0.4827	0.3794
	(0.0002)	(0.5057)	(0.2176)	(0.0002)	(0.2381)	(0.1462)	(0.2655)	(0.2144)
N	9452	9452	9452	9452	9452	9452	9452	9452

Note: Standard errors in parentheses.
The dependent variable is the number of entries.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

Findings show significant variation in factors driving firm entries across high-tech manufacturing (HT_MAN), high-tech knowledge-intensive services (HT_KIS), and non-high-tech (NON_HT) sectors. Spatial and economic determinants uniquely shape both high-tech firms' location patterns. Urban areas attract high-tech firms due to high population density, while neighbouring areas' density has little effect. Affluent areas also drive high-tech entries, reinforcing their dependence on

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 | Firm entries determinants by sector at the 3-digit level (panel poisson regression with spatial lags).

Variable	COD_210	COD_260	COD_590	COD_600	COD_610	COD_620	COD_630	COD_720
HIGHTECH	−0.0014	−0.0016	−0.0003	−0.0012	−0.0014*	−0.0009***	−0.0010	−0.0001
	(0.0022)	(0.0009)	(0.0004)	(0.0014)	(0.0006)	(0.0002)	(0.0006)	(0.0006)
W_HIGHTECH	0.0048	0.0082	−0.0016	−0.0521	0.0035	0.0010	0.0142	−0.0029
	(0.0138)	(0.0062)	(0.0048)	(0.0311)	(0.0053)	(0.0025)	(0.0078)	(0.0050)
POPDEN	−4.35e-06	6.92e-06	0.0000	−0.0000	0.0001***	0.0001**	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
W_POPDEN	0.0004	0.0001	0.0001	0.0001	−0.0001	−0.0000	0.0001	0.0002**
	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
INCOME	0.0001	0.0001**	0.0001***	0.0001	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
W_INCOME	0.0001	0.0001***	0.0001***	4.53e-07	0.0001**	0.0001***	0.0001*	0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
UNEMPLOYMENT	0.0000	0.0000	0.0000**	0.0001**	0.0000**	0.0000***	0.0000**	0.0000
	(0.0000)	(0.0000)	(6.18e-06)	(0.0000)	(8.94e-06)	(3.78e-06)	(9.88e-06)	(9.30e-06)
W_UNEMPLOYMENT	−0.0000	0.0002*	0.0001	−0.0001	0.0000	0.0001*	−0.0001	0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
ESTDEN	4.59e-06	0.0000	0.0000**	−0.0000	0.0000*	0.0000	0.0000	−4.55e-06
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
W_ESTDEN	−0.0003	−0.0006**	0.0001	0.0017	0.0002	−0.0001	−0.0005*	−0.0000
	(0.0004)	(0.0002)	(0.0001)	(0.0010)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
LARGE	−0.0019	0.0232**	0.0080	0.0117	0.0092	0.0105**	0.0104	0.0080
	(0.0208)	(0.0074)	(0.0065)	(0.0171)	(0.0057)	(0.0039)	(0.0081)	(0.0072)
W_LARGE	0.0467	0.0003	−0.0168	−0.0106	−0.0249	−0.0070	0.0080	−0.0291
	(0.0342)	(0.0187)	(0.0148)	(0.0365)	(0.0138)	(0.0088)	(0.0183)	(0.0161)
UNIVERSITY	−1.3742	0.2049	0.3986	2.5226**	0.8447**	0.8464	0.9717	0.9730**
	(1.4145)	(0.7297)	(0.4640)	(0.8517)	(0.2947)	(0.4599)	(0.5077)	(0.3447)
W_UNIVERSITY	−3.2206	−2.1848	−0.8173	−3.5426	0.8729	−3.6457*	3.2259	−3.6440
	(6.9778)	(3.1700)	(2.5230)	(6.6817)	(2.0510)	(1.7766)	(2.9601)	(2.6930)
TECHPARKS	3.1265**	0.7522	0.7900*	−0.2126	0.6405*	0.9502**	0.8898*	1.6224***
	(1.1228)	(0.5219)	(0.3506)	(0.8560)	(0.2572)	(0.3126)	(0.4129)	(0.3493)
W_TECHPARKS	−0.4472	1.3688	−2.0152	1.0432	0.4129	2.7249**	−0.0262	2.5188*
	(3.0819)	(1.5106)	(1.2668)	(2.5352)	(1.0336)	(0.9687)	(1.7244)	(1.0562)
INCUBATOR	−0.5849	0.7643*	1.1415***	1.4325*	1.5107***	1.3900***	1.4189***	0.7170**
	(0.8504)	(0.3068)	(0.2268)	(0.5802)	(0.1882)	(0.1509)	(0.2718)	(0.2733)
W_INCUBATOR	−2.0989	0.6382	0.6977	0.7656	0.4820	−0.0913	−1.0443	−0.4438
	(1.9547)	(0.8961)	(0.6787)	(1.4322)	(0.5603)	(0.4955)	(0.9213)	(0.6895)
DISTANCE	−0.0488	0.0023	−0.0083	−0.0088	0.0021	−0.0045	−0.0060	−0.0192
	(0.0289)	(0.0078)	(0.0059)	(0.0149)	(0.0043)	(0.0032)	(0.0068)	(0.0086)
Constant	−8.8678***	−8.0666***	−6.8292***	−8.7784***	−6.7591***	−5.038***	−7.1763***	−7.7581***
	(1.6268)	(0.6638)	(0.4627)	(1.2786)	(0.3930)	(0.2330)	(0.5519)	(0.4488)
Lnalpha	−16.1412	−0.0363	−1.1205*	−15.5628	−16.3260	−0.3377*	−1.0021	−17.2159
	(1364.52)	(0.3929)	(0.5123)	(873.2267)	(525.2396)	(0.1654)	(0.6749)	(416.6126)

