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RESEARCH ARTICLE

What conditions favor high-potential entrepreneurship? Unpacking the nexus between the industrial structure and startup typologies

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Abstract In this paper, we question the implicit assumption that more entrepreneurship drives more innovation and growth, asserting that specific typologies of entrepreneurship are responsible for these phenomena. A growing number of studies has analyzed this relationship while focusing on the overall level of entrepreneurship. This paper exploits recent advancements in measuring the sophistication and connectedness of economic systems, brought by the notions of economic complexity and relatedness, to study the nexus of industrial structure and high-potential forms of entrepreneurship. The present study uses a panel dataset for Italy for the period 2015–2019. The results show a differentiated pattern among the high-potential startups considered, with relatedness and complexity having a positive effect for innovative startups, a negative one for high-growth startups, and no effect for pioneers. These results inform potential entrepreneurs of the importance of analyzing how external conditions can have distinctive effects on the process of opportunity identification among different typologies of high-potential startups.

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Plain English Summary In this paper, we question the implicit assumption that more entrepreneurship drives more innovation and growth, arguing that only specific typologies of entrepreneurship are responsible for these phenomena. In recent years, researchers have highlighted the importance of the factors external to the startups to explain the entrepreneurial dynamics. In particular, specialized and sophisticated economic systems have often been associated with a high level of entrepreneurship. Accordingly, we investigated the differentiated effects that industrial systems have on the high-potential typology of startups, namely, innovative startups, high-growth startups, and pioneers. Upon analyzing the case of Italy across a 5-year period (2015–2019), we found that certain compositions of industrial structure may either favor or hinder the typologies of the aforementioned startups. These results inform potential entrepreneurs of the importance to analyze how external conditions can distinctively affect the process of opportunity identification among different forms of high-potential startups.

Keywords Entrepreneurship · Gazelles · Pioneers · Innovative startups · Economic complexity · Relatedness

JEL Classification L26 · M13 · R11

1 Introduction

A consensus has emerged in the literature bridging entrepreneurship and economic development on the importance of the former as a vehicle to promote growth and social prosperity (Schumpeter, 1934). What remains blurred are the mechanisms governing this kind of relationship, for example, related to the context where entrepreneurship takes place. This relationship is prominent for two main reasons. First, the function of entrepreneurship (e.g., creating new value for society) is tightly embedded in the industrial structure of the area in which it develops. Second, entrepreneurship emerges in different forms, in response to the endowments of a particular context and the opportunity identified thanks to the entrepreneurial agency effect (Du & O'Connor, 2018; Urbano et al., 2019; Vedula et al., 2019).

Notably, the relationship between entrepreneurship and the industrial structure has been the subject of an increasing number of studies in recent years, especially those explaining the relevance of factors capable of generating more entrepreneurship. There are two key drivers of this discussion. The first is related to the increasing awareness that, despite common global trends, entrepreneurship should be better contextualized within local environments to understand its variability in birth patterns, scale-up mechanisms, and the influence of resources external to firms as the institutional settings (Audretsch, 2012; Stam & Van de Ven, 2021). The second concerns new theoretical and empirical insights related to the underlying and invisible characteristics of the industrial structure. This has been supported by the growing acceptance of notions such as economic complexity and relatedness to measure both the pure concentration of certain activities and their level of sophistication and network structure (Hidalgo & Hausmann, 2009; Hidalgo et al., 2007).

In this regard, studies have assessed the entrepreneurship—industrial structure nexus, focusing on entrepreneurship and spatial agglomeration (Bosma & Sternberg, 2014), entrepreneurship and related and unrelated variety (Bishop, 2012; Content et al., 2019; Ejdemo & Örtqvist, 2020), entrepreneurship and local knowledge (Colombelli, 2016; Colombelli & Quatraro, 2018), entrepreneurship and specialization and diversification economies (Antonietti & Gambarotto, 2020; Capozza et al., 2018), and complexity and pioneer firms (Jara-Figueroa et al., 2018).

The abovementioned works deserve merit for beginning to disentangle the relationship between entrepreneurship and industrial structure. Nevertheless, some gaps remain. The first is that many studies measure entrepreneurship as the simple formation of a new firm (see Bishop, 2012; Content et al., 2019; Ejdemo & Örtqvist, 2020), thereby underestimating the mechanisms that govern the various typologies, especially the most high-potential startups (Audretsch, 2012; Colombelli, 2016). The main risk in taking overall entrepreneurship as a monolithic typology is that the specific links between the industrial structures and different forms of high-potential entrepreneurship may be obscured. This could lead to an underestimation of the variation of opportunity recognition and the local search for competitive advantage according to the vision and strategies of entrepreneurial projects (Baron, 2006; Gruber et al., 2008; Vedula et al., 2019). In this regard, the literature has reported how high-potential entrepreneurship relies on different origin factors, which also serve diverse functions in economic development (Nightingale & Coad, 2014; Shane, 2009).

Second, few analyses have concentrated on the effect of complexity on entrepreneurship (see Jara-Figueroa et al., 2018; Iftikhar et al., 2022); many have analyzed relatedness. Complexity, as a measure of the aggregated performance embedded in the realization of most complex products and services, is the new frontier for analyzing the structural composition of an economy. However, there are possibly controversial effects of economic complexity on entrepreneurship. Naudè (2022) include the negative scale effects, the technological distance between leading firms and SMEs, and the increasing difficulties linked to "inventing" in more sophisticated economies. Iftikhar et al. (2022) consider economic complexity a proxy of knowledge utilization and thus a way to reduce spillover that may lead to new firm creation. These suggest the importance of investigating the effect of economic complexity on entrepreneurship, especially high-potential entrepreneurship.

Given this premise, the present study aims to shed light on the different effects of industrial structure (measured by relatedness and complexity) on overall new firm creation and different typologies of high-potential entrepreneurship, concentrating on those categories that contribute most to local prosperity in terms of innovation or growth. For the present study, beyond tout court entrepreneurship, we decided to rely on three additional categories: innovative, high-growth, and pioneer startups. The decision to include these specific categories is their different links with the industrial structure in which they are embedded. Innovative startups are a typology of entrepreneurship based on R&D and university–industry relationships with a possible effect on industrial prototyping and knowledge spillover. High-growth startups exemplify a typology of entrepreneurship based on breakthrough and scalable business models with a possible effect on productivity and employment. Pioneers represent early adopters with possible effects on path exploration and market niche development. The present work explores this relationship for the Italian case at the NUTS-3 regions level for the 2015–2019 period.

The paper is organized as follows. Section 2 presents the literature review and the hypothesis development for each category of startup. Section 3 explains the data collection processes and the methodologies adopted. Sections 4 and 5, respectively, present the empirical strategies and discussion of the results. Section 6 concludes the paper.

2 Literature review and hypotheses development

In recent decades, perspectives on the origin of entrepreneurship centered on employment substitution theory have been progressively replaced by theoretical advancements on the new role of entrepreneurial agents, new managerial models, and the creative use of productive inputs (Audretsch & Thurik, 2001; Thurik, 2009). During this re-conceptualization, theoretical approaches focused on the idiosyncratic role of individuals have been supplemented by the role of local contexts, which are no longer perceived as theoretical constraints but as focal elements to explain differences in entrepreneurial dynamics (Feldman, 2001). Accordingly, regional characteristics represent potential sources of competitive advantages for new entrants (Delgado et al., 2010). In this respect, recent research has shown how local contexts equipped with adequate supportive structures represent the missing explanation of the different rates of high-potential entrepreneurship (Stam & Van Der Ven, 2021).

In particular, the composition of industrial structure has been the object of several studies aimed to show valid explanatory drivers of entrepreneurship. Two notions have recently been adopted to conceptualize and measure industrial structure: relatedness and economic complexity (Balland et al., 2022; Hidalgo, 2021).

The former refers to how close two products, industries, or technologies are in terms of commonalities (Juhász et al., 2021). Relatedness was first analyzed by management scholars to understand the similarity of capabilities by observing the incidence of co-occurrence between products at the plant level (Teece et al., 1994). It then gained increasing popularity in many fields of economic studies to explain how the connectedness of local knowledge bases represents possible learning channels toward different diversification trajectories of territories (Balland et al., 2019; Boschma, 2017).

The latter, economic complexity, explains the sophistication of productive capabilities by looking at the basket composition of cities, regions, and countries in terms of the ubiquity and diversity of goods, services, patents, or industries (Hidalgo, 2021; Hidalgo & Hausmann, 2009). The more "diverse" a region is in its production capabilities, the more unique ("rare") the specializations and the faster its economic growth will be (Balland et al., 2022). In this framework, economic systems are conceived as combinatorial spaces of knowledge inputs that are present in different quantities and distributed in the geographical zone, while economic complexity extracts how and where these inputs are combined (Hidalgo, 2021).

