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REGULAR ARTICLE

New England's Pinnacle: fostering quality entrepreneurial ecosystems

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Abstract

This paper has assessed the dynamics of entrepreneurial ecosystems across the US states. To do this, we have used the Startup Formation Rate (SFR) and the Entrepreneurial Quality Index (EQI) from a novel data set called the Startup Cartography Project, which spans from 1988 to 2014. For this purpose, we have applied the Phillips and Sul (Econometrica 75:1771–1855, 2007, Econometrics 24:1153–1185, 2009)'s club clustering algorithm in order to identify the existence of absolute or regional convergence. Our results suggest the existence of two and three clubs convergence, respectively. More importantly, when attending EQI, California and Massachusetts form a club, which is evidence of the importance of quality entrepreneurship over quantity. Furthermore, from a geographical point of view, SFR clubs show a scattered distribution throughout the national territory, while the EQI clubs are more homogeneous. In this sense, we apply the Local Moran I test to the EQI club that is formed by California and Massachusetts to analyze the possible spillover effects of these states, to their neighbours. Finally, this gives valuable information for designing entrepreneur policies at different levels.

Keywords Entrepreneurial ecosystems · Entrepreneurship · USA · Convergence · Cluster · Spatial econometrics

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1 Introduction

Over the recent decades, the USA had a deep conversion and restructuring of its economic structure, trusting more on small businesses, entrepreneurship, and entrepreneurship for innovation and competitiveness rather than large corporations based on economies of scale cite (Jing et al., 2015). For this, the USA is considered the leader in terms of transferring from management to an entrepreneurial economy (Audretsch et al., 2002).

Nevertheless, an increasing body of literature has honed in on the regional level for comprehending the evolution of the business landscape in a particular area (Andersson & Koster 2011; Fritsch & Wyrwich 2017b; Luo & Chong Luo and Chong (2019) or Fritsch & Wyrwich 2017b). In this vein, various factors influencing variations in self-employment rates among different regions within a country have been pinpointed (Cheng & Li, 2011). These disparities reflect the distinctive attributes inherent to each region.

In this context, investigating whether intra-country the different US states could form clubs would confirm if entrepreneurship culture spreads between neighbouring regions. In this respect, as it is well-known, entrepreneurship has been treated with special attention in the literature, being very extensive and concluding that entrepreneurship is a geographical singularity influenced by the national context and, particularly, by the regional situation. Despite the existence of different national particularities which could affect entrepreneurship,[1] i.e., the behaviour of GDP (Carmona et al., 2016), the Unemployment rate (Parker & Robson, 2004), the level of education in a territory (Amorós et al., 2019; Thai & Turkina, 2014), the existence of an administrative and institutional issues and/or legal framework (see Porter & Stern, 2001; Sölvell et al., 2003, among others).

In this regard, the concept of entrepreneurial ecosystem emerges in the literature as the composition of startups and the organizations and other actors[2] which assist them (see Roundy et al., 2017; or Bergman & McMullen 2022, for instance). In this line, Mason & Brown (2014) expand the list of assisting organizations to startups with firms of venture capital, law firms, and accounting services. Indeed, it is worth noting that for entrepreneurs the location choice is frequently not explicitly made when they begin: they initiate in the area where they live and/or work, and rationally choose what kind of firm (in a particular product-market) to start (Audretsch et al., 2022). Furthermore, according to Brown and Mason (2017), Riaz et al. (2022) and Audretsch (2023), this work aligns with the idea that entrepreneurial ecosystems are temporary and geographically influenced. It supports the view that these ecosystems are shaped by regional institutional, socioeconomic, and cultural factors.

Additionally, Andrews et al. (2022) provides a novel set of entrepreneurial ecosystem statistics for the United States (called Startup Cartography Project), which allows the evaluation of entrepreneurial ecosystems at multiple levels of geographic

[1] See Almeida et al. (2021) for an extension of these factors.

[2] Spigel (2017) provides an exhaustive list, including human resource advisors, incubating and accelerating firms, co-working facilities, mentors, talent, universities, physical infrastructure, or open markets.

analysis, empowering academics and policymakers to consider the power of place in novel ways. They also suggest two *new* ways of collecting quality and quantity in entrepreneurship not seen until now: “The Startup Formation Rate (SFR, hereafter), which is based on the quantity of new business registrants within a given population; and the Entrepreneurial Quality Index (EQI, hereafter), as the average growth potential (or “quality”) of any given group of new firms.” Measurement of an entrepreneurial ecosystem needs to somehow link the measurement of entrepreneurship to these potentially skewed outcomes. Hence, by assessing the potential of an entrepreneurial ecosystem, it is necessary to check not only the quantity of new startups being formed there but also their growth potential, that is, their “entrepreneurial quality”. Attending to the distinction quality *vs.* quantity, i.e., the SFR and the EQI, there is an increasing number of studies published in the last five years that analyze the factors (see Xie et al., 2021 for a deep debate of this issue) that delimit the difference between both concepts. In this regard, Shane (2009) asserted that the government should endow only those companies that possess considerable growth potential, and the preference of seeking entrepreneurial development is suggested to recognise those startups (Mason & Brown, 2013). More recently, academics have documented the necessity of considering high-impact ‘unicorn ventures’ (see Acs et al., 2016 and Acs et al., 2017), which can reflect the quality of regional entrepreneurship.

The literature concerning regional entrepreneurship has pursued to respond to a key question: Why do certain regions have different patterns of entrepreneurial activity than others? In our case, we try to disentangle that question by attending to the US states to recognize the different paths of regional entrepreneurship in the USA and the intrinsic relationship among them. Thus, we probe the extent to which variable included in Andrews et al. (2022) Startup Cartography Project, i.e., SFR and IQE, for the USA states exhibit convergence club and the character of that convergence. We firstly test for evidence of both global convergence (convergence to a national average) and evidence of convergence club, i.e., by separating groups of states converging, employing Phillips & Sul (2007, 2009)’s club convergence methodology. Given the evidence on regional differences in SFR and EQI, club convergence would appear to be the most likely outcome. As a result, regional differences could become more firmly established if some states converge at a lower rate than that achieved by other faster-growing states or clubs of states. This might create a challenge to entrepreneurship policy. Thus, if a different converge club exists, we could state that it could influence economic activity by region. Our results evidence that global convergence would be implausible. In this respect, we find two clubs, when attending SFR and three clubs, when attending EQI. In this latter case, it is remarkable the existence of a club formed by Massachusetts and California, but this finding is not surprising. Additionally, regarding the results obtained when attending to EQI, we extend our analysis using the Local Moran I to test the existence of “Hot Spots and Cold Spots”. Finally, these results bring some policy implications differentiating by states and regions concerning entrepreneurship.

The remainder of this paper is organized as follows. Section 2 addresses the theoretical background of this topic. Section 3 describes the data and the methodology applied in the study. Afterwards, the empirical results are shown in Section 4.

Finally, we accomplish the paper and discuss the potential policy implications of the results obtained in Section 5 and 6.

2 Theoretical background

From an economic point of view, entrepreneurship is viewed as an essential promoter of growth and regional wealth through its progressive effects on productivity, innovation, employment, and competition (see Acs & Armington, 2006; Braunerhjelm et al., 2010; Mittelstädt & Cerri 2009, among others). Thus, there exists a considerable discussion in the literature regarding the effect of economic conditions on entrepreneurship. In this sense, the literature distinguishes two cases: when economic recessions occur, this pushes people into entrepreneurship, because of the absence of paid-employment opportunities and due to the higher availability of second-hand capital equipment during recessions, being called necessity entrepreneurship (Carmona et al., 2016); and the opposite case, the so-called opportunity entrepreneurship (Fairlie & Fossen, 2018).

In this sense, as Burke et al. (2021) claim, opportunity entrepreneurs create a more considerable economic contribution than necessity entrepreneurs. Suppose a higher proportion of entrepreneurs in high-growth regions are opportunity entrepreneurs. In that case, economic growth will be more remarkable, being this key for the distinction between the economic situation and the different types of entrepreneurs. Indeed, some authors argue that this distinction may be a proxy of quality entrepreneurship, the classic struggle between quantity *vs.* quality. Thus, this distinction is widely treated in empirical studies, which demonstrates how entrepreneurship rates vary between and within countries (Cheng & Li, 2011), national contexts (see Wennekers et al., 2005, for instance), or regional environments (Cravo et al., 2015; Luo & Chong, 2019).

For this reason, there exists a strand in the literature that has focused on the characteristics attending to a regional level as a base for understanding the development of entrepreneurship in a given territory (see, for instance, Almeida et al., 2021; Fritsch & Wyrwich, 2017a, 2019). Nonetheless, one has to take into account the existence of factors that push alterations in entrepreneurship variables among different regions or states in a country, being a signal of the existence of particular features of each region that can influence the participation in entrepreneurship (Ross et al., 2015) or additionally, these particular features could spread across regions, forming clusters or clubs where the ideas and skills amongst individuals, institutions and firms could be transmitted, blooming the pass-through of knowledge through the region (Claver-Cortés et al., 2020; Singh, 2005; Zhu et al., 2019). Consequently, a given region's business and economic context would be more and more competitive in a given area. The regions that hold those clusters would experiment with more sharp economic growth (Wolman & Hincapie, 2015).[3]

[3] In this sense, Audretsch & Feldman (1996) suggest that business activity could rest toward spatial clustering.

Regional studies have highlighted at least three distinct drivers of agglomeration: knowledge spillovers, input–output linkages, and labour market pooling. Although the literature on grouping states or regions by attending the entrepreneurship variables is limited, cluster theory demonstrates that entrepreneurship is related to spatial factors due to geographic interdependence among different locations (Lado-Sestayo et al., 2017; Almeida et al., 2021). Indeed, the greater the accessibility of regional variables, the more profound attention to be transferred to regional, spatial analysis a growing topic in research on regional economies (Stuetzer et al., 2018; Fritsch & Wyrwich, 2021). In this regard, Delgado et al. (2010, 2014) show evidence that a strong cluster environment surrounding a particular region boosts the incentives and possibilities for entrepreneurial endeavours. Companies within these geographically concentrated clusters collaborate, sharing technologies, skills, knowledge, input, consumers, and institutions, thereby facilitating agglomeration. In this sense, the use of spatial analysis allows us to recognize the possible spatial dependence or grouping between regions, i.e., a process where a given region's growth or new firms is subjective by what happens in adjacent regions (Audretsch & Keilbach, 2007).