(Continues)

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 | (Continued)

Variable	COD_210	COD_260	COD_590	COD_600	COD_610	COD_620	COD_630	COD_720
Alpha	9.77e-08	0.9643	0.3261	1.74e-07	8.12e-08	0.7134	0.3671	3.34e-06
	(0.0001)	(0.3789)	(0.1671)	(0.0002)	(0.0000)	(0.1180)	(0.2478)	(0.0000)
N	9452	9452	9452	9452	9452	9452	9452	9452

Note: Standard errors in parentheses.
The dependent variable is the number of entries.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

financial ecosystems and purchasing power (Faggio et al. 2017; Feldman and Kogler 2010). Additionally, income spillovers from neighbouring areas notably influence high-tech entries, highlighting regional economies interconnected nature (Asheim et al. 2011). In contrast, non-high-tech firms face competitive pressures from high-tech firms in neighbouring areas, lowering entries in those areas. This suggests that non-high-tech firms tend to avoid high-density, high-income areas where the dominance of high-tech firms intensifies competition for resources, driving up operational costs, and instead strategically locate in less dense, lower-income areas that better align with their cost-sensitive business models and simpler production requirements (Baldwin et al. 2003).

Labour availability, indicated by unemployment rates, plays a leading role in firm location decisions across all sectors. High-tech firms often choose areas with flexible labour markets and access to educational institutions that help build a skilled workforce (Moretti 2012; Arauzo-Carod et al. 2010). High-tech manufacturing, particularly, shows a preference for locations near provincial capitals, with more developed infrastructure and logistics (Scott 2006; Fujita et al. 1999). By contrast, knowledge-intensive services appear less tied to physical infrastructure and exhibit broader spatial dispersion (Rosenthal et al. 2003). A key finding is the dual role of large establishments. While they may anchor high-tech clusters (Méndez-Ortega and Arauzo-Carod 2019Méndez-Ortega and Arauzo-Carod 2019), they also deter non-high-tech firms, probably due to resource competition and supply chain dominance (Clarysse et al. 2005; Colombo and Delmastro 2002). This suggests that cluster policies should be balanced to prevent excessive market concentration.

After discussing high-tech versus non-high-tech industries' location determinants, we explore whether specific high-tech industries share these determinants. The baseline estimation (see Table 5) reveals important distinctions across both high-tech manufacturing and knowledge-intensive services. Income per capita consistently shows a positive and statistically significant effect on firm entries across all sectors, underscoring the local purchasing power role in attracting new firms. Likewise, population density is also significant in most knowledge-intensive sectors, suggesting that urbanisation is an important driver, while unemployment boosts up entries in almost all sectors. Universities, technology parks, and incubators exhibit selective impacts: incubators strongly drive firm entries, especially in services, while technology parks influence both sectors. The distance to the provincial capital shows negative and significant effects in several sectors, particularly manufacture of pharmaceutical (COD_210), video and TV production (COD_590) and R&D (COD_720), confirming the urban areas' centripetal pull.

Introducing spatial lag variables (see Table 6) adds nuance to firm location determinants. The income-per-inhabitant spatial lag is positive and significant in nearly all sectors, indicating that high-income neighbouring municipalities exert a reinforcing pull on firm entries. However, some spatial lags (e.g., universities and business incubators) exhibit inconsistent or even negative coefficients, particularly in manufacturing. Interestingly, technology parks have strong positive effects in certain sectors (e.g., computer programming -COD_620- and R&D -COD_720), reinforcing the regional innovation ecosystems importance. Overall, spatial models demonstrate that firm entries depend on both local and neighbouring-area traits, highlighting the innovation-driven economic activity spatial interdependence.