The effects of industrial structures on entrepreneurship have been investigated by several authors. Large part of these have measured the overall formation of new firms, without explicitly introducing different forms of high-potential entrepreneurship to the debate (e.g., Bishop, 2012; Content et al., 2019; Ejdemo & Örtqvist, 2020). While only recently, few studies started to focus on specific forms of high-potential entrepreneurship (e.g., Antonietti & Gambarotto, 2020; Colombelli, 2016). This gap has important theoretical consequences because the same external industrial context may affect the emergence of distinct forms of entrepreneurship in different ways (Ali et al., 2020). Accordingly, the capabilities of entrepreneurs to leverage and use the existing resources, and thus to recognize business opportunities, vary according to the

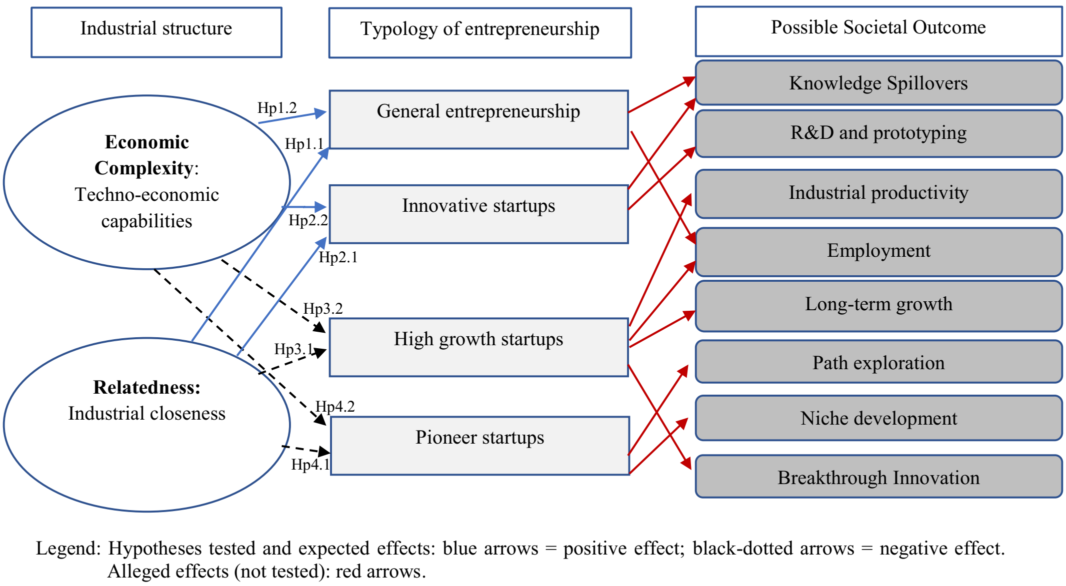

Fig. 1 Theoretical framework

characteristics of their entrepreneurial projects and the problems to be solved (Baron, 2006). The contexts where entrepreneurs generate new ideas contribute to defining "cognitive schemas" (Vedula et al., 2019), which influence the abovementioned process of opportunity identification by entrepreneurial agents. Building on the assumption that a local search (in terms of resources, markets, and competencies) first occurs in the surrounding external environments (Gruber et al., 2008), we can hypothesize a different outcome considering the influence of the supportive structure on the recognition of new opportunities according to the different goals and early-stage strategies of new ventures. This occurs through a mechanism of internalization of external opportunities because the versatility of resources produces different outcomes thanks to the vision and generative capacities of different business model typologies (Auerswald & Dani, 2022).

In the remaining part of this section, we present the theoretical argument for the relationship between the industrial structure and the four typologies of startups considered in this study (i.e., overall entrepreneurship, innovative startups, high-growth startups, and pioneers). The theoretical framework of this research is synthesized in Fig. 1.

2.1 Overall entrepreneurship

Entrepreneurship has recently been associated with the capacity of new firms to exploit knowledge and/or resources left unexplored by incumbents (Audretsch et al., 2015). The literature on the topic has shown how highly related industrial structures can favor the process of spillover being appropriated by individuals who create new firms (Colombelli & Quatraro, 2018; Rocha, 2013), particularly in less technological sectors (Mazzoni et al., 2022). The presence of dense networks (in terms of resources and/or relationships) supports specialization and efficiency, which may lead to the formation of new ventures (Content et al., 2019). Individuals may find a favorable career choice to start a new business in the local context, aiming for the possibility to provide complementary products/services to incumbents while facing a lower risk for their embeddedness in the existing system. Based on this premise, our hypothesis is the following:

> Hp1.1: A high level of relatedness positively influences the creation of new firms.

While few studies have investigated the effect of complexity on entrepreneurship with differentiated results (Du & O'Connor, 2021; Iftikhar et al., 2022;

Nguyen, et al., 2021), highly complex economies are supposed to have a double effect. On one side, the higher the level of variety the higher is market demand with more possibilities for individual entrepreneurs to start up new activities concerning everyday products/services.

On the other side, a more complex economic structure needs bigger quantities of new entrants to feed the business ecology of value chains. In this sense in a sophisticated local economy, new ventures with expected medium–low returns may find more opportunities to explore and exploit.

Hp1.2: A high level of complexity positively influences the creation of new firms.

2.2 Innovative startups

An innovative startup is defined as having the capacity to introduce new business models, products, processes, services, organizational formats, logistics, and productive architectures (Fritsch, 2019). This wide-ranging definition makes it very difficult to establish a clear-cut limit, especially for the problematic aspects linked to innovation output measures. It has been commonly used as an approach based on the utilization of inputs that are likely assimilable to the production of innovative outputs, such as the number of resources and/or financial investments dedicated to R&D. In this framework, the actors involved can be reconducted to universities and corporate startups (Coad et al., 2021). The former exploit knowledge, resources (intellectual property), and internal and external partnerships developed at universities (e.g., due to the mobility of scientists), thereby transforming high-potential research into the selling of products and/or services while relying on dedicated structures to develop their ideas (Perkmann et al., 2013). The latter, corporate startups (sometimes spinoffs of existing businesses), identify business opportunities with an extensive knowledge of problems, which was usually developed over years of work experience that allowed the identification of limits, gaps, and possible sought-after models (Coad et al., 2021).

Highly connected industrial structures represent a very promising arena of opportunities for innovative startups. This is due to the fact that existing business problems, which are often well-known to experts in a given industry, can be successfully addressed by innovative startups, thus revealing new market channels in the idea-generation phase of a company (Czarnitzki & Delanote, 2013; Schneider & Veugelers, 2010). This process is often due to the strong connection between academics belonging to STEM disciplines and industrial leaders at the territorial level, creating a win–win relationship among universities, research centers, and firms open to collaboration (Capozza et al., 2018; Cavallo et al., 2020; Colombelli, 2016). As confirmed by the findings of the relevant literature (Antonietti & Gambarotto, 2020; Capozza et al., 2018; Innocenti & Zampi, 2019), there is a strong dependence between economic systems characterized by a high level of knowledge connection and startups that originate from universities or the exploitation of protected inventions. On the basis of this, our hypothesis is as follows:

Hp2.1: A high level of relatedness positively influences the creation of innovative startups.

However, no studies have investigated the complexity/innovative startups nexus to date.

Complex economic local systems represent a crucial pool of opportunities for innovative startups, as inventions and idea generation that originate from research spillovers need a very high-quality business environment in terms of material and nonmaterial resources and skills.

This is particularly relevant for innovative startups because their success depends not only on the quality of the business idea, which is often very high, but also on their capacity to find the right fit between the value proposition and a responsive external environment.

Considering the subtle association between complex economies and the presence of agents, firms, and institutions with high-level dynamic capabilities, we hypothesize what follows:

Hp2.2: A high level of complexity positively influences the creation of innovative startups.

2.3 High-growth startups

High-growth firms (HGFs) represent a small proportion of companies that outperform the competition in terms of sales, employment, productivity, value-adding, or market share (Brown et al., 2017; Coad et al., 2014; Moreno & Coad, 2015). Applying this framework to the business logic of startups allows to identify typologies of startups registering high growth performance in the first years of their lives are defined as "gazelles." Despite existing controversy regarding their capacity to create a direct form of socio-economic wealth, high-growth startups (HGSs) have reached more consensus as promoters of disruptive innovation (Acs et al., 2008).

The literature on HGFs has extensively analyzed individual factors that can affect the rapid growth of firms (Coad et al., 2014). However, few papers have observed geographical aspects (Stam, 2005) and territorial determinants (Teruel & De Wit, 2017), while also remaining very silent on the knowledge combination process and cluster aspects (Audretsch, 2012). It should be remembered that the heterogeneous presence of HGSs may be due to the opportunity-scanning process conducted by aspirant entrepreneurs who may find the presence of highly codified and rigid cognitive schemas inconvenient in terms of market share and positioning (Vedula et al., 2019).

As anticipated, considering the capacity of HGSs to outperform their competition, the process may be compared to that of breakthrough innovations (Castaldi et al., 2015), suggesting that the presence of distant sectors (i.e., those not closely related) may favor the rise of firms able to integrate distant knowledge—and thus become HGFs. Hence, it is reasonable to hypothesize that a more connected local industrial structure may hamper the idea-generation process of new businesses, as the serendipitous search by aspirant entrepreneurs is limited with a focus on known problems, addressing incremental innovation. Based on what has previously been argued, the hypothesis we test in this regard is as follows:

Hp3.1: A high level of relatedness negatively influences the creation of HGSs.

HGSs represent the outcome of the divergent representation of business problems and the search for alternative solutions able to boost internal capabilities relying on the introduction of new business models (Coad et al., 2021).

Highly sophisticated economic systems are characterized by the presence of big players that may prevent the scalability of business models, thereby absorbing new ideas (Autio, 2009; Naudè, 2022). In this regard, the local search in the external environment (Gruber et al., 2008) may be impeded by the presence of market leaders that prevent the growth of potential competitors with ad hoc killing strategies (e.g., acquisition, price competition, and talent hiring measures). Therefore, a highly complex economic system, often characterized by the presence of strong monopolies, can result in a crowding out for aspirant business leaders who find more difficulties in the execution of promising business plans because of the lack of available market channels and valuable human resources that are necessary for their projects. On the basis of this, we hypothesize what follows:

Hp3.2: A high level of complexity negatively influences the creation of HGSs.