Similarly, according to Saridakis et al. (2019), if entrepreneurial rates align, it is probably a result of the synchronization of economic growth and business cycles, along with the convergence of economic policies. But keep in mind that national economies and the people living there also play a role in shaping entrepreneur's rates. The specific industries prevalent in a country, such as agriculture and tourism, can significantly impact the overall landscape of entrepreneurs. However, as indicated, there may exist different intra-country behaviour of the regions that compound a state. Thus, the analysis of convergence among them emerges as a valid way to assess and capture the different patterns that can occur. In this sense, the convergence clubs or club clustering algorithm has been applied in the literature. From an economic theory point of view, the term convergence usually indicates the hypothesis that all economies would finally converge in terms of per capita output, for instance. However, in relation to this topic, traditional papers typically separated all individuals into subgroups based on some previous information (such as geographic location) and subsequently tested the convergence hypothesis for each subgroup, respectively (Du, 2017).

Attending to the application of this methodology is widely used in other fields of study, such as energy, environmental economics, house prices, or tourism, but, as far as we know, its use on this topic is scarce. However, we can highlight Saridakis et al. (2020) which examines entrepreneurship rates in 12 UK regions applying the Phillips & Sul (2007) model and demonstrating a North–Middle–South divide (in contrast to the findings of Burke et al. (2009), which suggest a North–South divide) where English southern regions indicate higher levels of entrepreneurship. Furthermore, Belitski & Korosteleva (2010) study entrepreneurialism at the city level, finding dependencies on city size, socioeconomic conditions, crime rate, or the situation of such a city.

Finally, extensive literature affirms that entrepreneurialism is geographically influenced by national, regional, or local contexts (Sternberg & Wennekers, 2005; Fritsch & Wyrwich, 2014). This spatial environment fosters knowledge exchange between individuals, institutions, and businesses, potentially spreading to neighboring regions and forming clusters of entrepreneurs. These clusters improve regional competitiveness and drive pronounced economic growth (Spencer et al., 2010; Zhu et al., 2019).

Moreover, Audretsch & Feldman (1996) emphasize that entrepreneurial activities tend to cluster spatially, and cluster theory underscores the link between entrepreneurship and spatial factors. These spatial analyses also uncover the potential transmission of indirect effects between neighbouring locations, referred to as spatial dependence, which, in turn, influences regional growth (Lado-Sestayo et al., 2017). In this line, Plummer (2010) delves into the spatial dependencies of entrepreneurial endeavours and advocates the incorporation of spatial econometric methods in entrepreneurial research, highlighting the tendency of new firms within the same industry to form geographical clusters, emphasizing their reliance on regional environments and proximate resources.

Despite the significance of spatial dependence in fostering entrepreneurialism within regions, there is still a need for further exploration in empirical studies on this topic. Audretsch & Keilbach (2007) argue that business creation processes exhibit spatial correlation and have an impact on adjacent regions. Thus, the importance of spatial dependence in the evolution of entrepreneurialism over time remains substantial, but empirical research in this area is still limited.

2.1 The entrepreneurial ecosystems

The concept of the entrepreneurial ecosystem has gained significant traction in both academic and policy circles. Following Stam & Van de Ven (2021), the concept of entrepreneurial ecosystems is compounded by two main terms coined from different disciplines, i.e., entrepreneurial and ecosystem. The first element refers to the exploration, evaluation, and exploitation of opportunities to create new goods and services (Schumpeter, 1934; Shane & Venkataraman, 2000) and, on the other hand, the second term, ecosystem, comes from a biological point of view and refers to a community of living organisms and nonliving elements that share a physical environment and interact with themselves, creating a complex nested system of multifarious associations and players. In this sense, the entrepreneurial ecosystem is envisioned as a dynamic institutionally embedded network that promotes interaction among interconnected stakeholders. This interaction facilitates resource mobilization, entrepreneurial initiatives, and the success of both new and existing firms (Lafuente et al., 2022).

Entrepreneurial ecosystems emphasize the relationships among factors such as policy, culture, human capital, market, access to finance, and innovation capacity that drive entrepreneurial success in a region (Acs et al., 2014). Audretsch et al. (2019b) categorize these ecosystems into three types: economic, technological, and societal, with economic outputs reflecting capital wealth, prosperity, and value creation. Colombelli et al. (2019) highlight that the developmental trajectory of an entrepreneurial ecosystem often hinges on a local "anchor tenant". In contrast, Roundy and Lyons (2023) argue that linking the terms "entrepreneurial" and “ecosystems” may distract from the central role of entrepreneurs, individual agency, and personal networks in the entrepreneurial process.

Entrepreneurial ecosystems play a pivotal role in stimulating employment opportunities, fostering innovation, and driving economic growth, as evidenced by Glaeser et al. (2010, 2015) or Akcigit & Kerr (2018) or as (Conti & Guzman, 2021) note, many startups from highly innovative economies to the United States, prompting the question of what advantages the U.S. entrepreneurial ecosystem offers compared to these economies, suggesting that US entrepreneurial ecosystem is widely perceived as relatively more successful.

The measurement of entrepreneurial ecosystems has evolved significantly, with early attempts relying on quantitative data, as noted by Leendertse et al. (2022) and exemplified by Ács et al. (2014). However, Rocha et al. (2021) critique these approaches for their dependence on static cross-sectional data, which limits their ability to capture the dynamic nature of ecosystems. In response, Riaz et al. (2022) advocate for more holistic methodologies that emphasize the interplay between entrepreneurial activity and its contextual environment, a perspective supported by Abootorabi et al. (2021); Liguori et al. (2019); Theodoraki et al. (2022). This shift marks a departure from earlier entrepreneurship studies, which predominantly focused on individual traits and personality, often overlooking the broader contextual influences on entrepreneurial behavior (Cavallo et al., 2019). Despite this progress, the field remains divided. While Theodoraki et al. (2022) highlight the diversity of methodologies in entrepreneurial ecosystem research-ranging from theoretical studies (Audretsch et al., 2019a; Nicotra et al., 2018; Roundy et al., 2018; Cao & Shi, 2021) to applied studies (Theodoraki et al., 2018; Audretsch & Belitski, 2017; Audretsch et al., 2019a; Colombelli et al., 2019; Liguori et al., 2019)-there is a notable imbalance. As Rocha et al. (2021) observe, the literature has historically favored conceptual and qualitative approaches, leaving quantitative research underdeveloped and often lacking definitional clarity. Moreover, Cho et al. (2022) argue that a critical gap remains: the absence of a temporal dimension in most studies. This omission is particularly problematic given the inherently dynamic and evolving nature of entrepreneurial ecosystems, which necessitates methodologies capable of capturing their continuous development over time. This line of reasoning leads to the following proposition:

Proposition 1 *Entrepreneurial ecosystems among US states evolve over time.*

Understanding and measuring the complex, non-linear relationships within entrepreneurial ecosystems remains a significant challenge. To address this, Johnson et al. (2022) propose a novel approach that leverages multiple high-volume data sources to accurately capture and analyze ecosystem dynamics. They stress the importance of robust database methodologies for measuring dynamic interactions, calling for further research to deepen insights into ecosystem behavior. This aligns with Colombo et al. (2019), who explore the governance of entrepreneurial dynamics and identify key players that influence these processes. Similarly, Roundy et al. (2018) advocate for the development of new methodologies, arguing that conventional linear approaches are inadequate for capturing the dynamic and evolving nature of ecosystems. Complementing this, Corrente et al. (2019) introduce a probabilistic ranking system to assess the variability of factors influencing entrepreneurial ecosystems, facilitating more nuanced comparisons.

Digital technologies play a critical role in shaping entrepreneurial ecosystems. According to Colombelli et al. (2024), digital tools facilitate knowledge sharing and collaboration among digitally skilled individuals, which in turn drives the development of innovative digital start-ups. These technologies also promote local territorial development by diminishing the importance of geographic distance, as digitization becomes a key mechanism for enabling knowledge spillovers. For example, in certain American regions, digital start-ups utilize knowledge from universities and firms to create new entrepreneurial opportunities within their ecosystems. These regions attract talented individuals who, through interactions with experienced peers, foster intellectual exchanges and the generation of new knowledge, fueling both innovation and ecosystem growth. Building on this, Audretsch and Belitski (2024a) highlight that younger enterprises operating in digitally advanced environments are particularly inclined to invest in R&D and innovation, underscoring the transformative power of digitalization in driving entrepreneurial success.

Audretsch et al. (2022), in their survey, argue that to consider an effective entrepreneurial ecosystem, there must exist a successful economic and societal performance. Hence, it is a pearl of wisdom in the geography of entrepreneurial literature, with some transcendent exceptions, for example, entrepreneurs who move to Silicon Valley to acquire venture capital (Conti & Guzman, 2021). In this sense, Guerrero et al. (2021) analyzes how the conditions of the environment change given the entrepreneurial stage of the enterprises within different places. Furthermore, Audretsch et al. (2021) and Audretsch and Belitski (2021) focus attention on the value of geographic heterogeneity across sub-national regions and cities and sources of variation in the quality of factors that foster entrepreneurship performance.

Indeed, the entrepreneurial ecosystem is typically examined from the perspective of spatial agglomeration, bearing some resemblance to concepts such as clusters and regional innovation systems (Alam & Bhowmick, 2023). In this way, another strand of entrepreneurial ecosystems has focused on spatial dimensions, emphasizing the relevance of regional proximity (Acs et al., 2017; Brown & Mason, 2017). Consequently, there has been a growing interest in studying entrepreneurial ecosystems to understand geographically bounded agglomeration effects (see Audretsch et al., 2019a). In this regard, Leendertse et al. (2022) suggest that the most appropriate level of analysis is the city or regional level. Consequently, we can highlight the empirical literature from a spatial perspective, focusing on the different elements that form entrepreneurial ecosystems (Stam, 2015; Stam & Spigel, 2018; Stam & Van de Ven, 2021), or from a local point of view (see Aoyama, 2013; Spigel, 2017; Colombelli et al., 2019; Neumeyer et al., 2019; Cavallo et al., 2019; Adams, 2021; Audretsch & Belitski, 2021; Shi & Shi, 2022; Leendertse et al., 2022; Muñnoz et al., 2022; Cavallo et al., 2023, among others).