5 | Conclusions

This paper analyses the factors shaping location choices across high-tech manufacturing, knowledge-intensive services, and non-high-tech sectors in Catalonia. The findings can be interpreted in relation to the expectations guiding the analysis. First, Hypothesis 1 proposed that high-tech firms would concentrate in urban areas characterised by strong agglomeration economies, skilled labour availability, and innovation infrastructures. The empirical results support this expectation. When controlling for spatial issues, high-tech firms show a clear preference for dense municipalities with higher income levels and access to innovation assets such as technology parks, universities, and incubators, confirming the importance of agglomeration economies and ecosystem resources in shaping their spatial concentration. Second, the analysis explored whether knowledge-intensive local characteristics exert a stronger influence on high-tech firm entry. The results instead indicate that several of these knowledge-related assets display a stronger association with non-high-tech firm entries. This finding suggests that innovation infrastructures may generate territorial externalities extending beyond high-tech activities, highlighting the presence of cross-sector spillovers within regional innovation systems.

In this regard, the empirical results do not fully align with the expectations underlying Hypothesis 2, inviting a more nuanced interpretation of how innovation ecosystems influence different

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

sectors, and highlighting the importance of considering cross-sector spillover effects within regional systems. This sectoral asymmetry reinforces the importance of industry-specific determinants in location theory.

The findings suggest strong connections between municipalities in shaping firm entry patterns. Income levels are particularly influential for most of firms, reinforcing the idea that local economies are closely linked rather than functioning in isolation, although this effect could be negative due to some crowding-out effects. Labour availability, as measured by unemployment rates, is relevant for most industries. The presence of large firms introduces a more complex dynamic: while they reinforce high-tech clusters as anchors, they may simultaneously create obstacles for non-high-tech firms by heightening competition for local resources. These results draw attention to the requirement for local and regional policies that carefully balance the advantages of clustering against potential negative effects on smaller or less specialised firms. Sectoral differences further highlight the importance of developing sector-specific innovation strategies.

By combining spatial econometrics with count data models, this paper adds to the literature on industrial location by offering a more detailed examination of the geographic patterns behind firm entries. The practical value of these findings lies in helping policymakers design local and regional strategies that promote innovation and achieve balanced growth. Concretely, regional development policies should move beyond solo efforts and promote cooperation across municipalities in the provision of knowledge and firm-support infrastructure, as firms' decisions are made considering areas larger than municipalities. The evidence of spatial spillovers indicates that coordinated efforts across local governments are key to tapping into shared regional strengths and assuring that both high-tech and non-high-tech firms can contribute to the economic future.

Overall, this paper fills a gap in the empirical literature by simultaneously considering several dimensions that have previously been only partially addressed. Namely, the joint consideration of both local and neighbour characteristics on firms' location decisions; the integration of the role of innovation ecosystems into location models; and the analysis of both high-tech manufacturing and knowledge-intensive services, focussing on their specificities but within the same framework. In contrast to earlier studies focussing either on agglomeration patterns (Arbia et al. 2012), on specific institutional mechanisms such as universities and spin-offs (Di Gregorio and Shane 2003), or on regional innovation systems in a largely descriptive manner (Smętkowski et al. 2021; Isaksen 2004), this paper integrates these dimensions within a unified spatial-econometric framework. This ecosystem perspective is consistent with evolutionary and regional innovation system approaches (Andersson and Hellerstedt 2009; Isaksen 2004), while extending them by providing firm-level econometric evidence on how spatial interactions shape entry patterns across municipalities.

Beyond the specificities of Catalonia, our results also offer broader lessons for other areas seeking to strengthen their innovation systems by attracting high-tech firms. In this sense, many of the mechanisms we have identified here (such as the role of agglomeration economies or the existence of research institutions) are likely to be common drivers in other institutional settings. Concretely, our results can be of interest for areas with similar innovation profiles in terms of leveraging spatial spillovers, supporting knowledge-intensive clusters and mitigating imbalances between core and peripheral areas, whilst for areas with lower technological profiles, these results can also be of interest for designing growth-path trajectories. Overall, although focused on Catalonia, our findings are transferable to other areas and provide relevant guidance for policymakers designing innovation-promotion policies.

Although the paper provides useful insights, its focus is limited to Catalonia, leaving its wider applicability uncertain, and further research comparing areas could offer valuable confirmation or reveal notable differences. Also, the paper only looks at the point when firms enter the market. We still do not know how these firms perform afterwards—whether they grow, survive, or shut down. Future research should follow these firms over time to understand their full trajectories. It would also help to explore environmental and sustainability factors. Examining how green technologies and related policies affect firm location decisions could introduce a much-needed dimension to the broader discussion on how regions balance economic growth with sustainable development.

Acknowledgements

Financial support by Generalitat de Catalunya (SGR2021-00729) and the Martí-Franquès Doctoral Scholarship (reference 2023PMF-PIPF-51) is acknowledged.

Conflicts of Interest

The authors declare no conflicts of interest..

Data Availability Statement

The data that support the findings will be available in Sistema de Análisis de Balances Ibéricos (SABI) at https://www.einforma.com/ following an embargo from the date of publication to allow for commercialisation of research findings.

Endnotes

[1] In this paper, we consider high-tech firms (see Table 1 and Section 3.1 for the detailed 3-digit codes) as those innovation-driven and knowledge-based firms that focus on developing and commercialising new technologies. Their strategies emphasise both the creation of technological knowledge (e.g., patents and inventions) and the exploitation of innovation, which involves refining products, expanding markets and optimising organisational structures. Successfully integrating both stages enhances their adaptability and competitiveness (Zakrzewska-Bielawska 2016).