2.4 Pioneers

Better market positioning, information advantages, and wise strategies push incumbents and new firms to pursue completely new activities (Ortega & García-Villaverde, 2011). This is the sum of creative bricolage acts by entrepreneurs (sum of strategy and actions) that lead organizations to proactively delineate a new competitive arena or perform as niche leaders (Baker & Nelson, 2005; Ruiz-Ortega et al., 2018). This relationship has been extensively investigated as a singular process of the firm and based on the exploitation of key resources, accumulation of tacit knowledge, and establishment of barriers put in place to control the competition (e.g., a new patent) (Park et al., 2020). Notwithstanding, few studies have theorized the key link with the industrial structure due to a mix of deliberate agency (e.g., re-qualification of competencies) mitigated by the condition of the context (e.g., the occurrence of external general shocks) (Plummer et al., 2020; Suarez & Lanzolla, 2007).

Based on the existing literature, pioneers can be defined as "first movers" or "early adopters" in specific products, processes, services, or industries. The relationship between the industrial structure and the origin of pioneers can be explained as a variation in the resource environments, lowering of institutional barriers, radically different use of technological endowments, or individual exploration through a mindful

Table 1 Dependent variables

Variables	Explanations	Source
Startups$_{(2015–2019)}$	Number of startups in the period, excluding the sole proprietorship firms	Movimprese
Innovative startups$_{(2015–2019)}$	Number of innovative startups in the period	Italian Chamber of Commerce
High-growth startups$_{(2015–2019)}$	$\sqrt[3]{\frac{\text{Employees}_t}{\text{Employees}_{t-3}}} - 1 > 0,2$ OECD formula, where $t-3$ is the year of birth and Employees$_{t-3} > 10$	Orbis
Pioneer startups$_{(2015–2019)}$	$\sum_{i}^{n} \text{newfirms}_{t-3}^{it}$ Where «i» are the firms «new to the province» (absence of new firms in sector «i» in the previous 3 years) and t is the year of birth	Orbis

deviation process (Baker & Nelson, 2005; Garud & Karnøe, 2001; Ortega & García-Villaverde, 2011).

Highly connected and specialized economies can fall into cognitive lock-in traps, which may prevent the regional process of knowledge recombination (Antonietti & Montresor, 2021). By contrast, the creation of new paths, a leap from existing paths, or the revisitation of existing ones may originate from the presence of unrelated sectors (Plummer et al., 2020). Accordingly, new pioneering firms may need an external environment that is open to path-breaking initiatives (i.e., less anchored to traditional industries and supportive of riskier industrial strategies that are new to the region. On the basis of this, our hypothesis is as follows:

Hp4.1: A high level of relatedness negatively influences the creation of pioneers.

To date, few studies have analyzed the effect of complexity on new pioneering firms (Jara-Figueroa et al., 2018). Complex economies are characterized by the presence of sophisticated productive systems, which make a riskier managerial choice to be the first mover in a given industry. Moreover, processes of mindful deviation in the style of Garud and Karnøe (2001) are rare because the opportunity space(s) left free by incumbents are often located in the hardest technical niches. In these niches, entrepreneurial behaviors oriented to exploitation are favored by a complex external environment in contrast with explorative behaviors that can more easily occur in less complex sectors with lower hurdles to overcome (March, 1991). Therefore, our hypothesis reads as follows:

Hp4.2: A high level of complexity negatively influences the creation of pioneers.

3 Data

As previously mentioned, the analysis was based on startups that arose in Italy during the 2015–2019 period, which represent the dependent variable of our empirical setting (Table 1). The investigation of the different typologies of a startup was performed at the smallest geographical level of investigation offered by the European Union (EU) classification system for units with comparable population sizes: the NUTS-3 regions (i.e., an Italian "province"). We choose Italy since it represents the case of a country historically anchored to industrial districts and thus particularly suited to investigating industrial specialization and diversification patterns (see Capozza et al., 2018).

The first classification was represented by all the startups born each year (excluding the sole proprietorship firms) in the considered period and was drawn from the MOVIMPRESE database. MOVIMPRESE database is composed of the statistical analysis of the birth-mortality rate of all Italian enterprises (divided by legal forms and reported for NACE rev.2 sectors, regions and provinces) conducted by InfoCamere, on behalf of Unioncamere, on the archives of all Italian Chambers of Commerce.

The second category of startups was represented by those that are defined as "innovative startups" according to the Law Decree known as Decreto Crescita 2.0, which was instituted in Italy in 2012. To be listed in this special section, the firm had to respect the following parameters: less than 5 years old, production value lower than 5 million Euro, no distribution of profits, a prevailing corporate purpose for the development, production, and commercialization of innovative products and services at a high technological level.

In addition, they have to respect at least one of these three requirements:

- Expenses in R&D and innovation are at least 15% of the yearly costs
- 1/3 of employees with a Ph.D. or 2/3 with a master's degree
- The startup is the holder, depositary, or licensee of a registered patent or software

Due to these particular parameters and requirements, a startup may be considered innovative and could thus be inscribed in this new special section. The rationale of this public policy intervention aimed to introduce innovative culture guarantees to some young firms with certain characteristics, with benefits such as favorable registration costs, tailored and flexible employment rules (labor regimes), tax incentives, faster and cheaper bankruptcy procedures, and government guarantees on bank debt. The data used to identify these startups were drawn from the Italian Chamber of Commerce database (Colombelli, 2016).

The third category of startups considered in this work was represented by the HGSs.

There is no consensus on the definition of HGSs because the choice of indicator typology and measurement approach can reveal different groups. Concerning the former, it is difficult to choose the best indicator to identify HGSs considering Gibrat's law, the heterogeneous antecedents that can influence firm growth (size, age, sector, and legal form), and the cascade effects on the connected industrial value chains (e.g., resellers, suppliers, and intermediaries) (Coad et al., 2014). Concerning the latter, it is important to distinguish between two approaches: firms that grow the most in a certain period (considering the whole population) and firms that register growth over a certain threshold in a given period. Here, we followed the second approach due to the possibility to compare HGFs across economies (following Coad et al., 2014). HGSs were defined based on their growth during the first 3 years of life (Eurostat-OECD, 2007; Moreno & Coad, 2015). In particular, we adapted the method used by the OECD, considering those startups with an average growth of 20% for a period of 3 years. Additionally, we decided to use employment rather than other measures of a firm's growth or other performance metrics (sales and profits) as a measure less fluctuant. Second, we decided to only consider firms with at least 10 employees in their first year of life. This aimed to avoid counting companies that hired very few employees during the first 3 years of life as having high growth. In this case, the data were drawn from the Orbis database.

Finally, the last category of startups is represented by the pioneer startups, which are firms "new to the province" that pertain to sectors that did not give birth to startups during the last 3 years in the considered province (for a similar approach, see Jara-Figueroa et al., 2018). To identify them, we also used data drawn from the Orbis database.

Considering the theoretical motivations (and empirical approaches drawn from the literature) adopted to define our startup categories, we do not find conceptual and data overlap among the three categories. On the conceptual side, we elaborate in the theoretical section on the different rationales and entrepreneurial goals that may lead to the birth of such typologies, finding substantial confirmation in the retrieved data. Accordingly, the highest overlap of retrieved firms is among the joint pool of HGSs and Pioneers and the overlap is well below the 1%.

This study presents two main variables of interest: Economic Complexity and Relatedness (for an extensive description of the methods, see Table 2 and Appendix Table 4). To compute the first variable, the economic complexity index (ECI), we used employment data (Innocenti et al., 2021; Mealy et al., 2019) drawn from a firm-level database (Orbis—Bureau Van Dijk) with industries disaggregated according to the Nomenclature of Economic Activities (NACE) industrial classification at the 4-digit level of all the analyzed provinces during the 2010–2014 period. We followed the methods proposed by Hidalgo and Hausmann (2009) and refined by Balland and Rigby (2017). Thus, for our case, we computed the ECI using the second eigenvector of the squared matrix of dimensions equal to the number of the considered provinces (103), where the elements capture the similarity in the industrial structure of province pairs.

Table 2 Independent variables employed in the analysis

Variables	Explanations	Source
Complexity$_{(2010–2014)}$	Second eigenvector of the squared matrix $M * M_T$	Orbis
Relatedness$_{(2010–2014)}$	$R_{pt} = \sum_{s=1}^{S} R_{ck}(\frac{n_{cp}+n_{kp}}{N_p})$	Orbis
Unemployment$_{(2010–2014)}$	Rate of unemployment for each province	Eurostat
Population density$_{(2010–2014)}$	Population on province's area (squared km)	Eurostat
GDP per capita$_{(2010–2014)}$	GDP per capita at constant prices in EUR	Eurostat
Unstable job$_{(2010–2014)}$	Percentage of workers with a temporary job	European Labor Force Survey
Human capital$_{(2010–2014)}$	Share of residents with tertiary education or higher	European Labor Force Survey
Migration$_{(2010–2014)}$	Province-specific net migration rate	Eurostat
Patent production$_{(2010–2014)}$	Patent production per thousand workers	Eurostat
Institutional quality$_{(2010–2014)}$	Composite index (corruption, government effectiveness, regulatory quality, rule of law, and voice and accountability)	A. Nifo & G. Vecchione (2014)

Regarding the second variable of interest, relatedness, many measures have been developed over the last 15 years (see Frenken et al., 2007; Hidalgo et al., 2007; Neffke et al., 2011). The present work adopted one of the most convenient methods used to measure the relatedness between industries following a co-occurrence analysis and thus did not rely on the number of digits shared to define the relatedness between sectors. For these interesting characteristics, this method has gained increasing consensus and has been widely applied in many fields, not only to study the relatedness between products as in the seminal work by Hidalgo and colleagues (2007) but also between technologies (Kogler et al., 2013), scientific topics (Guevara et al., 2016), and industries as in the present work (Boschma et al., 2012; Innocenti & Lazzeretti, 2019; Mazzoni et al., 2022).