The role of open innovation in entrepreneurial ecosystems is closely tied to geographical proximity. Audretsch & Belitski (2024b) investigate how proximity influences knowledge collaboration between Schumpeterian firms and external partners-such as suppliers, customers, universities, and consultants-and its impact on innovation output. Their study builds on earlier research on knowledge spillovers and partner diversity, arguing that firms benefit significantly from collaborating with geographically close partners, particularly in regions with high concentrations of wealth and knowledge-intensive industries. However, they also highlight the challenges and opportunities that co-location presents. Expanding on this, Audretsch & Belitski (2024c) emphasize that the effectiveness of knowledge collaboration depends on firms' ability to establish strong ties, which can reduce transaction and opportunity costs. Similarly, Yasin et al. (2024) note that knowledge spillovers are not limited to a single region but can extend across regions, generating positive externalities. This is especially beneficial for resource-constrained firms, such as small businesses and startups, which gain significantly from being co-located with knowledge sources. As Audretsch et al. (2023); Belitski et al. (2024) argue, localized knowledge transfers foster more sustained R&D collaboration compared to distant interactions, underscoring the critical role of proximity in driving innovation and entrepreneurial success. In agreement with these arguments, we develop the second proposition as follows:

Proposition 2 *The nurturing of entrepreneurial ecosystems in a given US state is facilitated by its geographical spillovers.*

3 Data and Methodology

3.1 The club convergence algorithm

The procedure developed by Phillips and Sul (2007, 2009) (PS, hereafter) is employed to assess the Startup Formation Rate (SFR, hereafter) and the Entrepreneurial Quality Index (EQI, hereafter)[4] convergence dynamics in a panel of the US states and detect any convergence clubs. The PS procedure has several advantages over other approaches. It identifies groups of individuals in the panel that shares similar behaviour in their convergence paths even when there is no total convergence. The process may expose the existence of multiple convergence clubs and, at the same time, let some individuals diverge. Additionally, the gathering of groups is based on the features of the data rather than on *a priori* assumptions, and it permits for heterogeneity amongst the time series included in the panel. Moreover, the PS test is robust when the series has a stationary trend and also under the presence of stochastic non-stationarity (Mérida et al., 2016). The method utilized contemplates cross-section elements (states) to be heterogeneous, and the dynamics of each of them are distinguished based on a single-factor model.

[4] For convenience, we have called EE the terminology used in the methodology and it is the abbreviation of the entrepreneurial ecosystem. EE represents both variables.

In the following specification (Eq. 1), δ_i quantify the average distance of the entrepreneurial ecosystem EE_{it} of each state concerning the common systematic part, μ_t, and ε_{it} is the error term.

$$EE_{it} = \delta_i \mu_t + \varepsilon_{it} \tag{1}$$

The model may consider other panel data aspects, where a_{it} and x_{it} represent the systematic and the transitory components, respectively and can be decomposed as follows

$$EE_{it} = a_{it} + x_{it} \tag{2}$$

Phillips & Sul (2007) further develop the following expression (Eq. 3) by dividing and multiplying Eq. (2) by the common component (μ_t), such as:

$$EE_{it} = \left(\frac{a_{it} + x_{it}}{\mu_t \mu_t} \right) = \delta_{it} \mu_t, \quad \forall i, t \tag{3}$$

where δ_{it} reflects the idiosyncratic component and μ_t represents the common trend component, both of which are time-varying. Particularly, δ_{it} gives evidence of the transition path of each individual to the common steady-state path, which is represented by μ_t. To remove the common component, therefore separating the idiosyncratic component, and to check if δ_i converges to a constant, δ, Phillips and Sul (2007) propose achieving ratios to describe a relative transition parameter, h_{it}:

$$h_{it} = \frac{EE_{it}}{N^{-1} \sum_{i=1}^{N} EE_{it}} = \frac{\delta_{it}}{N^{-1} \sum_{i=1}^{N} \delta_{it}} \tag{4}$$

h_{it} estimates how the variable of interest for individual i evolves relative to the panel average.[5] The null of the PS test could be expressed within a semiparametric model for δ_{it}:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t) t^{\alpha}}, t \geq 1, \sigma_i \geq 0 \quad \forall i \tag{5}$$

where δi is fixed, ξ_{it} is independent and identically distributed across i, $L(t)$ is slowly varying, increasing and divergent at infinity and, α corresponds to the decay rate such δit converges to δi when $\alpha \geq 0$. In this regard, the null and alternative hypotheses of convergence are, respectively:

$$H_0 : \delta_{it} = \delta \;\; and \;\; \alpha \geq 0$$

$$H_1 : \delta_{it} \neq \delta, \;\; \forall i \;\; or \;\; \alpha < 0$$

The default hypothesis of convergence can be tested following the regression model:

[5] In case of ultimate convergence amongst the individuals, $h_{it} \to 1$ and $H_{it} \to 0$ as $t \to \infty$, where $H_{it} = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2$ reflects for the cross-sectional change of the relative transition growth path.

$$log(H_1/H_t) - 2logL(t) = \hat{c} + \hat{b}logt + u_t \tag{6}$$

In this regression model, $L(t) = log(t)$ and $\hat{b} = 2\hat{\alpha}$, being $\hat{\alpha}$ is the OLS estimate of α and when $\hat{b} \geq 0$ it is said that there exists panel convergence; the contrary reflects divergence in the panel. Phillips & Sul (2007) model uses the one-sided t test and the null hypothesis is accepted at the 5% level. Additionally, the sign of $\hat{b}$ specifies if the ratio of cross-sectional variance H_1/H_t rises or drops over time. When $\hat{b}$ is positive (negative), the cross-sectional variance (H_t) leans to be lesser (greater) than the early cross-sectional variance (H_1). Furthermore, when this $\hat{b}$ coefficient is positive (negative) and statistically significant, the log(t) test would suggest convergence (divergence) among the cross-sectional units of the sample. Following Mendez (2020), attending to its sign and the magnitude of $\hat{b}$ provides different patterns of convergence. If $\hat{b} < 0$, it is said that there exists divergence. When $0 \leq \hat{b} < 2$, the model suggests relative convergence or convergence in growth rates. If $\hat{b} \geq 2$, the model suggests convergence in levels (that is, absolute convergence). Finally, the speed of convergence can be estimated as $\hat{b}/2$.

Finally, if the null hypothesis is rejected, this implies that there is no full convergence in the panel, but there may be different subgroups displaying different convergent patterns. Due to an empirical clustering algorithm, the PS method allows identifying the number of convergence clubs in the data set in addition to the diverse members who are contained in each of those clubs[6].

3.2 Local Moran I: The Hot Spot–Cold Spot analysis

To assess the spatial structure observed in quality clubs (EQI), we performed a spatial autocorrelation analysis at the state level. Local Moran I, also known as "Hot Spot–Cold Spot" analysis, is a spatial statistics methodology employed to detect significant spatial clustering patterns within geographical datasets. Widely utilized in the field of spatial statistics and spatial pattern analysis (see Anselin, 1995), it is utilized to identify geographic regions that exhibit either high or low concentrations of similar values, commonly referred to as "hot spots" and "cold spots", respectively. Moran's I statistic read as:

[6] The procedure starts by ordering individuals in the panel agreeing to their last observation. Later, log(t) regression is run for the highest k individuals within the group, where $N > k \geq 2$, to develop the subgroup G_k and estimate its convergence t-statistic, t_k, with $t_k > -1.65$. The subsequent step involves adding one member at a time to subgroup Gk and performing the log(t) regression again to compute its respective t-statistic. The subgroup G_k will enhance the first convergence club if the t-statistic is over zero. Finally, we suggest compiling another log(t) regression for the rest of the individuals to appreciate if they all converge, which could mean that they form the second and, thus, last club. However, the former steps should be taken for these individuals to examine whether they can be clustered in two or more convergence clubs. It could be possible that no clubs can be formed at all, which would denote that these individuals diverge. See the original work of Phillips & Sul (2007) for more on the issue.

$$I = \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2}, \quad (7)$$

with z, being the objective variable of the study in deviations from the mean (or fully standardized, such that the variance equals one) and w_{ij} the weight matrix.[7]

Since this analysis needed to be performed statically, we decided to calculate quality averages across states for the years 1988–1994, 1995–2000, 2001–2007, and 2008–2014. These subperiods align with different economic conjunctures in the US economy, which may be of interest to our analysis. In the late 1980s to the mid-1990s, the country enjoyed sustained growth, driven by technological advancements and globalization, with low inflation. The late 1990s saw a tech-driven economic boom (often referred to as the "dot-com bubble") with record stock markets. From 2001 to 2007, there was a brief recession, followed by a housing bubble and concerns about financial stability. The period from 2008 to 2014 was marked by the severe impact of the global financial crisis, leading to a deep recession and a slow recovery, necessitating significant government stimulus and monetary measures.

3.3 Data

To achieve the proposed objective, we used the Startup Formation Rate (SFR) and the Entrepreneurial Quality Index (EQI) for the 49 states of the USA and Washington, DC, during the period 1988–2014, the Startup Cartography Project (SCP), which offers a new set of entrepreneurial ecosystem statistics for the United States. According to Andrews et al. (2022), SFR is a measure of the formation of new companies (within a defined cohort of firms for a given period and geographic range). EQI is a measure of the average quality within any cohort, allowing the probability of a growth outcome to be calculated within a specific population of start-ups. These different dimensions capture not only the quantity, but also the quality of entrepreneurialism,[8] which is critical to analyze the impact of an entrepreneurial ecosystem. Importantly, from a dynamic perspective, they can affect the ecosystem pillars over time.

4 Empirical results

In this section, according to the abovementioned econometric strategy, we show the results of the estimates to deepen the absolute and relative club convergence attending to different variables of "The Startup Cartography Project", represented by the

[7] We estimate the test using different forms of weights matrices such as binary (rook and queen) contiguity matrix of order 1 and distance matrices (k-nearest neighbours with different numbers of k).

[8] The effects of the quality of entrepreneurial ecosystems are likely to be perceived at the aggregate level (the quantity and/or quality of entrepreneurship in a particular territory), not necessarily by the individual entrepreneur.

