Entrepreneurial Ecosystems and Interregional Flows of Entrepreneurial Talent

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Abstract: The quality of entrepreneurial ecosystems not only enables local startups, but also affects the attraction and supply of non-local founders. We conceptualize entrepreneurial ecosystems as open systems with inflows and outflows of entrepreneurial talent. Beyond individual agency, these talent flows are driven by the quality of the origin and destination entrepreneurial ecosystems. We use network analysis and gravity models to study the interregional flows of founders of non-local startups within Italy, and find empirical evidence for creation, attraction and supply mechanisms of entrepreneurial ecosystems. Entrepreneurial ecosystems provide a supportive environment for the creation of local startups, but also attract non-local (potential) founders. In addition, we reveal an escalator mechanism: (prospective) entrepreneurs tend to move from good to better entrepreneurial ecosystems.

Keywords: entrepreneurial ecosystems; innovative startups; talent flows; non-local founders; complex systems; gravity models

1. Introduction

The entrepreneurial ecosystem approach is central to analyzing the conditions that enable productive entrepreneurship to emerge in particular places (Stam, 2015; Audretsch & Belitski, 2017; Wurth et al., 2022). Entrepreneurial ecosystems are a set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship within a particular territory (Stam, 2015; Stam & Spigel, 2018; Stam & Van de Ven, 2021). The entrepreneurial ecosystem approach provides a complex systems view of the entrepreneurial economy as a complex evolving system. The entrepreneurial ecosystem label may be viewed as shorthand for a complex economic system that enables or constrains the emergence of new economic activities realized through entrepreneurial action (Stam & Van de Ven, 2021). A number of studies have developed metrics for analyzing entrepreneurial ecosystems as units of analysis (e.g., Audretsch & Belitski 2017; Stam & Van der Ven, 2021, Leendertse et al. 2022). As with any novel scientific approach, a number of weaknesses are discovered in the entrepreneurial ecosystem approach and new challenges emerge as a result of the knowledge accumulation process (Wurth et al., 2022). In particular, the explicit reference to the science of complex systems (Simon, 1962; Holland, 2006) points to a possible misspecification of the phenomenon, as it is difficult to define and measure complex systems. Nonlinear dynamics, openness, distributed agency, and limited decomposability are among the properties of complex adaptive systems (Martin & Sunley, 2007) that may require further theoretical and empirical development of the entrepreneurial ecosystem approach.

In this paper, we address the openness of entrepreneurial ecosystems. Complex economic systems, including entrepreneurial ecosystems, are not self-contained entities but exhibit permeable boundaries. This is due to the agency of entrepreneurial actors who move freely between different locations and help create invisible knowledge links between entrepreneurial economies at the local and global scale (Stam, 2007; Schäfer & Henn, 2018). Accordingly, in many cases, successful entrepreneurs are not only the result of a set of enabling conditions in the ecosystem in which the startup is founded, but also the product of other entrepreneurial ecosystems in which these founders have been located before. This perspective helps define entrepreneurial ecosystems as multiscale and open systems. Previous research has highlighted the lack of such an open systems perspective on entrepreneurial ecosystems (Lange & Schmidt, 2021; Theodoraki & Catanzaro, 2022), recognizing the limitations of artificially tying the relationship between productive entrepreneurship and enabling conditions (Colombo et al., 2019) and the presence of nested geographies (Brown & Mason, 2017).

This paper aims to provide new insights into the role of entrepreneurial ecosystems as enablers, attractors, and suppliers of entrepreneurial talent. Entrepreneurial talent can be home-grown, creating local startups, but it can also come from other regions and create non-local startups. In this paper, we address this caveat by answering the following research question: *To what extent and how does the quality of entrepreneurial ecosystems at origin and destination affect the prevalence of non-local startups*?

Flows of entrepreneurial talent can strengthen the quality of the receiving region and diminish the quality of the area left behind (Anelli et al., 2019), triggering virtuous cycles of entrepreneurial ecosystem development in the receiving region and potential vicious cycles of entrepreneurial ecosystem development in the sending region. This can lead to an increase in overall (national) prosperity, while also increasing regional inequality. This paper offers new insights into entrepreneurship-led economic development, a development model that has become prevalent in economic development policy (Qian & Acs, 2023), without sufficient analytical knowledge on how to improve entrepreneurial-driven development and what unintended consequences it may have.

We focus on the interregional mobility of founders, analyzing data of Italian innovative startups and using an entrepreneurial ecosystem index (cf. Stam & Van de Ven, 2021; Leendertse et al., 2022) constructed with fine-grained data across 105 NUTS-3 regions. Italy is historically characterized by industrial districts with large interregional disparities (Capozza et al., 2018), several core economic regions, very low entrepreneurship rates (GEM 2021), and low interregional mobility (Bonifazi et al., 2017). An ideal test area to study the impact of heterogeneity in the quality of entrepreneurial ecosystems on the presence of non-local startups.