Then, some control variables were added to the model (Table 2). First, following other studies on new firm formation, we controlled for the unemployment rate at time t as a possible determinant of new firm formation, as stated in the entrepreneurship debate (see Audretsch & Fritsch, 1994). Then, we also included the population density in all models. This variable was used to control for urbanization levels and was measured as the population and area ratio of provinces. Third, gross domestic product (GDP) per capita, a measure available in Eurostat, was used to capture the economic development of each province. GDP can be considered a proxy for the general economic prosperity of a province (Lacalle-Calderon et al., 2017). Additionally, there was a control for the percentage of workers with a temporary job over the total number of workers in each province (e.g., Vignoli et al., 2012). This indicator was computed using data from the European Labor Force Survey, which is a comparative large-sample survey designed for collecting high-potential labor market data. We also introduced a variable to account for the human capital, which considers the number of graduates over the working-age population—a variable often associated with high entrepreneurial performance. One other aspect that may influence entrepreneurial activities is the migration between provinces. Migration typically occurs from less economically advantaged areas to more economically advantaged ones (Faggian et al., 2017). Higher flows have been observed for employment reasons, and migrants are usually relatively young and active. Therefore, we added the province-specific net migration rate, taken from Eurostat data to the model specification. We also controlled for the innovativeness of the province. For this reason, we used the patent production of each province computed as the annual patent production per thousand workers to proxy for the innovation capacity of a local territory (Bae & Koo, 2008). Finally, an indicator of institutional quality was included in the model since this is widely considered a key factor in favoring entrepreneurial activities at all geographical levels, with even greater relevance when an analysis is performed at the sub-national level (Audretsch, et al., 2022; Stam & Van De Ven, 2021). The index used here was presented by Nifo and Vecchione (2014) and was largely used for the analysis of the Italian case for accuracy and the smaller unit of analysis (provinces). This is a composite index that considers five dimensions: corruption, government effectiveness, regulatory quality, rule of law, and voice and accountability.

4 Econometric strategy

We analyzed the effect of industrial relatedness and complexity (2010–2014) on the birth of four different typologies of startups in Italian provinces (103) for the 2015–2019 period. Considering the possible presence of zeros for particular typologies of high-potential entrepreneurship (we have 8% for Innovative Startups), we treated the birth of startups in the local context as a count variable, evaluating zeros as informative data and using the population density to account for regional differences (for a similar approach see Audretsch & Lehmann, 2005; Fritsch & Falck, 2007; Bonaccorsi et al., 2013; Colombelli & Quatraro, 2018).

Given the nature of our dependent variables, both discrete and non-negative, the literature suggests employing an estimation strategy under the umbrella of the Poisson family (Hausman et al., 1984). Given the high variability of our dependent variables across provinces and sectors, we conducted a likelihood ratio test with the null hypothesis that the overdispersion coefficient is zero and the results (reported in each model) indicate the appropriateness of the negative binomial regression—a generalization of the Poisson model (Hilbe, 2011). We used panel negative binomial regression techniques with year and province (NUTS-3) fixed effects as well as a 5-year lag between dependent and independent variables to estimate our models. Mathematically, the estimated models took the following form:

$$\begin{aligned} Y_{i,t+5} = \alpha_i + \lambda_i + \beta_1 \text{Complexity}_{i,t} \\ + \beta_2 \text{Relatedness}_{i,t} + \beta_3 Unemp_{i,t} \\ + \beta_4 \text{Pop dens}_{i,t} \cdots + \beta_n \text{Controls}_{i,t} + \epsilon_{i,t} \end{aligned}$$

The correlation matrix did not report a particularly high correlation level. However, to detect the presence of multicollinearity, a variance inflation factor (VIF) test was performed for all the tested models reporting max VIF values that reached the highest value of 5.25 (10 is usually considered the threshold), suggesting that multicollinearity was not an issue in these models (Hair et al., 1995). For all of the dependent variables, we followed a stepwise approach. Here, we reported four models for each dependent variable. Model 1 (a-b-c-d) with all the controls but without the variables of interest (complexity and relatedness), models 2 and 3 (a-b-c-d) tested with the variables of interest separately, and model 4 (a-b-c-d), which was the complete model with both complexity and relatedness together. Then, we included model 5 (a-b-c-d) aimed at identifying curvilinear effects of the variables of interests which includes also the squared value for complexity and relatedness. As a final robustness check, we added model 6 (a-b-c-d) to control for the well-known developmental differences between the north and south of Italy, through the inclusion of macro-regional dummies.

5 Results and discussion

The main results (Table 3) indicate that complexity plays a positive role in favoring overall entrepreneurship and innovative startups (as defined by Italian law). A one-unit change in complexity had a multiplicative effect (of approximately 6%) on the overall birth of startups, whereas, for innovative startups, this effect reached a value of approximately 37%. The results show that also relatedness is significant for the birth of innovative startups; a one-unit change in relatedness resulted in an increase of 57% in the birth of innovative startups. Conversely, both economic complexity and relatedness were shown to be significant and negative for HGSs and resulted in negative multiplicative effects of 16% and 33%, respectively. Finally, we did not find significant effects for pioneer startups. Overall, five out of our eight hypotheses were confirmed.

In addition, the assessment of the curvilinear effect of our two main variables of interest revealed an exponential effect of complexity for innovative startups and an inverse curvilinear effect of relatedness on HGSs. The former confirms the need for innovative startups to be embedded in sophisticated areas, which work both as resource contributors and recipients of innovative products and services. The latter demonstrates the positive contribution of relatedness for the birth of HGSs, up to a certain threshold, becoming negative afterward. This result is very informative as helps to finely characterize our previous findings,

Table 3 Results from negative binomial regression

	Model 1a All startups	Model 2a All startups	Model 3a All startups	Model 4a All startups	Model 5a All startups	Model 6a All startups	Model 1b Innovative	Model 2b Innovative	Model 3b Innovative	Model 4b Innovative	Model 5b Innovative	Model 6b Innovative
Complexity		0.0590***		0.0602***	0.0601***	0.0386*		0.292**		0.322**	0.249*	0.00557
		(0.0226)		(0.0225)	(0.0227)	(0.0213)		(0.138)		(0.138)	(0.135)	(0.146)
Relatedness			0.0332	0.0369	−0.143	0.0280			0.412*	0.454**	−0.643	0.329*
			(0.0302)	(0.0300)	(0.284)	(0.0274)			(0.213)	(0.208)	(2.006)	(0.171)
Complexity^2					−0.00387						0.195**	
					(0.0108)						(0.0779)	
Relatedenss^2					0.0374						0.226	
					(0.0587)						(0.412)	
Unemployment	−0.000134	−0.000168	−0.0000917	−0.0000927	−0.000151	−0.000345	−0.0154	−0.0155	−0.0159	−0.0160	−0.0211	−0.0103
	(0.00197)	(0.00200)	(0.00195)	(0.00198)	(0.00199)	(0.00203)	(0.0133)	(0.0134)	(0.0132)	(0.0133)	(0.0136)	(0.0131)
Population density	0.000658***	0.000646***	0.000658***	0.000652***	0.000638***	0.000662***	0.000571*	0.00063**	0.00044	0.000508*	0.000390	0.000261
	(0.000186)	(0.000193)	(0.000182)	(0.000188)	(0.000184)	(0.000190)	(0.000306)	(0.00031)	(0.000298)	(0.000297)	(0.000297)	(0.000397)
GDP per capita	−0.00987***	−0.00971***	−0.00961***	−0.00940***	−0.00920**	−0.0133***	−0.0296*	−0.0369**	−0.0290*	−0.0367**	−0.0295*	−0.122***
	(0.00357)	(0.00358)	(0.00358)	(0.00359)	(0.00369)	(0.00338)	(0.0168)	(0.0171)	(0.0168)	(0.0171)	(0.0171)	(0.0276)
Unstable job	0.0346	0.0282	0.0296	0.0234	0.0179	0.131	2.194	2.367*	2.066	2.264*	2.393*	2.222*
	(0.199)	(0.199)	(0.198)	(0.198)	(0.198)	(0.193)	(1.394)	(1.392)	(1.378)	(1.372)	(1.360)	(1.260)
Human capital	0.554*	0.477	0.544*	0.466	0.436	0.342	−0.905	−1.167	−1.159	−1.404	−1.542	−4.031**
	(0.306)	(0.306)	(0.306)	(0.306)	(0.308)	(0.280)	(2.032)	(2.048)	(2.018)	(2.029)	(2.063)	(1.988)
Migration	0.0445	0.0517	0.0377	0.0445	0.0381	0.0617	0.506	0.627	0.430	0.547	0.379	−0.0997
	(0.0623)	(0.0624)	(0.0622)	(0.0623)	(0.0630)	(0.0614)	(0.459)	(0.447)	(0.456)	(0.442)	(0.458)	(0.411)
Patent stock	0.0569	0.0600	0.0572	0.0602	0.0622	0.0388	0.583	0.618*	0.632*	0.678*	0.623*	0.576*
	(0.0735)	(0.0735)	(0.0736)	(0.0736)	(0.0736)	(0.0601)	(0.364)	(0.368)	(0.366)	(0.370)	(0.364)	(0.346)
Institutional quality	0.195**	0.184**	0.199**	0.189**	0.188**	0.187**	0.0549	−0.0299	0.0979	−0.00285	0.00845	0.836
	(0.0850)	(0.0841)	(0.0849)	(0.0840)	(0.0840)	(0.0766)	(0.458)	(0.452)	(0.459)	(0.450)	(0.452)	(0.542)
North-West						1.466***						6.432***
						(0.343)						(1.878)
North-East						1.610***						2.888***
						(0.322)						(0.752)
Center						0.895***						4.456***
						(0.304)						(1.536)
Cons	40.59***	34.69***	43.22***	37.58***	37.29***	36.90***	−637.8***	−661.7***	−611.7***	−634.8***	−647.6***	−546.0***
	(8.676)	(8.938)	(8.940)	(9.169)	(9.190)	(8.283)	(53.66)	(54.44)	(54.81)	(55.37)	(55.69)	(54.01)
Log likelihood	−2167.1	−2163.7	−-2166.5	−2162.9	−2162.7	−2142.89	−997.76	−995.56	−995.89	−993.21	−990.05	−981.63