Startup Formation Rate (SFR) and the Entrepreneurial Quality Index (EQI) for the US states from 1988 to 2014. Firstly, we employ the Hodrick–Prescott (HP) filter to obtain the series of SFR and EQI trends. Once we have extracted these trends, we apply the algorithm of Phillips & Sul (2007, 2009) (see Du, 2017 and Sichera & Pizzuto 2019). Then, the log(t) convergence test is addressed to check if there is global convergence among the US states for each variable independently. In Table 1, we assess the notion of convergence based on the log(t) convergence test of Phillips & Sul (2007, 2009), which establishes that the log(t) test is based on a nonlinear dynamic factor model that allows the transitional heterogeneity modelling. As we can see in Table 1, the null hypothesis is that the countries are fully converged. In this sense, whether the value of the t-statistic is greater than −1.65 could be evidence of convergence among this group. In our case, the findings for the two entire samples show that the null hypothesis of panel convergence is rejected at the 5% significance level, implying that the US states are not converging to the same steady state. Thus, the log(t) regression coefficient is negative and statistically significant for all the variables.

Furthermore, the coefficient $\hat{b}$ allows us to account for the speed of adjustment. In this sense, the sign of the point estimate is negative for all the cases (since $\hat{b} = 2\sigma = \hat{\sigma} = \hat{b}/2$, the values being −0.316/2 and −0.875/2, respectively), implying that the speed of convergence for each variable is weak for the US states at the overall level. Additionally, these results indicate that the US states are not at the same level. The overall sample for a given variable suggests evidence of no conditional/relative convergence towards the average, as the value of the log(t) parameter is −13.535 for SFR, and −159.555 for EQI.

Figures 1 and 2 plot the panel relative transition path for the US states for SFR and EQI, respectively. These paths describe the pattern of the states in comparison to the panel average during the sample period. Following Phillips & Sul (2007, 2009), the relative transition path seems to tend to a common point for all the states following the presumption of the model. They also refer that the relative transition paths of members of each club converge into distinct constants, that is when groups of countries converge to different equilibrium points. From a bird's eye, these paths gave us a chance to track the behaviour of each country path relative to the sample average, depending on the variable observed.

Table 1 Global convergence test (log(t) test)

Variable	$\hat{b}$ coefficient	SE	t-stat	Speed of convergence
SFR	−0.316	0.023	−13.535	−0.158
EQI	−0.875	0.005	−159.555	−0.437

The clubs have been obtained by means of the algorithm suggested by Phillips & Sul (2007, 2009) in which the groups are formed by US states denoting similar convergence speeds to the panel average. The *t-stat* is the convergence test statistic and is a simple one-sided *t-test* with a critical value of −1.65 (see Phillips & Sul (2007, 2009) for further details). SE denotes Standard Error

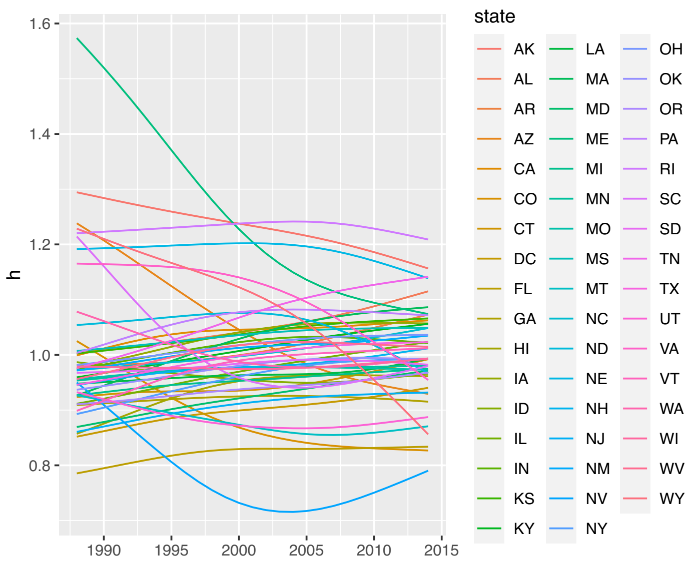


Fig. 1 Panel transition paths for SFR

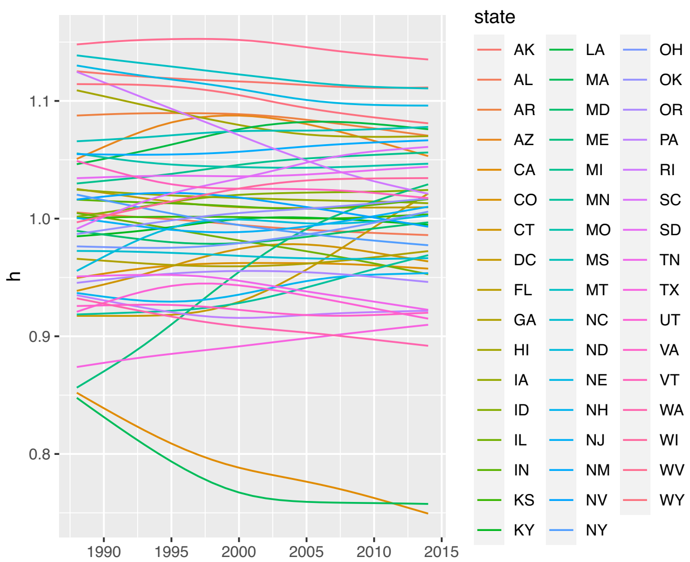


Fig. 2 Panel transition paths for EQI

Figures 1 and 2 also show that the US states display both convergence and divergence at some point. However, the divergence is more accused, consequently, the results sustain the panel result, suggesting that all the states are not converging. It is worth noting the extremely divergent behaviour, in contrast with the rest of the

US states, of California and Massachusetts (see green and orange lines at the bottom of Fig. 2), which could be evidence of a club formation.

Once the log(t) test for full panel/absolute convergence is addressed for each variable and the different transition paths plotted and that absolute convergence is rejected for all cases, we applied the Phillips & Sul (2007, 2009) club clustering algorithm to test the existence of different groups of convergence for each variable. So, Table 2 shows the application of this algorithm for SFR. Here, we can see that the US states can be grouped into two clubs, formed by 45 and 5 US states, respectively. Then, we test the possibility of club merging Phillips & Sul (2009) and Sichera & Pizzuto (2019) but, unfortunately, no club can be merged when using the club convergence merging algorithm. Thus, the number of clubs is the same as those obtained at the beginning of our procedure. Furthermore, the club clustering algorithm suggests that the null hypothesis of club convergence is rejected for club 1 because its t-stat is lower than −1.65 (−4.364 < −1.65), implying that states in club 1 do not move towards convergence. The contrary occurs for club 2, i.e., the club clustering algorithm suggests that the null hypothesis of club convergence is accepted for club 2 because its t-stat is higher than −1.65 (9.526 > −1.65), implying that these five states in club 2 move towards convergence, even although their levels of SFR might differ.

Additionally, attending to the speed of adjustment, the sign of the coefficient estimated for club 1 is negative (−0.129), being a weak convergence or weak speed of adjustment (Saba & Ngepah, 2022). Furthermore, Johnson (2020) states how to measure the strength of the convergence procedure in each club by attending to the coefficient obtained in the log(t) test for each club. As mentioned in the methodology section, as the coefficient is lower than 0, the US states belonging to this club diverge. Attending club 2, the sign of the coefficient is positive (0.983), which is evidence of a strong speed of adjustment of SFR. Also, attending to the strength of the convergence, we have to look again at the value of the coefficient

Table 2 Club convergence in SFR

Club convergence in SFR					
Club	No. of states	$\hat{b}$ coefficient	SE	t-stat	States
1	45	−0.129	0.029	−4.363	NV, CO, FL, WY, MT, UT, GA, AZ, NJ, DC, VA, HI, ID, ND, OR, MD, MO, MI, SC, MN, SD, CT, OK, WI, NY, LA, WA, NH, VT, WV, IN, TX, IL, NM, OH, NC, MS, KY, IA, CA, KS, PA, AR, ME, AK
2	5	0.983	0.103	9.526	MA, AL, NE, TN, RI

The tests of club merging have as a null hypothesis that Club i and Club j can be considered a joint convergence club (Camarero et al., 2013). The test is also distributed as a one-sided t-statistic with a 5% critical value of −1.65

obtained in the log(t) test for the club. In this case, as the coefficient is placed between 0 and 2, the SFR of these states would converge in growth rates.

The plot of the transition paths for each club represented in Fig. 3 shows how the lines follow different patterns of the process of convergence in RSF for clubs 1 and 2 relative to the sample average. We can also see that the US states forming these clubs would not exhibit convergence over the period studied. More in-depth, Fig. 3 panel (a) shows the behaviour of the states in Club 1. During this period, their paths seem to separate and indicate changes from their initial level. For panel (b), i.e., club 2, we can highlight that, although the paths also seem to be separated at the beginning of the plot, they follow a process to a similar endpoint. At the bottom of Fig. 3 the average transition path for each club is revealed. As we can see, clubs 1 and 2 start from different levels but, over time, diverge sharply. Thus, this Fig. 3 supports our findings previously shown in Table 2.

Now, in Table 3, we propose the application of this algorithm for EQI. We can see that the US states can be grouped initially into four clubs, formed by 2, 8, 10 and 30 US states, respectively. We have to highlight the members of club 1, which are two of the most representative US states regarding the birth of startups, due to the proximity to the best universities around the world: California and Massachusetts.