References

Aernoudt, R. 2004. "Incubators: Tool for Entrepreneurship?" *Small Business Economics* 23, no. 2: 127–135. https://doi.org/10.1023/B:SBEJ.0000027665.54173.23.

Andersson, M., and K. Hellerstedt. 2009. "Location Attributes and Start-Ups in Knowledge-Intensive Business Services." *Industry & Innovation* 16, no. 1: 103–121. https://doi.org/10.1080/13662710902728126.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Antonietti, R., G. Cainelli, and C. Lupi. 2013. "Vertical Disintegration and Spatial Co-Localization: The Case of KIBS in the Metropolitan Region of Milan." *Economics Letters* 118, no. 2: 360–363. https://doi.org/10.1016/j.econlet.2012.11.031.

Arauzo-Carod, J.-M. 2021. "Location Determinants of High-Tech Firms: An Intra-Urban Approach." *Industry & Innovation* 28, no. 10: 1225–1248. https://doi.org/10.1080/13662716.2021.1929868.

Arauzo-Carod, J.-M., E. Coll-Martínez, and C. Turcu. 2024. "Location Attributes Explaining the Entry of Firms in Creative Industries: Evidence From France." *Annals of Regional Science* 72, no. 1: 223–254. https://doi.org/10.1007/s00168-022-01196-w.

Arauzo-Carod, J.-M., D. Liviano, and M. Manjón-Antolín. 2010. "Empirical Studies in Industrial Location: An Assessment of Their Methods and Results." *Journal of Regional Science* 50, no. 3: 685–711. https://doi.org/10.1111/j.1467-9787.2009.00625.x.

Arauzo-Carod, J.-M., and M. Manjón-Antolín. 2012. "(Optimal) Spatial Aggregation in the Determinants of Industrial Location." *Small Business Economics* 39, no. 3: 645–658. https://doi.org/10.1007/s11187-011-9335-6.

Arbia, G., G. Espa, D. Giuliani, and A. Mazzitelli. 2012. "Clusters of Firms in an Inhomogeneous Space: The High-Tech Industries in Milan." *Economic Modelling* 29, no. 1: 3–11. https://doi.org/10.1016/j.econmod.2011.01.012.

Asheim, B. T., R. Boschma, and P. Cooke. 2011. "Constructing Regional Advantage: Platform Policies Based on Related Variety and Differentiated Knowledge Bases." *Regional Studies* 45, no. 7: 893–904. https://doi.org/10.1080/00343404.2010.543126.

Audretsch, D. B., and M. Belitski. 2017. "Entrepreneurial Ecosystems in Cities: Establishing the Framework Conditions." *Journal of Technology Transfer* 42, no. 5: 1030–1051. https://doi.org/10.1007/s10961-016-9473-8.

Audretsch, D. B., and E. E. Lehmann. 2005. "Does the Knowledge Spillover Theory of Entrepreneurship Hold for Regions?" *Research Policy* 34, no. 8: 1191–1202. https://doi.org/10.1016/j.respol.2005.03.012.

Baldwin, R., R. Forslid, P. Martin, G. Ottaviano, and F. Robert-Nicoud. 2003. *Economic Geography and Public Policy*. Princeton University Press.

Barile, S., C. Simone, F. Iandolo, and A. Laudando. 2022. "Platform-Based Innovation Ecosystems: Entering New Markets Through Holographic Strategies." *Industrial Marketing Management* 105: 467–477. https://doi.org/10.1016/j.indmarman.2022.07.003.

Behrens, K. 2016. "Agglomeration and Clusters: Tools and Insights From Coagglomeration Patterns." *Canadian Journal of Economics – Revue canadienne d'économie* 49, no. 4: 1293–1339. https://doi.org/10.1111/caje.12235.

Bessant, J. 2003. *High Involvement Innovation: Building and Sustaining Competitive Advantage Through Continuous Change*. John Wiley & Sons.

Bhardwaj, B. 2019. "Role of Knowledge Management in Enhancing the Entrepreneurial Ecosystems Through Corporate Entrepreneurship and Strategic Intent in High-Tech Firms." *Journal of the Knowledge Economy* 10, no. 4: 1831–1859. https://doi.org/10.1007/s13132-019-00614-3.

Cameron, A. C., and P. K. Trivedi. 2013. *Regression Analysis of Count Data*. Cambridge University Press.

Cao, X., G. Zeng, T. Teng, and Y. Si. 2018. "The Best Spatial Scale of Firm Innovation Networks: Evidence From Shanghai High-Tech Firms." *Growth and Change* 49, no. 4: 696–711. https://doi.org/10.1111/grow.12252.

Carlino, G., and W. R. Kerr. 2015. "Agglomeration and Innovation." In *Handbook of Regional and Urban Economics*, edited by G. Duranton, J. V. Henderson, and W. C. Strange. Elsevier.