Table 3 (continued)

LR test overdisp.	1861.35***	1867.92***	1821.46***	1830.04***	1824.46***	1822.55***	443.11***	463.19***	439.50***	460.33***	438.91***	441.18***
AIC	4354.2	4349.4	4355.0	4349.8	4353.3	4315.8	2015.5	2013.1	2013.8	2010.4	2008.1	1993.3
BIC	4396.6	4396.0	4401.7	4400.8	4412.7	4379.4	2058.0	2059.8	2060.5	2061.3	2067.5	2056.9
	Model 1c High growth	Model 2c High growth	Model 3c High growth	Model 4c High growth	Model 5c High growth	Model 6c High growth	Model 1d Pioneers	Model 2d Pioneers	Model 3d Pioneers	Model 4d Pioneers	Model 5d Pioneers	Model 6d Pioneers
Complexity		−0.149**		−0.168**	−0.162**	−0.0554*		−0.0506		−0.0496	−0.0421	−0.0587
		(0.0745)		(0.0746)	(0.0754)	(0.0305)		(0.0724)		(0.0724)	(0.0710)	(0.0716)
Relatedness			−0.368***	−0.388***	2.040*	−0.403***			−0.0551	−0.0533	0.926	−0.0133
			(0.122)	(0.122)	(1.053)	(0.120)			(0.102)	(0.102)	(1.049)	(0.102)
Complexity^2					−0.0442						0.0422	
					(0.0466)						(0.0365)	
Relatedenss^2					−0.496**						−0.206	
					(0.212)						(0.220)	
Unemployment	−0.00995	−0.0100	−0.0115	−0.0116	−0.0101	−0.0103	0.0110	0.0112*	0.0109	0.0110	0.0112*	0.00953
	(0.00897)	(0.00869)	(0.00889)	(0.00859)	(0.00824)	(0.0131)	(0.00675)	(0.00673)	(0.00676)	(0.00674)	(0.00673)	(0.00655)
Population density	0.000253	0.00024	0.00036	0.000367	0.000682**	0.000261	−0.000614*	−0.00062*	−0.00060*	−0.000609*	−0.000584	−0.000802**
	(0.000291)	(0.00028)	(0.00029)	(0.000288)	(0.000336)	(0.000397)	(0.000348)	(0.00034)	(0.00034)	(0.000348)	(0.000356)	(0.000383)
GDP per capita	0.0491***	0.0544***	0.0496***	0.0553***	0.0540***	−0.122***	0.0244**	0.0246**	0.0242**	0.0243**	0.0264**	0.0262**
	(0.0145)	(0.0135)	(0.0139)	(0.0129)	(0.0118)	(0.0276)	(0.0118)	(0.0118)	(0.0118)	(0.0117)	(0.0118)	(0.0125)
Unstable job	−0.983	−1.139	−0.964	−1.133	−0.944	2.222*	−0.616	−0.591	−0.619	−0.594	−0.560	−0.255
	(0.833)	(0.828)	(0.843)	(0.838)	(0.839)	(1.260)	(0.699)	(0.698)	(0.701)	(0.700)	(0.698)	(0.692)
Human capital	0.716	0.991	0.641	0.946	1.406	−4.031**	−1.485	−1.387	−1.486	−1.389	−1.293	−1.205
	(1.206)	(1.203)	(1.190)	(1.185)	(1.193)	(1.988)	(1.025)	(1.035)	(1.024)	(1.034)	(1.034)	(1.008)
Migration	−0.412	−0.389	−0.311	−0.280	−0.183	−0.0997	0.103	0.110	0.114	0.121	0.137	0.0693
	(0.262)	(0.259)	(0.261)	(0.259)	(0.253)	(0.411)	(0.206)	(0.206)	(0.207)	(0.207)	(0.207)	(0.207)
Patent stock	−0.0871	−0.110	−0.135	−0.157	−0.134	0.576*	0.140	0.132	0.139	0.131	0.127	0.127
	(0.242)	(0.238)	(0.239)	(0.235)	(0.236)	(0.346)	(0.203)	(0.203)	(0.203)	(0.203)	(0.202)	(0.209)
Institutional quality	0.521**	0.561**	0.498**	0.540**	0.631**	0.836	0.0169	0.0136	0.00518	0.00236	0.0115	−0.202
	(0.254)	(0.256)	(0.254)	(0.255)	(0.258)	(0.542)	(0.269)	(0.269)	(0.270)	(0.270)	(0.271)	(0.267)
North-West						6.432***						0.661
						(1.878)						(0.985)
North-East						2.888***						−0.695
						(0.752)						(0.612)
Center						4.456***						−1.221**
						(1.536)						(0.528)

Table 3 (continued)

Cons	−661.5***	−651.9***	−696.0***	−687.2***	−678.5***	−546.0***	160.6***	165.1***	155.7***	160.2***	160.9***	146.6***
	(32.63)	(32.33)	(34.00)	(33.60)	(33.25)	(54.01)	(26.46)	(27.22)	(28.02)	(28.79)	(28.80)	(29.00)
Log likelihood	−1469.88	−1467.85	−1465.37	−1462.84	−1459.79	−1453.09	−1293.36	−1293.12	−1293.21	−1292.98	−1291.8	−1288.12
LR test overdisp.	695.46***	698.02***	655.14***	657.58***	662.54***	655.38***	119.43***	120.84***	112.14***	113.26***	114.45***	113.02***
AIC	2959.8	2957.7	2952.8	2949.7	2947.6	2936.2	2606.7	2608.2	2608.4	2610.0	2611.7	2606.3
BIC	3002.2	3004.4	2999.4	3000.6	3007.0	2999.8	2649.2	2654.9	2655.1	2660.9	2671.1	2669.9

Standard errors are in parenthesis ***$p<0.01$, **$p<0.05$, *$p<0.1$; Number of observations 515, all models include Year and Nuts-3 FE

suggesting how the affinity of locations and industrial activities hamper the rise of HGSs only if they are too high.

As an additional robustness check, we controlled for the effects of different types of activities (service/manufacturing), including technological intensity,[1] and obtained three types of dependent variables for each group of startups.[2] The group of overall startups did not register particular changes, except for high-tech manufacturing, in which we did not find a positive or significant effect for complexity. Furthermore, the quadratic term of complexity turned out to be negative in the model with low-tech service startups, implying that everyday business services for consumers and professionals can be smothered by excessively sophisticated economic systems.

The most relevant change occurred for the group of HGSs. Only startups active in low-tech sectors registered a significant effect of complexity and relatedness, which was coherent with models 1c–5c. This result is highly informative, as almost 50% of HGSs are in this group, implying that high-growth everyday business startups are hampered as in the case of overall startups.

Pioneers instead did not report different results, in terms of significance, from models 1d–5d.

The control variables showed largely diversified results. While the GDP per capita was significant across all models, the effect was negative with respect to general and innovative startups while being positive regarding HGSs and pioneers. Population density had a positive effect on all the models regarding the general startups and all models except 3b regarding innovative startups, while the effect was not significant in all the models testing the effect on HGSs.

[1] We define four new typologies of dependent variable exploiting the Eurostat indicators on high-tech industry and knowledge—intensive services and thus defining LT manufacturing, HT manufacturing, LT services, and HT services (aggregating medium–high and medium–low in the respective group) according to the correspondent list of NACE rev.2 codes (please check this link for the codes: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf). Startups with NACE codes not included in the list have been excluded.

[2] We did not include innovative startups, as the Italian Ministry of Economic Development already provides some distinctive criteria (reported in Sect. 3) that qualify them as owners of significant technological tangible or intangible assets or lead by staff, equipped with human capital.

While it turns out to be negative for pioneers, meaning that urbanization is an important tool favoring new firm formation but not necessarily for the insurgence of rapidly growing firms. Coherently, it seems to downplay the insurgence of firms in new sectors, which is also likely due to the already high diversification of urbanized areas.

Other interesting results were related to our last control, institutional quality. This variable was shown to be significant, with a positive effect on the overall number of startups shown by Italian provinces and also regarding the HGSs, while no significance was detected regarding the other two categories of startups. This reflects the notion that institutional quality might favor the insurgence of new firms tout court and also foster their growth since a higher quality of institutions might play an important role from many perspectives (regulation, connections with institutions, etc.). This has less to do with the insurgence of firms' establishments in new industries firstly because major policies tend to reinforce preexisting specializations in the area, and secondly because this is more closely related to industrial or individual patterns. Also, regarding the innovative startups, institutional quality may play a minor role with respect to other categories and determinants. In fact, for this category, the innovativeness of the province seems to be important and shows a significant and positive effect on the patent stock variable. In addition, regarding the robustness check connected to the well-known developmental differences between the north and south of Italy, we controlled for macro-regional differences including the relative dummies. The general results remained largely unchanged. However, the provinces located in the north and center of Italy outperformed the south in overall and innovative startups. By contrast, the south had a slightly higher performance concerning the HGFs compared to the north, and, finally, the center showed a lower performance regarding the pioneer startups. Finally, considering the impact of pre-existing entrepreneurial institutions should be framed in a wide perspective of industrial evolution. In this regard, the literature has shown the crucial effect of historically rooted entrepreneurial role models, especially for their contribution to the knowledge accumulation capacity that favors the learning process at the local level (Cosci et al., 2022). For this reason, we performed an additional robustness test, including controls for historical factors and the persistence of startup activities in Italy. In order to rule out potential spurious correlations, we add two historical variables accounting for entrepreneurial activity of approximately one century ago (1927) derived from ISTAT data and divided by industry and services. The results (Table 6) do not show a significant effect for the high-potential entrepreneurship categories. However, both industry and services historical entrepreneurial activities show a significant and positive effect on the overall entrepreneurial activity, in line with the results by Cosci et al. (2022).