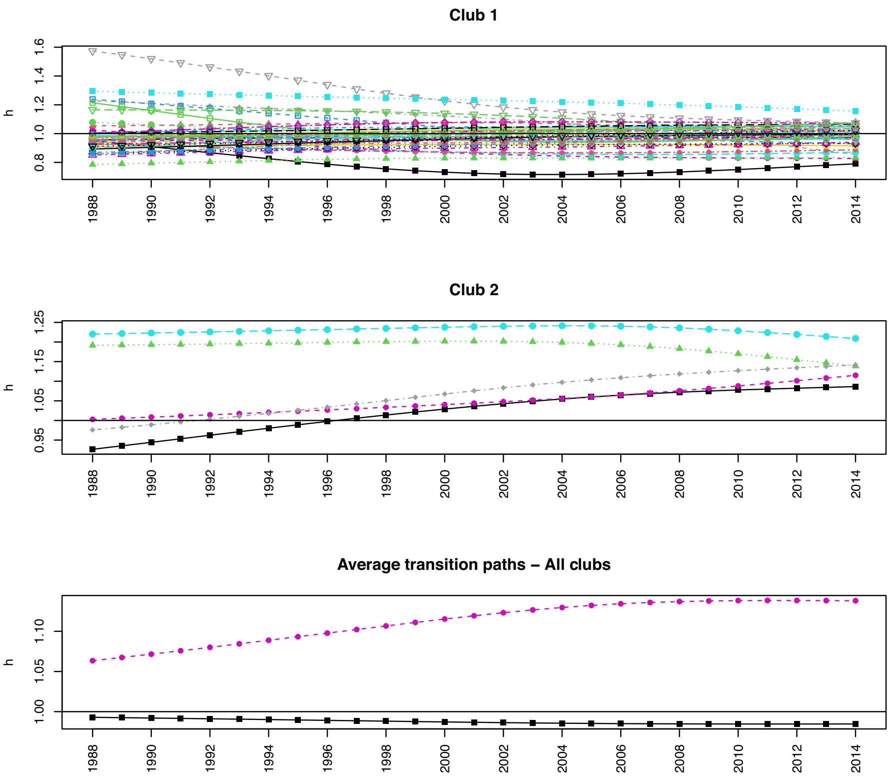


Fig. 3 Convergence transition paths and Average transition paths for all clubs: SFR

Table 3 Club convergence in EQI

Club	No. of states	$\hat{b}$ coefficient	SE	t-stat	States
Club convergence in EQI					
1	2	3.374	1.382	2.442	CA, MA
2	8	0.159	0.046	3.435	WA, TX, UT, VA, PA, TN, IL, RI
3	10	0.964	0.109	8.852	OR, NH, CO, CT, NC, MN, GA, NY, AL, NV
4	30	0.140	0.051	2.734	KY, MD, ND, KS, OH, FL, NJ, IA, IN, OK, VT, DC, ID, ME, WI, SD, MO, AZ, MI, SC, NM, HI, AR, LA, MS, WY, NE, MT, AK, WV
Club merging algorithm					
1	2	3.374	1.382	2.442	CA, MA
2	18	−0.028	0.028	−1.012	WA, TX, UT, VA, PA, TN, IL, RI, OR, NH, CO, CT, NC, MN, GA, NY, AL, NV
3	30	0.140	0.051	2.734	KY, MD, ND, KS, OH, FL, NJ, IA, IN, OK, VT, DC, ID, ME, WI, SD, MO, AZ, MI, SC, NM, HI, AR, LA, MS, WY, NE, MT, AK, WV

The tests of club merging have as a null hypothesis that Club i and Club j can be considered a joint convergence club (Camarero et al., 2013). The test is also distributed as a one-sided t-statistic with a 5% critical value of −1.65

This result is in line with that analyzed by Qian & Zhao (2018), which focuses on high-technology entrepreneurship in California and Massachusetts, proposed by the seminal paper of Saxenian (1996). Then, we test the possibility of the club merging algorithm of Phillips & Sul (2009). In this sense, clubs 2 and 3 can be merged when using this club convergence merging algorithm (this new club now includes 18 US states (10+8)) (see Sichera & Pizzuto 2019). Indeed, if we look at the bottom of Table 3, we find the new clubs proposed by this methodology. In this regard, the club clustering algorithm suggests that the null hypothesis of club convergence is accepted for club 1 because its t-stat is higher than −1.65 (2.442 > −1.65), implying that states in club 1 do move towards convergence, even although their levels of EQI might differ. Similar results are achieved for clubs 2 and 3.

Additionally, attending to the speed of adjustment, the sign of the coefficient estimated for clubs 1 and 3 is positive (3.374 and 0.140), being evidence of a strong speed of adjustment (Saba & Ngepah, 2022). Again, Johnson (2020) suggests how to measure the strength of the convergence procedure in each club by attending to the coefficient obtained in the log(t) test for each club. As mentioned in the methodology section, as the coefficient in club 1 is above 2, the model suggests convergence in levels (that is, absolute convergence). For its part, club 2 shows a negative coefficient, implying that there exists divergence amongst US states. Finally, attending to club 3, the coefficient is placed in the range between 0 and 2, these states would converge in growth rates.

In Fig. 4 are plotted the transition paths for each club. As shown, the lines follow different curves of the convergence process in EQI for clubs 1, 2 and 3 relatives to the sample average. We can see heterogeneity amongst the US states forming these clubs in terms of convergence over the period studied. More in-depth, Fig. 4 shows the behaviour of the US states in Club 1. During this period, their paths seem to separate and indicate changes from their initial level and their paths start at the same point and go down following a common trend over time.

Furthermore, we can suggest that the US states forming club 2 start from a different level and get different groupuscules at the end of the sample. For club 3, we can highlight that, although the paths also seem to be separated at the beginning of the plot, they follow a process to a similar endpoint. Finally, in Fig. 4 the average transition path for each club is displayed. As we can see, the three clubs start from different levels but, over time, diverge sharply. It is worth noting that, club 1 seems to diverge from the mean downwards and move away from the rest and clubs 2 and 3 run in parallel, but with a slight divergence. Thus, this Fig. 4 supports our findings previously shown in Table 3.

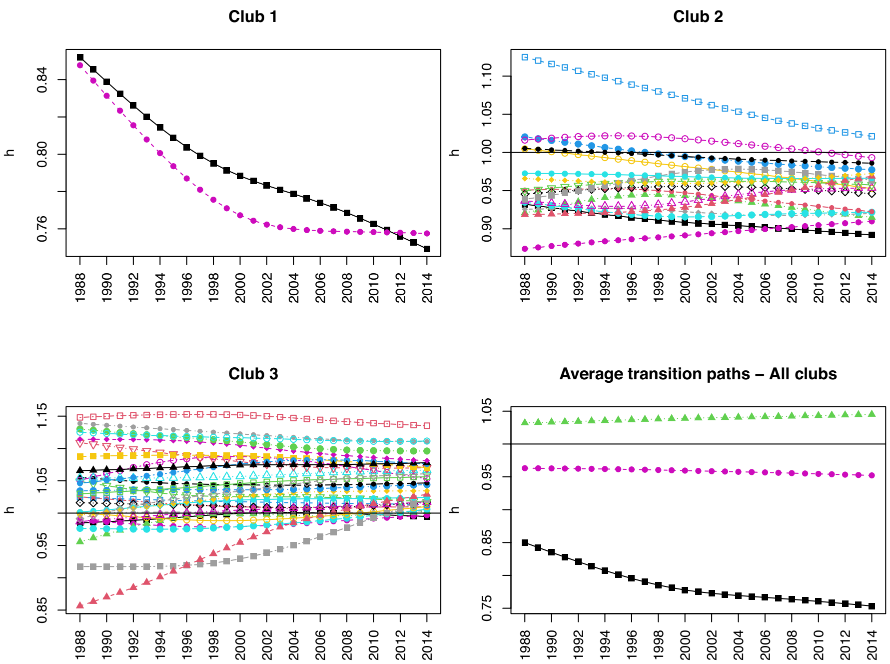


Fig. 4 Convergence transition paths and Average transition paths for all clubs: EQI

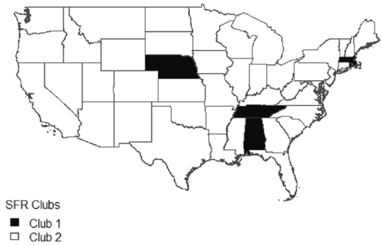


Fig. 5 Geographical distribution of convergence clubs: SFR

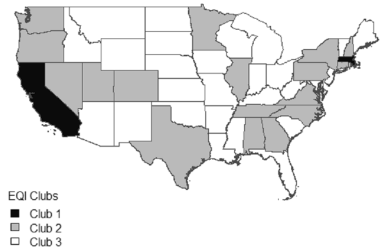


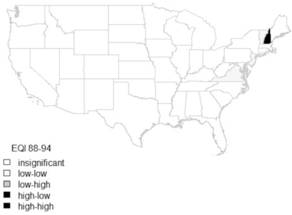
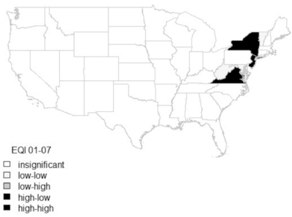
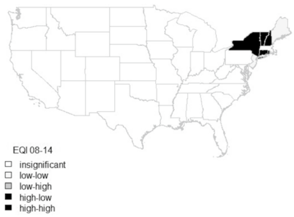
Fig. 6 Geographical distribution of convergence clubs: EQI

At first glance, attending to a geographical criterion reflected in Fig. 5, the first club represents states spread all over the country (orange colour). The second club is scattered in the Middle and East of the country (it is defined by yellow colour). For its part, Fig. 6 is represented in a geographical way the resulting clubs. As we can see, club 1 is formed by California and Massachusetts (remember that Silicon Valley and MIT or Harvard are located in these states). The rest of the clubs are indistinctly spread around the country. These results are not surprising because are consistent with the common understanding of the geography of US entrepreneurship and furthermore, they are in line with those obtained by Andrews et al. (2022).

Recalling the results obtained for the EQI, we found three clubs and, focusing on the first club, this is formed by California and Massachusetts. Although not surprisingly, this evidence of the different patterns regarding the quality of entrepreneurship differs by state and more intrinsic, it matches with the most prominent states regarding knowledge, innovation and growth of the USA. Thus, as abovementioned, the objective now is clear: we try to disentangle the possible spillover effects of the preponderance of these states, i.e., California and Massachusetts, to their neighbours. To this end, we apply the Local Moran I to detect the spatial dependency of quality entrepreneurship in both states. In this respect, as mentioned previously, Plummer (2010) justifies why entrepreneurial activity can be spatially dependent, supporting the application of spatial econometric methods on this topic.