Cheng, K.-H., Y.-C. Chiao, H.-Y. Shih, T.-Y. Lee, and T.-S. Cho. 2011. "Agglomeration and Competition Among Chinese Cities: An Investigation of Taiwanese High-Tech Foreign Direct Investment." *Growth and Change* 42, no. 4: 517–548. https://doi.org/10.1111/j.1468-2257.2011.00566.x.

Clarysse, B., M. Wright, A. Lockett, E. Van de Velde, and A. Vohora. 2005. "Spinning out New Ventures: A Typology of Incubation Strategies From European Research Institutions." *Journal of Business Venturing* 20, no. 2: 183–216. https://doi.org/10.1016/j.jbusvent.2003.12.004.

Colombo, M. G., and M. Delmastro. 2002. "How Effective are Technology Incubators?: Evidence From Italy." *Research Policy* 31, no. 7: 1103–1122. https://doi.org/10.1016/S0048-7333(01)00178-0.

Combes, P. P., and G. Duranton. 2006. "Labour Pooling, Labour Poaching, and Spatial Clustering." *Regional Science and Urban Economics* 36, no. 1: 1–28. https://doi.org/10.1016/j.regsciurbeco.2005.06.003.

Di Gregorio, D., and S. Shane. 2003. "Why Do Some Universities Generate More Start-Ups Than Others?" *Research Policy* 32, no. 2: 209–227. https://doi.org/10.1016/S0048-7333(02)00097-5.

Doloreux, D., and R. Shearmur. 2023. "Does Location Matter? STI and DUI Innovation Modes in Different Geographic Settings." *Technovation* 119, no. 1: 1–11. https://doi.org/10.1016/j.technovation.2022.102609.

Duranton, G., and D. Puga. 2004. "Micro-Foundations of Urban Agglomeration Economies." In *Handbook of Regional and Urban Economics: Cities and Geography*, Ch. 48, edited by J. V. Henderson and J. F. Thisse, Vol. 4, 2063–2117. Elsevier. https://doi.org/10.1016/S1574-0080(04)80005-1.

Egeln, J., S. Gottschalk, and C. Rammer. 2004. "Location Decisions of Spin-Offs From Public Research Institutions." *Industry & Innovation* 11, no. 3: 207–223. https://doi.org/10.1080/1366271042000265384.

Eurostat. 2013. *Science, Technology and Innovation in Europe – 2013 Edition*. Publications Office of the European Union. http://sev4enterprise.org.gr/wp-content/uploads/2014/05/KAINOTOMIA-5.pdf.

Faggio, G., O. Silva, and W. C. Strange. 2017. "Heterogeneous Agglomeration." *Review of Economics and Statistics* 99, no. 1: 80–94. https://doi.org/10.1162/REST_a_00604.

Feldman, M. P., and D. F. Kogler. 2010. "Stylized Facts in the Geography of Innovation." In *Handbook of the Economics of Innovation*, edited by B. H. Hall and N. Rosenberg, Elsevier.

Ferdinand, J. P., and U. Meyer. 2017. "The Social Dynamics of Heterogeneous Innovation Ecosystems: Effects of Openness on Community–Firm Relations." *International Journal of Engineering Business Management* 9: 1–16. https://doi.org/10.1177/1847979017721617.

Fotheringham, A. S. 2023. "A Comment on 'A Route Map for Successful Applications of Geographically-Weighted Regression': The Alternative Expressway to Defensible Regression-Based Local Modelling." *Geographical Analysis* 55, no. 1: 191–197. https://doi.org/10.1111/gean.12347.

Fotheringham, A. S., M. E. Charlton, and C. Brunsdon. 1998. "Geographically Weighted Regression: A Natural Evolution of the Expansion Method for Spatial Data Analysis." *Environment & Planning A* 30, no. 11: 1905–1927. https://doi.org/10.1068/a301905.

Fujita, M., P. R. Krugman, and A. Venables. 1999. *The Spatial Economy: Cities, Regions and International Trade*. MIT Press.

Galaso, P., and J. Kovářík. 2021. "Collaboration Networks, Geography and Innovation: Local and National Embeddedness." *Papers in Regional Science* 100, no. 2: 349–377. https://doi.org/10.1111/pirs.12578.

G eneralitat de Catalunya. 2022. El Digital Innovation Hub de Catalunya: Per a la Transformació Digital de les Empreses. https://politiquesdigitals.gencat.cat/ca/economia/digital-innovation-hub-DIH4CAT/index.html#googtrans(ca|en.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Glaeser, E. L., H. D. Kallal, J. A. Scheinkman, and A. Shleifer. 1992. "Growth in Cities." *Journal of Political Economy* 100, no. 6: 1126–1152. https://doi.org/10.1086/261856.

Gordon, P., and K. Kourtit. 2020. "Agglomeration and Clusters Near and Far for Regional Development: A Critical Assessment." *Regional Science Policy & Practice* 12, no. 1: 387–396. https://doi.org/10.1111/rsp3.12264.