These results offer an interesting departure point with respect to the hypotheses developed and to the literature that analyzes the nexus between industrial structure and entrepreneurship. While the results of relatedness impact different typologies of entrepreneurships and are in line with existent literature, thereby confirming that the agglomeration effect positively stimulates innovative startups, the results of complexity are more controversial to interpret. Recent works on this theme suggest that the benefit of increasing economic complexity for laggard countries and regions is supposed to be bigger, considering also the presence of more business opportunities to explore in comparison to the most sophisticated ones (Du & O'Connor, 2021; Nguyen et al., 2021). This context raises the following question: does this relationship hold for high-potential entrepreneurship? Based on the analysis conducted on Italian provinces, we confirm the problems evidenced by Naudè (2022), who hypothesized that the high level of complexity "ossifies" the most productive typologies of entrepreneurship. In particular, we found two contrasting scenarios for innovative startups and HGSs. While in the first case, relatedness and complexity played a positive role in the birth of innovative startups, the opposite effect was observed for HGSs. Innovative startups represent the creative spark of an economic system because their prototypal solutions and strong connection with academia and research centers have a symbiotic relationship with a complex and highly connected industrial structure. On the other hand, HGSs are often involved in fierce competition, which gives rise to a market saturation effect. With the advent of increasingly complex production paradigms (e.g., those based on data as the main assets), global leaders tend to preserve their monopolistic positions by killing competition, which represents a high risk of "lonely scaling." Moreover, economic inputs are also combined in complex ways, with individual creativity finding increasing cognitive barriers to overcome. In other words, the entrepreneurial result that emerges from the complex interaction between structure and agency tends to become more difficult to develop. The extensive presence of too many specialized assets and an excessively high level of complementarity may prevent the birth of the most innovative ideas, which can already be protected by intellectual property and be part of established productive workflows (Sautet, 2013; Naudè, 2022). Moreover, the analysis of the level of industrial technological intensity suggests novel explanations. The negative effects of complexity and relatedness in HGSs active in the provision of low-tech services may be interpreted as the cost of the whole economic system, which hinders the everyday entrepreneurship that originates competition and contributes to the creation of new jobs and societal wealth (Welter et al., 2017).

6 Concluding remarks

Economic complexity and relatedness are notions that characterize the industrial structure of countries, regions, and cities. The development and refinement of economic complexity and relatedness indexes provide the opportunity to quantify the capabilities available in a country as well as all the subtle structures (e.g., the knowledge and skills acquired through education and work experience). In addition, this has the advantage of being comparable over time and across different units of analysis. The depicted structure has often been represented as a positive sign for entrepreneurship and economic growth.

The results of our analysis offer novel insights into the industrial structure and entrepreneurship typologies, suggesting caution in assuming a general positive effect of economic complexity and relatedness. In the present study, we found two divergent results: a positive and strong effect of highly sophisticated and connected economies on innovative startups and a negative but weaker effect on the birth of HGSs. The former represents a positive result for the innovation capacity of a territory, strengthening the connections among industries, research centers, incubators, and other elements that characterize highly developed areas. Concerning the latter, HGSs may bring new scalable business models with considerable societal wealth, creating new jobs (especially in terms of everyday entrepreneurship) and reinforcing the capacity of regions to attract and retain human capital. Overall, we empirically contributed to enriching the debate on what could be the effect of these two opposite forces on the development of entrepreneurship policies for the future of cities and place-based industries.

Moreover, our variables were shown to have no substantial effect on pioneer startups. Pioneers can support the rise of new trajectories in the region and favor the cross-fertilization of ideas to promote path rejuvenation.

Notwithstanding, this analysis is not without limits. A first limitation is that we proxied innovative startups using the Italian Chamber of Commerce register. As suggested by Fritsch (2019), innovation is a concept that is very difficult to capture and operationalize by considering a country's level of development (i.e., what is innovative in one place could not be in another). A good proxy to overcome this bias could be observing the activity of venture capitals funds as careful observers of the phases of startup development from the early stage to buyouts. Their screening actions could vary according to the legal form of venture capital funds, with private investors being more oriented toward high-return public to societal delivery (Fritsch, 2019).

Second, we ultimately could not observe the persistence of growth among HGSs. Understanding the stages of their growth and the milestones of their lifecycles is fundamental for policymakers to produce sound policies (Moreno & Coad, 2015). Without observing the persistence of growth among HGSs over a long period, it is difficult also to assess the economic and financial reasons behind their growth and the scalability of their business models.

Third, despite the efforts of the management literature to evaluate the pioneering propensity in relation to firm characteristics and behavior (Ortega & García-Villaverde, 2011; Ortega et al., 2018), the lack of a common and robust empirical definition of pioneers makes the measurement of this phenomenon difficult. Future research is required to analyze the spatial determinants of this typology of entrepreneurs as potential trigger agents of new industrial path formation.

Another limit of our work relates to the absence of an indicator for "unrelatedness." Particularly in the long run, this could be a driver of higher growth and also show an important effect of favoring the insurgence of firms arising from the intersection of apparently distant sectors such as the case of pioneers (Pinheiro et al., 2018). Finally, the importance of consolidating the analysis for other countries and longer periods can be important to either reinforce or disregard our findings.

Despite the acknowledged limitations, this study makes some important contributions to the entrepreneurship literature, showing that the context and, particularly, the industrial composition and sophistication of the area have distinctive effects on the opportunity identification process that generates the birth of startups with different goals and ambitions (Vedula et al., 2019). In this respect, some entrepreneurial implications may also be drawn. Our results underline how the founders of potential startups should carefully evaluate where to locate their firms while considering that the specialization and complexity level of the area may affect the conversion process of their business ideas into new ventures. This in turn could favor or hinder collaborations, access to tangible and intangible resources, and potential market development.

Appendix

Table 4 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Startups	515	1340.887	2216.307	165	17,990
Innovative startups	515	16.406	39.633	0	480
High-growth startups	515	63.408	98.376	3	942
Pioneer startups	515	30.75	7.948	13	63
Complexity	515	−0.028	1.014	−1.716	2.043
Relatedness	515	2.35	0.242	1.501	3.171
Unemployment	515	10.56	5.171	2.667	27.53
Population density	515	266.765	350.353	19.814	2772.127
GDP per capita	515	31.142	8.25	17.924	66.883
Unstable job	515	0.163	0.045	0.067	0.38
Human capital	515	0.13	0.028	0.067	0.221
Migration	515	−0.008	0.195	−0.72	0.47
Patent production	515	0.153	0.162	0	1.647
Institutional quality	515	0.591	0.262	0	1

Table 5 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1) Startups	1.00													
2) Innovative	0.824	1.00												
3) Hgfs	0.888	0.830	1.00											
4) Pioneers	−0.100	−0.156	−0.209	1.00										
5) Complexity	0.064	0.106	0.021	0.097	1.00									
6) Relatedness	0.401	0.411	0.449	−0.162	-0.056	1.00								
7) Unemploy	0.040	0.005	0.151	−0.235	−0.441	0.197	1.00							
8) Pop.Den	0.640	0.580	0.607	−0.068	0.033	0.299	0.016	1.00						
9) GDP	0.318	0.379	0.244	0.074	0.433	0.117	−0.749	0.272	1.00					
10) Unstable job	−0.163	−0.167	−0.140	−0.065	−0.424	0.171	0.510	−0.217	−0.536	1.00				
11) HC	0.316	0.373	0.352	−0.068	0.165	0.440	−0.221	0.214	0.469	−0.308	1.00			
12) Migration	0.079	0.156	0.045	0.089	0.315	0.075	−0.688	0.078	0.783	−0.408	0.423	1.00		
13) Patents	0.038	0.099	0.020	0.113	0.247	−0.004	-0.500	0.098	0.596	−0.437	0.261	0.486	1.00	
14) IQI	−0.064	0.012	−0.034	−0.066	-0.026	−0.076	0.320	0.010	−0.406	0.020	−0.172	−0.495	−0.270	1.00