Respecting the Local Moran I test, we heed the results obtained from the application of the club convergence algorithm on EQI, because it provides more interesting insights. Thus, we apply the Local Moran I to that data set in Table 4 to test the existence of a spatial structure that can be observed in quality clubs (EQI). Therefore, we analyse the temporal changes of the spatial patterns and spatial dependence, which is also known as the “Hot Spot–Cold Spot” analysis, of quality entrepreneurship. We show how statistical results from spatial dependency analysis changed during

Table 4 Local Moran I for EQI

EQI 88-94	EQI 95-00
	
EQI 01-07	**EQI 08-14**
	

Note: Own elaboration from the application of the Local Moran I.

Note: Own elaboration from the application of the Local Moran I

1988–2014 (we have divided the sample into four equal periods that correspond to different economic events) in each of the two states. The goal is to evaluate the temporal changes of the spillover effects of quality entrepreneurship across regions.

As can be observed in Table 4, the number of states with entrepreneurship quality index (EQI) significantly similar to their surroundings is limited. Focusing on the two states with the highest entrepreneurship quality (California and Massachusetts), the test shows that California does not appear as significant in any subperiod, thereby confirming its status as a high-quality entrepreneurship outlier within its geographical region. In the case of Massachusetts, despite not emerging as significant in any subperiod, it is close to states that recurrently appear as "Hot spots", indicating states with high EQI surrounded by states of high EQI. These results seem to suggest that Massachusetts also qualifies as an outlier within its geographical vicinity, belonging to a different cluster compared to its surroundings. As can be observed in Table 4, as the time period used advances, those spillover effects are more evident, focusing on the New England region, where Massachusetts is located.

As we can see, in the last period considered, i.e., 2008–2014, Massachusetts is surrounded by different states (in dark colour) that, casually, shape this region, that is, Connecticut, Rhode Island, Vermont, and New Hampshire and, in a lighter colour, Maine. Consequently, it seems that Massachusetts may be a lighthouse in the New England region.

In this sense, according to Leamer (2007), this spatial concentration of entrepreneurial activity can be attributed to the diminished transaction costs, including lower transportation and communication expenses. This phenomenon arises from the geographic clustering of individuals, households, and businesses, as explained by Leamer (2007). Nonetheless, it exerts a positive influence, thereby substantiating the potential existence of spillover effects originating from the state with the highest EQI (Massachusetts) towards the rest of the states with lower levels but forming a high EQI cluster.

5 Discussion

This paper aims to examine the time dynamics within entrepreneurial ecosystems, following the suggestion of Stam and Van de Ven (2021) and Buratti et al. (2023), who emphasize the need to address the entrepreneurial ecosystems topic 'over a longer period of time.' On the other hand, we follow Cohen (2006), Cavallo et al. (2019) and Audretsch and Belitski (2021), who argue for the need to understand and delimit the geographical dimensions in which an entrepreneurial ecosystem is developed.

Thus, having proposed two key propositions: First, entrepreneurial ecosystems among US states evolve over time. Second, the nurturing of entrepreneurial ecosystems in a given US state is facilitated by its geographical spillovers. These propositions underpin the current analysis and findings. We argue that understanding the evolution of entrepreneurial ecosystems over time and space necessitates a longitudinal perspective to map and track these changes from their inception (Cho et al., 2022), contrasting to those studies that propose a static view of entrepreneurial ecosystems (see Spigel, (2017) or Acs et al., (2018), among others).

In this regard, one might expect some convergence amongst US states but, one can also find reasons to expect that the trends of transition may be very different across states (Phillips & Sul, 2009). To this end, we have used a novel data set developed by Andrews et al. (2022), i.e., "The Startup Cartography Project". For this reason, we have applied the club clustering algorithm to "quantity entrepreneurship" represented by SFR, and "quality entrepreneurship", represented by EQI, and our findings suggest the no existence of a global convergence within US states for both variables, although we have found two and three clubs, respectively. In cases of global convergence, the impact of a global measure, such as federal policy, would affect all states collectively. However, in our scenario, this federal policy loses influence over states or groups, resulting in varied effects, particularly as differences between them widen.

Clusters form because entrepreneurial ecosystems are not a single variable but should be considered holistically (Theodoraki et al., 2018; Abootorabi et al., 2021), taking into account the combination of elements that constitute them. In terms of the SFR, we find that the states forming each club do not follow any discernible pattern. In contrast, for the EQI, it can be observed antagonistic dynamic behaviour amongst clusters (see Fig. 4). This divergence may indicate that regional differences could persist and even enlarge over time. These findings suggest that limited business capital and structural differences between states might influence entrepreneurial ecosystems, affecting both the quantity (SFR) and quality (EQI) of entrepreneurship. For example, in our case, Massachusetts and California are two states where important nuclei of innovation, university, knowledge, and capital are located, such as Silicon Valley, MIT, or Harvard, among others. Therefore, we believe that the formation of new clusters will necessarily require the combination of all the factors identified in the literature (Colombelli et al., 2019). However, there are examples of isolated entrepreneurial ecosystems that, although significant at the local level, do not have a regional reach (Leendertse et al., 2022).

This aligns with the findings of Cohen (2006), or Alam and Bhowmick (2023), who identified the key actors that transform a community into an entrepreneurial ecosystem. In order to grow and evolve entrepreneurial ecosystems, each element must be reinforced, assuming that all components are equally important in creating the necessary environmental conditions to foster entrepreneurship in a specific region (Leendertse et al., 2022; Cavallo et al., 2023).

Attending to the spatial analysis, we suggest the existence of spillovers may only occur in Massachusetts, which could be a spillover generator among its neighbours (Audretsch & Feldman, 1996; Colombelli et al., 2019; Audretsch & Belitski, 2021). Nonetheless, a determinant that could exert an influence on the observed outcomes is the distance between states and their neighbours. Distance is a crucial factor in the generation of agglomeration economies and connections, which are potentially essential for the existence of spillovers (Qian & Zhao, 2018). In this regard, the relatively small size of Massachusetts and its neighbouring states results in a reduced inter-state distance, a condition not shared by California.

This study provides further insight into the existing literature on knowledge spillovers (Audretsch & Feldman, 1996; Cavallo et al., 2019, 2023) and highlights the critical role of regional knowledge heterogeneity. In this manner, the sub-national entrepreneurial ecosystem valuation may provide a lighter view of the heterogeneity of applicable factors within the country, i.e., as Audretsch & Belitski (2017) claim, the most appropriate spatial demarcations are the immediate urban or city-region context. The process of creating new firms depends upon the availability of better resources combined with good institutions. This idea is extended to the expansion of young companies and the technological recovery of firms overall. However, the necessary factors to intensify an entrepreneurial ecosystem (human capital, talent or managerial capacity, among others) are structural and the need for investment, resources, and time to mature (Audretsch et al., 2022; Cavallo et al., 2023) so, it seems that quality flourishes over quantity. Recognizing the potential of entrepreneurial ecosystems at the regional level may provide a more precise diagnostic of the entrepreneur problem, given that the decision of performing a business and innovating, takes place in a particular location surrounded by determined factors.

6 Conclusion

Regional entrepreneurship grouping is a key element because it could influence regional economic behaviour. For that, there is a rising interest related to the determinants of entrepreneurship and regional convergence amongst academics (Andersson & Koster, 2011). At this time, despite entrepreneurship being influenced by national and regional factors, the combination of both factors is missing in the literature on the creation of regional entrepreneurial ecosystems. Thus, the entrepreneurial ecosystem framework has captured the interest of both scholars and policymakers, as it enables policymakers to develop an environment that fosters entrepreneurship and creates opportunities for new ventures (Alam & Bhowmick, 2023).

Usually, identifying the distinctions in convergence patterns through states is significant to the design and employment of fostering policy as policymakers do not want to undesirably influence the business creation of the respective state and governments would have diverse policy instruments that support entrepreneurship. Public policies and intermediary organizations are to influence and shape this environment in such a manner that it generates the desired degree of entrepreneurship. These policies would be oriented toward detecting market failures in order to improve the conditions of resource endowments, the demand for these resources, or allocation barriers across actors. Furthermore, modifying the regulatory environment could foster the availability of resources and promote competitiveness.

Additionally, these policies can be implemented through specific tools such as public programs for providing direct support to entrepreneurs. For this reason, it is important to make this distinction, i.e., quantity *vs.* quality entrepreneurship, because it cannot be possible to observe a common behaviour when attending to quantity entrepreneurial activity and, conversely this common behaviour can be appreciated when attending to quality entrepreneurial activity. Consequently, our results reveal the importance of not measuring entrepreneurship in terms of quantity. Attending to quality, we have identified three strata that exhibit very marked differences, which are becoming more pronounced over time. Therefore, policies should be aimed at the implementation and consolidation of the various facets collected in the literature, highlighting the need for governmental policies to coordinate with other factors and create synergies with the environment. Finally, as Guzman & Stern (2020) indicates, if entrepreneurial quality is associated with future economic growth, then quality measures can serve as effective leading indicators of a region's economic performance. Policymakers, for instance, can employ the quality entrepreneurship index to determine whether a particular region is cultivating the kind of entrepreneurship that is likely to produce significant economic returns.

Future research endeavours may delve into the effect of distance on the occurrence of quality entrepreneurship spillovers. It is intriguing to consider an analysis with finer geographical granularity, for instance, dissecting the data by county within California, as a macro local entrepreneurial ecosystem. Furthermore, our findings suggest that coordination policies aimed at promoting high-quality entrepreneurship may not yield effective results if implemented among geographical units that, despite their proximity, possess substantial distance between their primary urban cores.

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Data availability The data that support the findings of this study are available from the corresponding author, upon reasonable request.

References

Abootorabi, H., Wiklund, J., Johnson, A. R., & Miller, C. D. (2021). A holistic approach to the evolution of an entrepreneurial ecosystem: An exploratory study of academic spin-offs. *Journal of Business Venturing, 36*(5), 106143.

Acs, Z., Åstebro, T., Audretsch, D., & Robinson, D. T. (2016). Public policy to promote entrepreneurship: A call to arms. *Small Business Economics, 47*, 35–51.

Acs, Z. J., & Armington, C. (2006). *Entrepreneurship, geography, and American economic growth*. Cambridge University Press.

Ács, Z. J., Autio, E., & Szerb, L. (2014). National systems of entrepreneurship: Measurement issues and policy implications. *Research Policy, 43*, 476–494.