Granstrand, O., and M. Holgersson. 2020. "Innovation Ecosystems: A Conceptual Review and a New Definition." *Technovation* 90–91: 102098. https://doi.org/10.1016/j.technovation.2019.102098.

Hanson, G. H. 2005. "Market Potential, Increasing Returns and Geographic Concentration." *Journal of International Economics* 67, no. 1: 1–24. https://doi.org/10.1016/j.jinteco.2004.09.008.

Harianto, W. H. N., and E. Sumarminingsih. 2021. "Geographically and Temporally Weighted Regression Model With Gaussian Kernel Weighted Function and Bisquare Kernel Weighted Function." *IOP Conference Series: Materials Science and Engineering* 1115, no. 1: 12063. https://doi.org/10.1088/1757-899X/1115/1/012063.

Hilbe, J. M. 2011. *Negative Binomial Regression*. Cambridge University Press.

Hsiao, C. 2007. "Panel Data Analysis – Advantages and Challenges." *Test* 16, no. 1: 1–22. https://doi.org/10.1007/s11749-007-0046-x.

Huber, F. 2012. "Do Clusters Really Matter for Innovation Practices in Information Technology? Questioning the Significance of Technological Knowledge Spillovers." *Journal of Economic Geography* 12, no. 1: 107–126. https://doi.org/10.1093/jeg/lbq058.

Isaksen, A. 2004. "Knowledge-Based Clusters and Urban Location: The Clustering of Software Consultancy in Oslo." *Urban Studies* 41, no. 5–6: 1157–1174. https://doi.org/10.1080/00420980410001675797.

Jacobs, J. 1969. *The Economy of Cities*. Jonathan Cape.

Jofre-Monseny, J. 2008. "The Scope of Agglomeration Economies: Evidence From Catalonia." *Papers in Regional Science* 88, no. 3: 575–590. https://doi.org/10.1111/j.1435-5957.2009.00226.x.

Jofre-Monseny, J., R. Marín-López, and E. Viladecans-Marsal. 2014. "The Determinants of Localization and Urbanization Economies: Evidence From the Location of New Firms in Spain." *Journal of Regional Science* 54, no. 2: 313–337. https://doi.org/10.1111/jors.12076.

Kostov, P. 2010. "Model Boosting for Spatial Weighting Matrix Selection in Spatial Lag Models." *Environment and Planning B: Planning and Design* 37, no. 3: 533–549. https://doi.org/10.1068/b35137.

Krugman, P. 1991. "Increasing Returns and Economic Geography." *Journal of Political Economy* 99, no. 3: 483–499. https://doi.org/10.1086/261763.

Liu, Y., Y. Ji, Z. Shi, and L. Gao. 2018. "The Influence of the Built Environment on School Children's Metro Ridership: An Exploration Using Geographically Weighted Poisson Regression Models." *Sustainability* 10, no. 12: 4684. https://doi.org/10.3390/su10124684.

Liviano, D., and J.-M. Arauzo-Carod. 2013. "Industrial Location and Interpretation of Zero Counts." *Annals of Regional Science* 50, no. 2: 515–534. https://doi.org/10.1007/s00168-012-0502-8.

Long, J. S. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Sage Publications.

Maddah, L., J.-M. Arauzo-Carod, and F. A. López. 2023. "Detection of Geographical Clustering: Cultural and Creative Industries in Barcelona." *European Planning Studies* 31, no. 3: 554–575. https://doi.org/10.1080/09654313.2021.2020218.

Mardalena, S., P. Purhadi, J. D. T. Purnomo, and D. D. Prastyo. 2022. "The Geographically Weighted Multivariate Poisson Inverse Gaussian Regression Model and Its Applications." *Applied Sciences* 12, no. 9: 4199. https://doi.org/10.3390/app12094199.

Marshall, A. 1890. *Principles of Economics*. Macmillan.

Medina, L., M. Cano-Kollmann, and I. Alvarez. 2020. "International Connectivity in the Generation of Information and Communication Technology (ICT) in Spain." *Competitiveness Review* 30, no. 3: 355–371. https://doi.org/10.1108/CR-08-2019-0072.

Méndez-Ortega, C., and J-M. Arauzo-Carod. 2019. "Locating Software, Video Game and Editing Electronics Firms: Using Microgeographic Data to Study Barcelona." *Journal of Urban Technology* 26, no. 3: 81. https://doi.org/10.1080/10630732.2019.1613866.

Méndez-Ortega, C., and J.-M. Arauzo-Carod. 2020. "Do Software and Video Game Firms Share Location Patterns Across Cities? Evidence From Barcelona, Lyon and Hamburg." *Annals of Regional Science* 64, no. 3: 641–666. https://doi.org/10.1007/s00168-019-00917-y.

Méndez-Ortega, C., M. J. Smit, and G. Micek. 2024. "Location Patterns and Drivers of Coworking Spaces in European Regions." *Tijdschrift voor Economische en Sociale Geografie* 115, no. 2: 281–301. https://doi.org/10.1111/tesg.12603.