Table 6 Robustness test using historical entrepreneurship data

	All startups	Innovative	High growth	Pioneers	All startups	Innovative	High growth	Pioneers
Complexity	0.0529**	0.436***	−0.171**	−0.0236	0.0436*	0.414***	−0.151*	−0.0257
	(0.0241)	(0.150)	(0.0814)	(0.0807)	(0.0234)	(0.151)	(0.0833)	(0.0802)
Relatedness	0.0546*	0.454**	−0.370***	−0.139	0.0432	0.460**	−0.394***	−0.142
	(0.0305)	(0.210)	(0.128)	(0.108)	(0.0293)	(0.203)	(0.128)	(0.108)
Unemployment	−0.000818	−0.0113	−0.0127	0.0119	−0.00101	−0.0120	−0.0136	0.0134*
	(0.00219)	(0.0140)	(0.00940)	(0.00776)	(0.00216)	(0.0141)	(0.00945)	(0.00783)
Pop. Den	0.000670***	0.000494*	0.000510*	-0.000552	0.000467**	0.000396	0.000555*	−0.000746*
	(0.000185)	(0.000300)	(0.000304)	(0.000358)	(0.000213)	(0.000328)	(0.000302)	(0.000386)
GDP	−0.0124***	−0.0572***	0.0523***	0.0215*	−0.0123***	−0.0587***	0.0545***	0.0204
	(0.00388)	(0.0211)	(0.0135)	(0.0131)	(0.00378)	(0.0213)	(0.0135)	(0.0129)
Unstable job	−0.000257	2.138	−0.880	−0.484	0.0778	2.505*	−1.008	−0.626
	(0.223)	(1.432)	(0.914)	(0.814)	(0.222)	(1.489)	(0.896)	(0.833)
HC	0.481	−1.363	0.369	−1.952*	0.622**	−1.517	0.185	−1.957*
	(0.314)	(2.114)	(1.255)	(1.110)	(0.304)	(2.119)	(1.257)	(1.097)
Migration	0.0571	0.379	-0.406	0.138	0.0621	0.310	−0.329	0.0698
	(0.0696)	(0.468)	(0.296)	(0.236)	(0.0670)	(0.472)	(0.303)	(0.239)
Patents	0.00350	1.039*	0.173	0.527	−0.0262	0.913	0.190	0.513
	(0.0924)	(0.610)	(0.372)	(0.325)	(0.0921)	(0.628)	(0.369)	(0.323)
IQI	0.196**	0.260	0.556*	0.0536	0.194**	0.230	0.570**	0.0964
	(0.0905)	(0.493)	(0.286)	(0.319)	(0.0891)	(0.497)	(0.283)	(0.317)
Histent industry	91.58***	101.2	−8.495	32.34				
	(24.35)	(65.04)	(28.03)	(46.91)				
Histent services					104.4***	52.60	−30.78	62.62
					(22.11)	(61.57)	(24.57)	(49.09)
Constant	38.97***	-619.3***	-692.0***	154.6***	35.48***	−620.2***	−700.1***	159.5***
	(9.634)	(56.12)	(36.02)	(32.06)	(9.397)	(55.81)	(36.89)	(32.06)
Observations	445	445	445	445	445	445	445	445
AIC	3824.7	1793.6	2608.4	2262.9	3815.1	1794.8	2607.0	2261.4
BIC	3878.0	1846.8	2661.7	2316.2	3868.4	1852.2	2660.2	2314.7
Log-likelihood	−1899.3	−883.8	−1291.2	−1118.5	−1894.6	−883.4	−1290.5	−1117.7

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Construction of variables of interests

Economic Complexity: to build the variable we proceeded as follows. Using employment data, we first defined the industrial specializations of the Italian provinces through the formula of the revealed comparative advantage[3] (RCA). Then, we operationalized the RCA as an adjacency matrix (*Mpi*), where *Mpi* is equal to 1 if the *p* has a relative specialization in *i*, and equal to 0 if not. Then, we calculated the complexity of each province based on employment data using the product matrix *W* equal to the product of matrix *Mpi* (row standardized) and its transpose M^T (row standardized), a squared matrix (with dimension 103×103). The elements along the principal diagonal of *W* represent the average ubiquity of the industrial classes, in which the row and column province have an RCA. The off-diagonal elements represent the product of the industrial classes in which province (*j*; row) has RCA and the ubiquity of the industrial classes in which province (*k*; column) has RCA. These elements thus capture the similarity in the industrial structure of province pairs. The complexity for each province is provided by the second eigenvector of matrix *W*.

Relatedness: to build this second variable of interest, we used again the RCA and computed the relatedness between every pair of industrial categories as the minimum of the conditional probability for every Italian province to find an RCA in industrial category *i*, given that the province already exhibits an RCA in category *j*. The result is an *n*n* matrix, where *n* represents the number of industrial categories considered, represented in this case by each NACE category disaggregated at the four-digit level of detail, and each cell contains the measure of relatedness between two industrial categories.

Since the aim of the study is to determine if the concentration in an area of a high level of proximity among industrial categories is a driver of entrepreneurship and if this has a different impact depending on the four categories of startups considered here. We need a synthetic indicator of the relatedness of the provinces; for this purpose, the values of relatedness among industrial categories present in our *n*n* matrix are used to compute a measure of provincial relatedness of the industries as follow:

$$R_{pt} = \sum_{s=1}^{S} R_{ck}\left(\frac{n_{cp} + n_{kp}}{N_p}\right)$$

where *p* represents the province, R_{ck} is the index of relatedness between the sector *c* and *k*, n_{cp} indicates the number of employees in the sector *c* of the province *p*, n_{kp} is the number of the employees of the sector *k* for the same province, and *N* represents the total number of workers of the considered province *p*. This indicator is added to control its effect on new firm formation. Synthetizing is a concentration measure computed summing up the proximity values for each sector by province.

[3] If a province exhibits a concentration of employees higher than the national average in an industrial category, it is then considered to have an RCA in that sector.

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References

Acs, Z.J., Parsons, W., & Tracy, S. (2008). High impact firms: Gazelles revisited. *An Office of Advocacy Working Paper, U.S. Small Business Administration*, 238.

Ali, A., Kelley, D. J., & Levie, J. (2020). Market-driven entrepreneurship and institutions. *Journal of Business Research, 113*, 117–128.

Antonietti, R., & Gambarotto, F. (2020). The role of industry variety in the creation of innovative start-ups in Italy. *Small Business Economics, 54*(2), 561–573.

Antonietti, R., & Montresor, S. (2021). Going beyond relatedness: Regional diversification trajectories and key enabling technologies (KETs) in Italian regions. *Economic Geography, 97*(2), 187–207.

Auerswald, P., & Dani, L. (2022). Entrepreneurial opportunity and related specialization in economic ecosystems. *Research Policy, 51*(9), 104445.

Audretsch, D.B. (2012). Determinants of high-growth entrepreneurship. In *Report prepared for the* OECD*/DBA*