Acs, Z. J., Estrin, S., Mickiewicz, T., & Szerb, L. (2018). Entrepreneurship, institutional economics, and economic growth: An ecosystem perspective. *Small Business Economics, 51*, 501–514.

Acs, Z. J., Stam, E., Audretsch, D. B., & O'Connor, A. (2017). The lineages of the entrepreneurial ecosystem approach. *Small Business Economics, 49*, 1–10.

Adams, S. B. (2021). From orchards to chips: Silicon valley's evolving entrepreneurial ecosystem. *Entrepreneurship & Regional Development, 33*(1–2), 15–35.

Akcigit, U., & Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy, 126*(4), 1374–1443.

Alam, A., & Bhowmick, B. (2023). Examining the domains of entrepreneurial ecosystem framework: A bibliometric analysis. *Journal of Global Entrepreneurship Research, 13*(1), 16.

Almeida, A., Golpe, A., & Justo, R. (2021). From hot to cold: A spatial analysis of self-employment in the United States. *Papers in Regional Science, 100*(4), 1005–1023.

Amorós, J. E., Poblete, C., & Mandakovic, V. (2019). R &d transfer, policy and innovative ambitious entrepreneurship: Evidence from Latin American countries. *The Journal of Technology Transfer, 44*(5), 1396–1415.

Andersson, M., & Koster, S. (2011). Sources of persistence in regional start-up rates-evidence from Sweden. *Journal of Economic Geography, 11*(1), 179–201.

Andrews, R. J., Fazio, C., Guzman, J., Liu, Y., & Stern, S. (2022). The startup cartography project: Measuring and mapping entrepreneurial ecosystems. *Research Policy, 51*(2), 104437.

Anselin, L. (1995). Local indicators of spatial association-LISA. *Geographical Analysis, 27*(2), 93–115.

Aoyama, Y. (2013). Entrepreneurship and regional culture: The case of hamamatsu and kyoto, japan. *Globalizing regional development in East Asia* (pp. 169–186). Routledge.

Audretsch, D., Cruz, M. & Torres, J. (2022). Revisiting entrepreneurial ecosystems.

Audretsch, D., Thurik, R., Verheul, I., & Wennekers, S. (2002). Understanding entrepreneurship across countries and over time. *Entrepreneurship: Determinants and policy in a European-US comparison* (pp. 1–10). Springer.

Audretsch, D. B. (2023). Institutions and entrepreneurship. *Eurasian Business Review, 13*(3), 495–505.

Audretsch, D. B., & Belitski, M. (2017). Entrepreneurial ecosystems in cities: Establishing the framework conditions. *The Journal of Technology Transfer, 42*, 1030–1051.

Audretsch, D. B., & Belitski, M. (2021). Towards an entrepreneurial ecosystem typology for regional economic development: The role of creative class and entrepreneurship. *Regional Studies, 55*(4), 735–756.

Audretsch, D. B., & Belitski, M. (2024a). Digitalization, resource mobilization and firm growth in emerging industries. *British Journal of Management, 35*(2), 613–628.

Audretsch, D. B., & Belitski, M. (2024b). Geography of knowledge collaboration and innovation in Schumpeterian firms. *Regional Studies, 58*(4), 821–840.

Audretsch, D. B., & Belitski, M. (2024c). Knowledge collaboration, firm productivity and innovation: A critical assessment. *Journal of Business Research, 172*, 114412.

Audretsch, D. B., Belitski, M., Caiazza, R., & Siegel, D. (2023). Effects of open innovation in startups: Theory and evidence. *Technological Forecasting and Social Change, 194*, 122694.

Audretsch, D. B., Belitski, M., & Cherkas, N. (2021). Entrepreneurial ecosystems in cities: The role of institutions. *PloS One, 16*(3), e0247609.

Audretsch, D. B., Belitski, M., & Desai, S. (2019). National business regulations and city entrepreneurship in Europe: A multilevel nested analysis. *Entrepreneurship Theory and Practice, 43*(6), 1148–1165.

Audretsch, D. B., Cunningham, J. A., Kuratko, D. F., Lehmann, E. E., & Menter, M. (2019). Entrepreneurial ecosystems: Economic, technological, and societal impacts. *The Journal of Technology Transfer, 44*, 313–325.

Audretsch, D. B., & Feldman, M. P. (1996). R &D spillovers and the geography of innovation and production. *The American Economic Review, 86*(3), 630–640.

Audretsch, D. B., & Keilbach, M. (2007). The theory of knowledge spillover entrepreneurship. *Journal of Management Studies, 44*(7), 1242–1254.

Belitski, M., Delgado-Márquez, B. L., & Pedauga, L. E. (2024). Your innovation or mine? the effects of partner diversity on product and process innovation. *Journal of Product Innovation Management, 41*(1), 112–137.

Belitski, M. & Korosteleva, J. (2010). Entrepreneurial activity across european cities.

Bergman, B. J., & McMullen, J. S. (2022). Helping entrepreneurs help themselves: A review and relational research agenda on entrepreneurial support organizations. *Entrepreneurship Theory and Practice, 46*(3), 688–728.

Braunerhjelm, P., Acs, Z. J., Audretsch, D. B., & Carlsson, B. (2010). The missing link: Knowledge diffusion and entrepreneurship in endogenous growth. *Small Business Economics, 34*(2), 105–125.

Brown, R., & Mason, C. (2017). Looking inside the spiky bits: A critical review and conceptualisation of entrepreneurial ecosystems. *Small Business Economics, 49*, 11–30.

Buratti, M., Cantner, U., Cunningham, J. A., Lehmann, E. E., & Menter, M. (2023). The dynamics of entrepreneurial ecosystems: An empirical investigation. *R &D Management, 53*(4), 656–674.

Burke, A., Lyalkov, S., Millán, A., Millán, J. M., & van Stel, A. (2021). How do country R &D change the allocation of self-employment across different types? *Small Business Economics, 56*(2), 695–721.

Burke, A. E., Fitzroy, F. R., & Nolan, M. A. (2009). Is there a North-South divide in self-employment in England? *Regional Studies, 43*(4), 529–544.

Camarero, M., Castillo, J., Picazo-Tadeo, A. J., & Tamarit, C. (2013). Eco-efficiency and convergence in OECD countries. *Environmental and Resource Economics, 55*(1), 87–106.

Cao, Z., & Shi, X. (2021). A systematic literature review of entrepreneurial ecosystems in advanced and emerging economies. *Small Business Economics, 57*, 75–110.

Carmona, M., Congregado, E., Golpe, A. A., & Iglesias, J. (2016). Self-employment and business cycles: searching for asymmetries in a panel of 23 OECD countries. *Journal of Business Economics and Management, 17*(6), 1155–1171.

Cavallo, A., Colombelli, A., D'Amico, E., & Paolucci, E. (2023). "Balanced'' or "polarized'' entrepreneurial ecosystem types? evidence from Italy. *The Journal of Technology Transfer, 48*(5), 1860–1889.

Cavallo, A., Ghezzi, A., & Balocco, R. (2019). Entrepreneurial ecosystem research: Present debates and future directions. *International Entrepreneurship and Management Journal, 15*, 1291–1321.

Cheng, S., & Li, H. (2011). Spatially varying relationships of new firm formation in the United States. *Regional Studies, 45*(6), 773–789.
Cho, D. S., Ryan, P., & Buciuni, G. (2022). Evolutionary entrepreneurial ecosystems: A research pathway. *Small Business Economics, 58*(4), 1865–1883.
Claver-Cortés, E., Marco-Lajara, B., Seva-Larrosa, P., Ruiz-Fernández, L., & Sánchez-García, E. (2020). Explanatory factors of entrepreneurship in food and beverage clusters in Spain. *Sustainability, 12*(14), 5625.
Cohen, B. (2006). Sustainable valley entrepreneurial ecosystems. *Business Strategy and the Environment, 15*(1), 1–14.
Colombelli, A., Paolucci, E., Raguseo, E., & Elia, G. (2024). The creation of digital innovative startups: the role of digital knowledge spillovers and digital skill endowment. *Small Business Economics, 62*(3), 917–937.
Colombelli, A., Paolucci, E., & Ughetto, E. (2019). Hierarchical and relational governance and the life cycle of entrepreneurial ecosystems. *Small Business Economics, 52*, 505–521.
Colombo, M. G., Dagnino, G. B., Lehmann, E. E., & Salmador, M. (2019). The governance of entrepreneurial ecosystems. *Small Business Economics, 52*, 419–428.
Conti, A., & Guzman, J. A. (2021). What is the US comparative advantage in entrepreneurship? Evidence from Israeli migration to the United States. *Review of Economics and Statistics, 105*(3), 528–44.
Corrente, S., Greco, S., Nicotra, M., Romano, M., & Schillaci, C. E. (2019). Evaluating and comparing entrepreneurial ecosystems using SMAA and SMAA-S. *The Journal of Technology Transfer, 44*, 485–519.
Cravo, T. A., Becker, B., & Gourlay, A. (2015). Regional growth and SMEs in Brazil: A spatial panel approach. *Regional Studies, 49*(12), 1995–2016.
Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography, 10*(4), 495–518.
Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy, 43*(10), 1785–1799.
Du, K. (2017). Econometric convergence test and club clustering using Stata. *The Stata Journal, 17*(4), 882–900.
Fairlie, R. W. & Fossen, F. M. (2018). Opportunity versus necessity entrepreneurship: Two components of business creation.
Fritsch, M., & Wyrwich, M. (2014). The long persistence of regional levels of entrepreneurship: Germany, 1925–2005. *Regional Studies, 48*(6), 955–973.
Fritsch, M., & Wyrwich, M. (2017a). The effect of entrepreneurship on economic development-an empirical analysis using regional entrepreneurship culture. *Journal of Economic Geography, 17*(1), 157–189.
Fritsch, M., & Wyrwich, M. (2017b). The long persistence of regional levels of entrepreneurship: Germany, 1925–2005. *Entrepreneurship in a Regional Context* (pp. 17–35). Routledge.
Fritsch, M., & Wyrwich, M. (2019). Regional entrepreneurship culture and growth. *Regional Trajectories of Entrepreneurship, Knowledge, and Growth* (pp. 69–94). Springer.
Fritsch, M., & Wyrwich, M. (2021). Does successful innovation require large urban areas? Germany as a counterexample. *Economic Geography, 97*(3), 284–308.
Glaeser, E. L., Kerr, S. P., & Kerr, W. R. (2015). Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics, 97*(2), 498–520.
Glaeser, E. L., Kerr, W. R., & Ponzetto, G. A. (2010). Clusters of entrepreneurship. *Journal of Urban Economics, 67*(1), 150–168.
Guerrero, M., Liñán, F., & Cáceres-Carrasco, F. R. (2021). The influence of ecosystems on the entrepreneurship process: A comparison across developed and developing economies. *Small Business Economics, 57*(4), 1733–1759.
Guzman, J. & Stern, S. (2020). The state of American entrepreneurship report for the European central bank on a quality-based approach to the measurement of entrepreneurship across time and location.
Jing, S., Qinghua, Z., & Landström, H. (2015). Entrepreneurship research in three regions-the USA, Europe and China. *International Entrepreneurship and Management Journal, 11*(4), 861–890.
Johnson, E., Hemmatian, I., Lanahan, L., & Joshi, A. M. (2022). A framework and databases for measuring entrepreneurial ecosystems. *Research Policy, 51*(2), 104398.