Mobile World Capital Barcelona, Barcelona City Council's International Economic Promotion and ACCIÓ Catalonia Trade & Investment. 2024. *Tech Hubs Overview 2024*. Barcelona. https://mobileworldcapital.com/en/report/tech-hubs-overview/.

Moretti, E. 2012. *The New Geography of Jobs*. Houghton Mifflin Harcourt.

Moriset, B. 2003. "The New Economy in the City: Emergence and Location Factors of Internet-Based Companies in the Metropolitan Area of Lyon, France." *Urban Studies* 40, no. 11: 2165–2186. https://doi.org/10.1080/0042098032000123231.

Nambisan, S., and R. A. Baron. 2013. "Entrepreneurship in Innovation Ecosystems: Entrepreneurs' Self-Regulatory Processes and Their Implications for New Venture Success." *Entrepreneurship Theory and Practice* 37, no. 5: 1071–1097. https://doi.org/10.1111/j.1540-6520.2012.00519.x.

Nan, M., and L. Huang. 2025. "Innovation Ecosystems: A Cross-Industry Examination of Knowledge Flows and Collaboration Dynamics." *Journal of the Knowledge Economy* 16, no. 1: 26–64. https://doi.org/10.1007/s13132-024-01986-x.

Nylund, P. A., and B. Cohen. 2017. "Collision Density: Driving Growth in Urban Entrepreneurial Ecosystems." *International Entrepreneurship and Management Journal* 13, no. 3: 757–776. https://doi.org/10.1007/s11365-016-0424-5.

Oghazi, P., V. Parida, J. Wincent, and R. Mostaghel. 2022. "Ecosystems Transformation Through Disruptive Innovation: A Definition, Framework and Outline for Future Research." *Journal of Business Research* 147: 16–26. https://doi.org/10.1016/j.jbusres.2022.03.073.

Pe'er, A., and T. Keil. 2013. "Are All Startups Affected Similarly by Clusters? Agglomeration, Competition, Firm Heterogeneity, and Survival." *Journal of Business Venturing* 28, no. 1: 354–372. https://doi.org/10.1016/j.jbusvent.2012.03.004.

Paasi, J., H. Wiman, T. Apilo, and K. Valkokari. 2023. "Modelling the Dynamics of Innovation Ecosystems." *International Journal of Innovation Studies* 7, no. 2: 142–158. https://doi.org/10.1016/j.ijis.2022.12.002.

Phan, P. H., D. S. Siegel, and M. Wright. 2005. "Science Parks and Incubators: Observations, Synthesis and Future Research." *Journal of Business Venturing* 20, no. 2: 165–182. https://doi.org/10.1016/j.jbusvent.2003.12.001.

Ratinho, T., and E. Henriques. 2010. "The Role of Science Parks and Business Incubators in Converging Countries: Evidence From Portugal." *Technovation* 30, no. 4: 278–290. https://doi.org/10.1016/j.technovation.2009.09.002.

Redding, S., and A. J. Venables. 2003. "South-East Asian Export Performance: External Market Access and Internal Supply Capacity." *Journal of the Japanese and International Economies* 17, no. 4: 404–431. https://doi.org/10.1016/j.jjie.2003.09.002.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Rosenthal, S. S., and W. C. Strange. 2004. "Evidence on the Nature and Sources of Agglomeration Economies." In *Handbook of Regional and Urban Economics*, edited by J. V. Henderson and J.-F. Thisse, 2119–2171. Elsevier B.V.

Rosenthal, S. S., W. C. Strange. 2003. "Geography, industrial organization, and agglomeration." *Review of Economics and Statistics* 85, no. 2: 377–393. https://www.jstor.org/stable/3211587.

Sari, M., P. Sutikno, and Purhadi. 2021. "Parameter Estimation and Hypothesis Testing of Geographically and Temporally Weighted Bivariate Poisson Inverse Gaussian Regression Model." *IOP Conference Series: Earth and Environmental Science* 880, no. 1: 12045. https://doi.org/10.1088/1755-1315/880/1/012045.

Schumpeter, J. A. 1934. *The Theory of Economic Development: An Inquiry Into Profits, Capital, Interest, and the Business Cycle*. Oxford University Press.

Scott, A. J. 2006. "Entrepreneurship, Innovation and Industrial Development: Geography and the Creative Field Revisited." *Small Business Economics* 26, no. 1: 1–24. https://doi.org/10.1007/s11187-004-6493-9.

Secundo, G., C. Spilotro, J. Gast, and V. Corvello. 2025. "The Transformative Power of Artificial Intelligence Within Innovation Ecosystems: A Review and a Conceptual Framework." *Review of Managerial Science* 19, no. 9: 2697–2728. https://doi.org/10.1007/s11846-024-00828-z.