International Workshop on "High-Growth Firms: local policies and local determinants, Copenhagen.
Audretsch, D., & Fritsch, M. (1994). On the measurement of entry rates. *Empirica, 21*(1), 105–113.
Audretsch, D. B., & Thurik, A. R. (2001). What's new about the new economy? Sources of growth in the managed and entrepreneurial economies. *Industrial and Corporate Change, 10*(1), 267–315.
Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy, 34*(8), 1191–1202.
Audretsch, D. B., Lehmann, E. E., & Hinger, J. (2015). From knowledge to innovation: The role of knowledge spillover entrepreneurship. In C. Antonelli & A. N. Link (Eds.), *Routledge Handbook of the Economics of Knowledge, New York*. Routledge.
Audretsch, D. B., Belitski, M., Caiazza, R., & Desai, S. (2022). The role of institutions in latent and emergent entrepreneurship. *Technological Forecasting and Social Change, 174*, 121263.
Autio, E. (2009). *The Finnish paradox: The curious absence of high-growth entrepreneurship in Finland,* Discussion Papers 1197, The Research Institute of the Finnish Economy.
Bae, J., & Koo, J. (2008). The nature of local knowledge and new firm formation. *Industrial and Corporate Change, 18*(3), 473–496.
Baker, T., & Nelson, R. E. (2005). Creating something from nothing: Resource construction through entrepreneurial bricolage. *Administrative Science Quarterly, 50*(3), 329–366.
Balland, P. A., & Rigby, D. (2017). The geography of complex knowledge. *Economic Geography, 93*(1), 1–23.
Balland, P. A., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: Relatedness, knowledge complexity and regional diversification. *Regional Studies, 53*(9), 1252–1268.
Balland, P. A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). The new paradigm of economic complexity. *Research Policy, 51*(3), 104450.
Baron, R. A. (2006). Opportunity recognition as pattern recognition: How entrepreneurs "connect the dots" to identify new business opportunities. *Academy of Management Perspectives, 20*(1), 104–119.
Bishop, P. (2012). Knowledge, diversity and entrepreneurship: A spatial analysis of new firm formation in Great Britain. *Entrepreneurship and Regional Development, 24*(7–8), 641–660.
Bonaccorsi, A., Colombo, M. G., Guerini, M., & Rossi-Lamastra, C. (2013). University specialization and new firm creation across industries. *Small Business Economics, 41*, 837–863.
Bosma, N., & Sternberg, R. (2014). Entrepreneurship as an urban event? Empirical evidence from European cities. *Regional Studies, 48*(6), 1016–1033.
Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain. *Papers in Regional Science, 91*(2), 241–256.
Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies, 51*(3), 351–364.
Brown, R., Mawson, S., & Mason, C. (2017). Myth-busting and entrepreneurship policy: The case of high growth firms. *Entrepreneurship & Regional Development, 29*(5–6), 414–443.
Capozza, C., Salomone, S., & Somma, E. (2018). Local industrial structure, agglomeration economies and the creation of innovative start-ups: Evidence from the Italian case. *Entrepreneurship & Regional Development, 30*(7–8), 749–775.
Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. *Regional Studies, 49*(5), 767–781.
Cavallo, A., Ghezzi, A., Colombelli, A., & Casali, G. L. (2020). Agglomeration dynamics of innovative start-ups in Italy beyond the industrial district era. *International Entrepreneurship and Management Journal, 16*(1), 239–262.
Coad, A., Daunfeldt, S. O., Hölzl, W., Johansson, D., & Nightingale, P. (2014). High-growth firms: Introduction to the special section. *Industrial and Corporate Change, 23*(1), 91–112.
Coad, A., Kaiser, U., & Kuhn, J. (2021). Spin doctors vs the spawn of capitalism: Who founds university and corporate startups? *Research Policy, 50*(10), 104347.
Colombelli, A. (2016). The impact of local knowledge bases on the creation of innovative start-ups in Italy. *Small Business Economics, 47*(2), 383–396.
Colombelli, A., & Quatraro, F. (2018). New firm formation and regional knowledge production modes: Italian evidence. *Research Policy, 47*(1), 139–157.
Content, J., Frenken, K., & Jordaan, J. A. (2019). Does related variety foster regional entrepreneurship? *Evidence from European Regions. Regional Studies, 53*(11), 1531–1543.
Cosci, S., Meliciani, V., & Pini, M. (2022). Historical roots of innovative entrepreneurial culture: The case of Italian regions. *Regional Studies, 56*(10), 1683–1697.
Czarnitzki, D., & Delanote, J. (2013). Young innovative companies: The new high-growth firms? *Industrial and Corporate Change, 22*(5), 1315–1340.
Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography, 10*(4), 495–518.
Du, K., & O'Connor, A. (2018). Entrepreneurship and advancing national level economic efficiency. *Small Business Economics, 50*(1), 91–111.
Du, K., & O'Connor, A. (2021). Examining economic complexity as a holistic innovation system effect. *Small Business Economics, 56*(1), 237–257.
Ejdemo, T., & Örtqvist, D. (2020). Related variety as a driver of regional innovation and entrepreneurship: A moderated and mediated model with non-linear effects. *Research Policy, 49*(7), 104073.
Eurostat-OECD. (2007). *Eurostat-OECD manual on business demography statistics*. Office for Official Publications of the European Communities.
Faggian, A., Rajbhandari, I., & Dotzel, K. R. (2017). The interregional migration of human capital and its regional consequences: A review. *Regional Studies, 51*(1), 128–143.
Feldman, M. P. (2001). The entrepreneurial event revisited: Firm formation in a regional context. *Industrial and Corporate Change, 10*(4), 861–891.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies, 41*(5), 685–697.
Fritsch, M., & Falck, O. (2007). New business formation by industry over space and time: A multidimensional analysis. *Regional Studies, 41*(2), 157–172.
Fritsch, M. (2019). The regional emergence of innovative start-ups: A research agenda. In D. B. Audretsch, E. E. Lehmann, & A. N. Link (Eds.), *A Research Agenda for Entrepreneurship and Innovation* (pp. 74–90). Edward Elgar.
Garud, R., & Karnøe, P. (2001). Path creation as a process of mindful deviation. In R. Garud & P. Karnøe (Eds.), *Path Dependence and Creation* (pp. 1–38). Lawrence Erlbaum Associates Publishers.
Gruber, M., MacMillan, I. C., & Thompson, J. D. (2008). Look before you leap: Market opportunity identification in emerging technology firms. *Management Science, 54*(9), 1652–1665.
Guevara, M. R., Hartmann, D., Aristarán, M., Mendoza, M., & Hidalgo, C. A. (2016). The research space: Using career paths to predict the evolution of the research output of individuals, institutions, and nations. *Scientometrics, 109*(3), 1695–1709.
Hair, J., Anderson, R. E., Tatham, R. L., & Black, W. F. (1995). *Multivariate data analysis*. Prentice Hall.
Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica, 52*(4), 909–938.
Hidalgo, C. A. (2021). Economic complexity theory and applications. *Nature Reviews Physics, 3*(2), 92–113.
Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences, 106*(26), 10570–10575.
Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science, 317*(5837), 482–487.
Hilbe, J. (2011). *Negative binomial regression*. Cambridge University Press.
Iftikhar, M. N., Justice, J. B., & Audretsch, D. B. (2022). The knowledge spillover theory of entrepreneurship: An Asian perspective. *Small Business Economics, 59*(4), 1401–1426.
Innocenti, N., & Lazzeretti, L. (2019). Do the creative industries support growth and innovation in the wider economy? Industry relatedness and employment growth in Italy. *Industry and Innovation, 26*(10), 1152–1173.
Innocenti, N., & Zampi, V. (2019). What does a start-up need to grow? An empirical approach for Italian innovative start-ups. *International Journal of Entrepreneurial Behavior & Research, 25*(2), 376–393.
Innocenti, N., Vignoli, D., & Lazzeretti, L. (2021). Economic complexity and fertility: Insights from a low fertility country. *Regional Studies, 55*(8), 1388–1402.
Jara-Figueroa, C., Jun, B., Glaeser, E. L., & Hidalgo, C. A. (2018). The role of industry-specific, occupation-specific, and location-specific knowledge in the growth and survival of new firms. *Proceedings of the National Academy of Sciences, 115*(50), 12646–12653.
Juhász, S., Broekel, T., & Boschma, R. (2021). Explaining the dynamics of relatedness: The role of co-location and complexity. *Papers in Regional Science, 100*(1), 3–21.
Kogler, D., Rigby, D., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies, 21*(9), 1374–1391.
Lacalle-Calderon, M., Perez-Trujillo, M., & Neira, I. (2017). Fertility and economic development: Quantile regression evidence on the inverse J-shaped pattern. *European Journal of Population, 33*, 1–31.
March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87.
Mazzoni, L., Innocenti, N., & Lazzeretti, L. (2022). What kinds of relatedness promote new firm formation? *Evidence from Italy. Industry and Innovation, 29*(1), 53–73.
Mealy, P., Farmer, J., & Teytelboym, A. (2019). Interpreting economic complexity. *Science Advances, 5*(1), eaau1705.
Moreno, F., & Coad, A. (2015). High-growth firms: Stylized facts and conflicting results. In J. Katz & A. Corbett (Eds.), *Entrepreneurship Growth: Individual, Firm, and Region* (pp. 187–230). Emerald Group Publishing Limited.
Naudé, W. (2022). From the entrepreneurial to the ossified economy. *Cambridge Journal of Economics, 46*(1), 105–131.
Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography, 87*(3), 237–265.
Nguyen, C. P., Nguyen, B., Tung, B. D., & Su, T. D. (2021). Economic complexity and entrepreneurship density: A nonlinear effect study. *Technological Forecasting and Social Change, 173*, 121107.
Nightingale, P., & Coad, A. (2014). Muppets and gazelles: Political and methodological biases in entrepreneurship research. *Industrial and Corporate Change, 23*(1), 113–143.
Nifo, A., & Vecchione, G. (2014). Do institutions play a role in skilled migration? *The Case of Italy. Regional Studies, 48*(10), 1628–1649.
Ortega, M. J., & García-Villaverde, P. M. (2011). Pioneer orientation and new product performance of the firm: Internal contingency factors. *Journal of Management & Organization, 17*(4), 474–497.
Ortega, M. J., García-Villaverde, P. M., & Parra-Requena, G. (2018). How structural embeddedness leads to pioneering orientation. *Technological Forecasting and Social Change, 134*, 186–198.
Park, G., Shin, S. R., & Choy, M. (2020). Early mover (dis) advantages and knowledge spillover effects on blockchain startups' funding and innovation performance. *Journal of Business Research, 109*, 64–75.
Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'este, P., ... & Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy*, *42*(2), 423–442
Pinheiro, F. L., Alshamsi, A., Hartmann, D., Boschma, R., & Hidalgo, C. A. (2018). *Shooting high or low: Do countries benefit from entering unrelated activities?*. https://doi.org/10.48550/arXiv.1801.05352
Plummer, L. A., Parker, S. C., & Reyes, S. C. (2022). Regional path breaking: the role of industry switching, industry

diversity, and new knowledge in new venture exit. *Entrepreneurship Theory and Practice, 46*(5), 1231–1255.
Rocha, H.O. (2013). Introduction. In: *Entrepreneurship and Regional Development*. London: Palgrave Macmillan. https://doi.org/10.1057/9781137298263_1
Ruiz-Ortega, M. J., García-Villaverde, P. M., & Parra-Requena, G. (2018). How structural embeddedness leads to pioneering orientation. *Technological Forecasting and Social Change, 134*, 186–198.
Sautet, F. (2013). Local and systemic entrepreneurship: Solving the puzzle of entrepreneurship and economic development. *Entrepreneurship Theory and Practice, 37*(2), 387–402.
Schneider, C., & Veugelers, R. (2010). On young highly innovative companies: Why they matter and how (not) to policy support them. *Industrial and Corporate Change, 19*(4), 969–1007.
Schumpeter, J. (1934). *Theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Harvard University Press.
Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. *Small Business Economics, 33*(2), 141–149.
Stam, E. (2005). The geography of gazelles in the Netherlands. *Tijdschrift Voor Economische En Sociale Geografie, 96*(1), 121–127.
Stam, E., & Van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics, 56*(2), 809–832.
Suarez, F. F., & Lanzolla, G. (2007). The role of environmental dynamics in building a first mover advantage theory. *Academy of Management Review, 32*(2), 377–392.
Teece, D. J., Rumelt, R., Dosi, G., & Winter, S. (1994). Understanding corporate coherence: Theory and evidence. *Journal of Economic Behavior & Organization, 23*(1), 1–30.
Teruel, M., & De Wit, G. (2017). *Determinants of high-growth firms: Why do some countries have more high-growth firms than others?* In Exploring the entrepreneurial society.
Thurik, A. R. (2009). Entreprenomics: Entrepreneurship, economic growth and policy. *Entrepreneurship, Growth and Public Policy, 10*(6), 219–249.
Urbano, D., Aparicio, S., & Audretsch, D. (2019). Twenty-five years of research on institutions, entrepreneurship, and economic growth: What has been learned? *Small Business Economics, 53*(1), 21–49.
Vedula, S., York, J. G., & Corbett, A. C. (2019). Through the looking-glass: The impact of regional institutional logics and knowledge pool characteristics on opportunity recognition and market entry. *Journal of Management Studies, 56*(7), 1414–1451.
Vignoli, D., Drefahl, S., & De Santis, G. (2012). Whose job instability affects the likelihood of becoming a parent in Italy? A tale of two partners. *Demographic Research, 12*, 41–62.
Welter, F., Baker, T., Audretsch, D. B., & Gartner, W. B. (2017). Everyday entrepreneurship—A call for entrepreneurship research to embrace entrepreneurial diversity. *Entrepreneurship Theory and Practice, 41*(3), 311–321.

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