Johnson, P. A. (2020). Parameter variation in the ‘log t’ convergence test. *Applied Economics Letters, 27*(9), 736–739.
Lado-Sestayo, R., Neira-Gómez, I., Chasco-Yrigoyen, C., et al. (2017). Entrepreneurship at regional level: Temporary and neighborhood effects. *Entrepreneurship Research Journal, 7*(4), 1–12.
Lafuente, E., Ács, Z. J., & Szerb, L. (2022). A composite indicator analysis for optimizing entrepreneurial ecosystems. *Research Policy, 51*(9), 104379.
Leamer, E. E. (2007). A flat world, a level playing field, a small world after all, or none of the above? A review of Thomas L. Friedman’s the world is flat. *Journal of Economic Literature, 45*(1), 83–126.
Leendertse, J., Schrijvers, M., & Stam, E. (2022). Measure twice, cut once: Entrepreneurial ecosystem metrics. *Research Policy, 51*(9), 104336.
Liguori, E., Bendickson, J., Solomon, S., & McDowell, W. C. (2019). Development of a multi-dimensional measure for assessing entrepreneurial ecosystems. *Entrepreneurship & Regional Development, 31*(1–2), 7–21.
Luo, B., & Chong, T. T. L. (2019). Regional differences in self-employment in China. *Small Business Economics, 53*(3), 813–837.
Mason, C., & Brown, R. (2013). Creating good public policy to support high-growth firms. *Small Business Economics, 40*, 211–225.
Mason, C., & Brown, R. (2014). Entrepreneurial ecosystems and growth oriented entrepreneurship. *Final Report to OECD, Paris, 30*(1), 77–102.
Mendez, C. (2020). Convergence clubs in labor productivity. *Convergence clubs in labor productivity and its proximate sources* (pp. 33–39). NY: Springer.
Mérida, A. L., Carmona, M., Congregado, E., & Golpe, A. A. (2016). Exploring the regional distribution of tourism and the extent to which there is convergence. *Tourism Management, 57*, 225–233.
Mittelstädt, A. & Cerri, F. (2009). Fostering entrepreneurship for innovation. *OECD Science, Technology and Industry Working Papers* 2008(5).
Muñoz, P., Kibler, E., Mandakovic, V., & Amorós, J. E. (2022). Local entrepreneurial ecosystems as configural narratives: A new way of seeing and evaluating antecedents and outcomes. *Research Policy, 51*(9), 104065.
Neumeyer, X., Santos, S. C., & Morris, M. H. (2019). Who is left out: Exploring social boundaries in entrepreneurial ecosystems. *The Journal of Technology Transfer, 44*, 462–484.
Nicotra, M., Romano, M., Del Giudice, M., & Schillaci, C. E. (2018). The causal relation between entrepreneurial ecosystem and productive entrepreneurship: A measurement framework. *The Journal of Technology Transfer, 43*, 640–673.
Parker, S. C., & Robson, M. T. (2004). Explaining international variations in self-employment: Evidence from a panel of OECD countries. *Southern Economic Journal, 71*(2), 287–301.
Phillips, P. C., & Sul, D. (2007). Transition modeling and econometric convergence tests. *Econometrica, 75*(6), 1771–1855.
Phillips, P. C., & Sul, D. (2009). Economic transition and growth. *Journal of Applied Econometrics, 24*(7), 1153–1185.
Plummer, L. A. (2010). Spatial dependence in entrepreneurship research: Challenges and methods. *Organizational Research Methods, 13*(1), 146–175.
Porter, M. E., & Stern, S. (2001). Innovation: location matters. *MIT Sloan Management Review, 42*(4), 28.
Qian, H., & Zhao, C. (2018). Space-time analysis of high technology entrepreneurship: A comparison of California and New England. *Applied Geography, 95*, 111–119.
Riaz, M. F., Leitão, J., & Cantner, U. (2022). Measuring the efficiency of an entrepreneurial ecosystem at municipality level: Does institutional transparency play a moderating role? *Eurasian Business Review, 12*(1), 151–176.
Rocha, A., Brown, R., & Mawson, S. (2021). Capturing conversations in entrepreneurial ecosystems. *Research Policy, 50*(9), 104317.
Ross, A. G., Adams, J., & Crossan, K. (2015). Entrepreneurship and the spatial context: A panel data study into regional determinants of small growing firms in Scotland. *Local Economy, 30*(6), 672–688.
Roundy, P. T., Bradshaw, M., & Brockman, B. K. (2018). The emergence of entrepreneurial ecosystems: A complex adaptive systems approach. *Journal of Business Research, 86*, 1–10.
Roundy, P. T., Brockman, B. K., & Bradshaw, M. (2017). The resilience of entrepreneurial ecosystems. *Journal of Business Venturing Insights, 8*, 99–104.

Roundy, P. T., & Lyons, T. S. (2023). Where are the entrepreneurs? A call to theorize the micro-foundations and strategic organization of entrepreneurial ecosystems. *Strategic Organization, 21*(2), 447–459.

Saba, C. S., & Ngepah, N. (2022). Convergence in renewable energy sources and the dynamics of their determinants: An insight from a club clustering algorithm. *Energy Reports, 8*, 3483–3506.

Saridakis, G., González, M. A. M., Hand, C., & Torres, Rebeca IM. (2020). Do regional self-employment rates converge in the UK? Empirical evidence using club-clustering algorithm. *The Annals of Regional Science, 65*(1), 179–192.

Saridakis, G., Mendoza Gonzalez, M. A., Muñoz Torres R. I., & Hand, C. (2019). Do self-employment rates converge? Evidence from European OECD countries. *JCMS: Journal of Common Market Studies, 57*(3), 551–562.

Saxenian, A. (1996). *Regional advantage: Culture and competition in Silicon Valley and Route 128*. Harvard University Press.

Schumpeter, J. A. (1934). *The Theory of Economic Development: An inquiry into profits, capital, credit, interest, and the business cycle*.

Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. *Small Business Economics, 33*, 141–149.

Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review, 25*(1), 217–226.

Shi, X., & Shi, Y. (2022). Unpacking the process of resource allocation within an entrepreneurial ecosystem. *Research Policy, 51*(9), 104378.

Sichera, R., & Pizzuto, P. (2019). Convergenceclubs: A package for performing the Phillips and Sul's club convergence clustering procedure. *R Journal, 11*(2), 142.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science, 51*(5), 756–770.

Sölvell, O., Lindqvist, G., Ketels, C. & Porter, M. E. (2003). The cluster initiative Greenbook.

Spencer, G. M., Vinodrai, T., Gertler, M. S., & Wolfe, D. A. (2010). Do clusters make a difference? Defining and assessing their economic performance. *Regional Studies, 44*(6), 697–715.

Spigel, B. (2017). The relational organization of entrepreneurial ecosystems. *Entrepreneurship Theory and Practice, 41*(1), 49–72.

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: A sympathetic critique. *European Planning Studies, 23*(9), 1759–1769.

Stam, E., & Spigel, B. (2018). Entrepreneurial ecosystems. In R. Blackburn, C. D. Clercq, & J. Heinonen (Eds.), *The SAGE handbook of small business and entrepreneurship* (pp. 407–422). London: SAGE.

Stam, E., & Van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics, 56*(2), 809–832.

Sternberg, R., & Wennekers, S. (2005). Determinants and effects of new business creation using global entrepreneurship monitor data. *Small Business Economics, 24*, 193–203.

Stuetzer, M., Audretsch, D. B., Obschonka, M., Gosling, S. D., Rentfrow, P. J., & Potter, J. (2018). Entrepreneurship culture, knowledge spillovers and the growth of regions. *Regional Studies, 52*(5), 608–618.

Thai, M. T. T., & Turkina, E. (2014). Macro-level determinants of formal entrepreneurship versus informal entrepreneurship. *Journal of Business Venturing, 29*(4), 490–510.

Theodoraki, C., Dana, L. P., & Caputo, A. (2022). Building sustainable entrepreneurial ecosystems: A holistic approach. *Journal of Business Research, 140*, 346–360.

Theodoraki, C., Messeghem, K., & Rice, M. P. (2018). A social capital approach to the development of sustainable entrepreneurial ecosystems: An explorative study. *Small Business Economics, 51*, 153–170.

Wennekers, S., Van Wennekers, A., Thurik, R., & Reynolds, P. (2005). Nascent entrepreneurship and the level of economic development. *Small Business Economics, 24*(3), 293–309.

Wolman, H., & Hincapie, D. (2015). Clusters and cluster-based development policy. *Economic Development Quarterly, 29*(2), 135–149.

Xie, Z., Wang, X., Xie, L., & Duan, K. (2021). Entrepreneurial ecosystem and the quality and quantity of regional entrepreneurship: A configurational approach. *Journal of Business Research, 128*, 499–509.

Yasin, M. Z., Esquivias, M. A., Lau, W., & Primanthi, M. R. (2024). Friend or foe? Revealing R &D spillovers from fdi in Indonesia. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(1), 100209.
Zhu, X., Liu, Y., He, M., Luo, D., & Wu, Y. (2019). Entrepreneurship and industrial clusters: Evidence from China industrial census. *Small Business Economics, 52*(3), 595–616.