Segarra-Blasco, A., J.-M. Arauzo-Carod, and M. Teruel. 2018. "Innovation and Geographical Spillovers: New Approaches and Empirical Evidence." *Regional Studies* 52, no. 5: 603–607. https://doi.org/10.1080/00343404.2018.1444273.

Serrano-Ruiz, J. C., J. Ferreira, R. Jardim-Gonçalves, and Á. Ortiz. 2025. "Relational Network of Innovation Ecosystems Generated by Digital Innovation Hubs: A Conceptual Framework for the Interaction Processes of Dihs From the Perspective of Collaboration Within and Between Their Relationship Levels." *Journal of Intelligent Manufacturing* 36, no. 3: 1505–1545. https://doi.org/10.1007/s10845-024-02322-5.

Smętkowski, M., D. Celińska-Janowicz, and K. Wojnar. 2021. "Location Patterns of Advanced Producer Service Firms in Warsaw: A Tale of Agglomeration in the Era of Creativity." *Cities* 108: 1–14. https://doi.org/10.1016/j.cities.2020.102937.

Spinazzola, M., V. Scuotto, and M. Pironti. 2025. "Professional Social Matching for Innovation and Technology Transfer in Multiscalar Innovation Ecosystems: A Conceptual Framework and First Exploratory Results." *Journal of Technology Transfer*. https://doi.org/10.1007/s10961-024-10174-7.

Squicciarini, M. 2008. "Science Parks' Tenants Versus Out-of-Park Firms: Who Innovates More? A Duration Model." *Journal of Technology Transfer* 33, no. 1: 45–71. https://doi.org/10.1007/s10961-007-9037-z.

Thomas, E., K. Faccin, and B. T. Asheim. 2021. "Universities as Orchestrators of the Development of Regional Innovation Ecosystems in Emerging Economies." *Growth and Change* 52, no. 2: 770–789. https://doi.org/10.1111/grow.12442.

Tu, W., L. Zhang, D. Sun, and W. Mao. 2023. "Evaluating High-Tech Industries' Technological Innovation Capability and Spatial Pattern Evolution Characteristics: Evidence From China." *Journal of Innovation & Knowledge* 8, no. 1: 100287. https://doi.org/10.1016/j.jik.2022.100287.

Tyas, S. W., Gunardi, and L. A. Puspitasari. 2023. "Geographically Weighted Generalized Poisson Regression Model With the Best Kernel Function in the Case of the Number of Postpartum Maternal Mortality in East Java." *MethodsX* 10: 102002. https://doi.org/10.1016/j.mex.2023.102002.

Viladecans-Marsal, E., and J.-M. Arauzo-Carod. 2012. "Can a Knowledge-Based Cluster be Created? The Case of the Barcelona 22@ District." *Papers in Regional Science* 91, no. 2: 377–400. https://doi.org/10.1111/j.1435-5957.2011.00383.x.

Weber, A. 1909. *Theory of Location of Industries*. University of Chicago Press.

Wei, Y. D., X. Bi, M. Wang, and Y. Ning. 2016. "Globalization, Economic Restructuring, and Locational Trajectories of Software Firms in Shanghai." *Professional Geographer* 68, no. 2: 211–226. https://doi.org/10.1080/00330124.2015.1054751.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Xiong, Z., Y. Chen, H. Tan, Q. Cheng, and A. Zhou. 2021. "Analysis of Factors Influencing the Lake Area on the Tibetan Plateau Using an Eigenvector Spatial Filtering Based Spatially Varying Coefficient Model." *Remote Sensing* 13, no. 24: 5146. https://doi.org/10.3390/rs13245146.

Xu, Y., X. Li, C. Tao, and X. Zhou. 2022. "Connected Knowledge Spillovers, Technological Cluster Innovation and Efficient Industrial Structure." *Journal of Innovation & Knowledge* 7, no. 3: 100195. https://doi.org/10.1016/j.jik.2022.100195.

Yashiro, N. 2023. "Rebooting the Innovation Ecosystems." In *OECD, OECD Economic Surveys: Finland 2022*. OECD Publishing.

Zakrzewska-Bielawska, A. 2016. "Perceived Mutual Impact of Strategy and Organizational Structure: Findings From the High-Technology Enterprises." *Journal of Management and Organization* 22, no. 5: 599–622. https://doi.org/10.1017/jmo.2015.55.

Zhang, X., P. Huang, L. Sun, and Z. Wang. 2013. "Spatial Evolution and Locational Determinants of High-Tech Industries in Beijing." *Chinese Geographical Science* 23, no. 2: 249–260. https://doi.org/10.1007/s11769-012-0581-6.

Zhu, P., J. Li, and Y. Hou. 2022. "Applying a Population Flow-Based Spatial Weight Matrix in Spatial Econometric Models: Conceptual Framework and Application to COVID-19 Transmission Analysis." *Annals of the Association of American Geographers* 112, no. 8: 2266–2286. https://doi.org/10.1080/24694452.2022.2060791.

14682257, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/grow.70127 by Spanish Cochrane National Provision (Ministerio de Sanidad), Wiley Online Library on [04/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License