Our analyses show a positive relationship between the quality of the entrepreneurial ecosystem and the prevalence of non-local startups. The quality of the entrepreneurial ecosystem in both destination and origin regions is important in explaining the mobility of (potential) founders between regions, explained respectively by attraction, creation, and supply mechanisms. This suggests that the quality of the entrepreneurial ecosystem not only promotes the creation of local startups, but also the attraction of non-local founders and even the extent to which some regions act as suppliers for potential founders moving to other regions.

The paper is organized as follows. In section 2, we discuss the theoretical background, i.e., the formation, attraction, and supply mechanisms in entrepreneurial ecosystems. In section 3, we describe the methodological framework, which consists of a mixed methodology necessary to deal with the complexity of the problem and the scarcity of data. After presenting an indicator of entrepreneurial ecosystem quality, we explain the process of collecting data from non-local founders, our econometric strategy and the qualitative analysis of micro-data from LinkedIn. In section 4, we present the results of our econometric estimation based on a Poisson Pseudo Maximum Likelihood (PPML) gravity model to test the inter-regional flows of non-local founders and explain how the quality of the entrepreneurial economy in the origin and destination regions affects these flows. To further test our results, we use a novel application of machine learning to PPML post-estimation techniques based on the Least

Absolute Shrinkage and Selection Operator (LASSO) used to select explanatory variables. The second part of section 4 reports the results of the qualitative analysis on a subsample of non-local founders using LinkedIn data on their biographies.

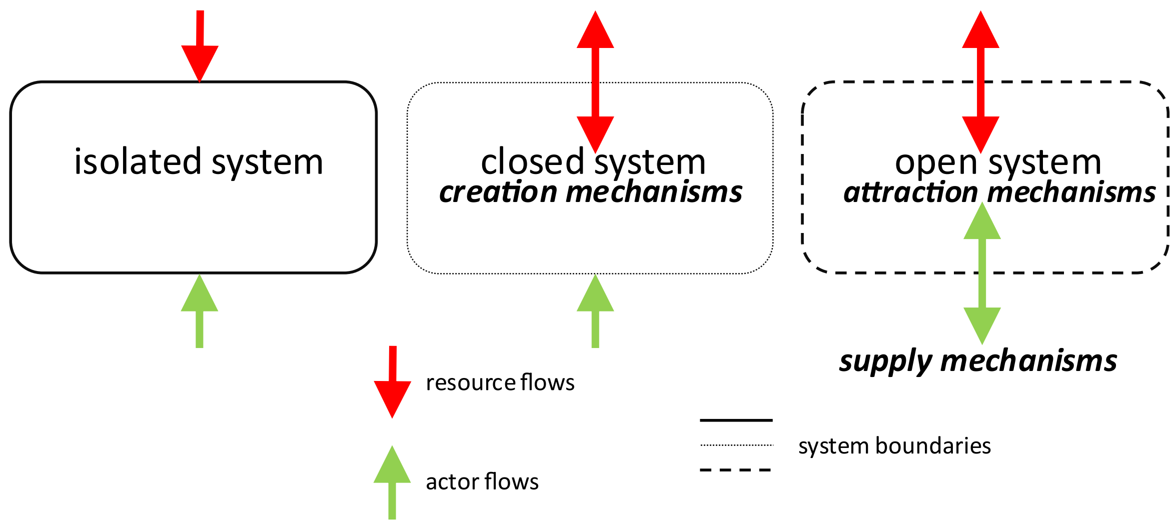
Our results are discussed in section 5, and we conclude with section 6, which also presents policy implications and a research agenda.

2. Creation, attraction and supply mechanisms in entrepreneurial ecosystems

2.1 Entrepreneurial ecosystems as open systems

The concept entrepreneurial ecosystem can be seen as a label for seeing the entrepreneurial economy as a complex system (Roundy et al., 2018; Stam & Van de Ven, 2021; Daniel et al., 2022). Systems, and thus also entrepreneurial eco-systems, can be isolated, closed or open (see Figure 1). Systems are isolated when there are no inflows or outflows of resources and actors: an example is an autarkic island economy, which is not connected to other economies with for example capital and trade flows. Systems can also be closed, meaning that there is an inflow or outflow of resources (e.g., funding or products) but no mobility of agents out of or into the system. Many studies of entrepreneurial ecosystems have analyzed them as closed systems: there may be resource flows beyond the boundaries of the system (including financial flows from outside, sales outside, and supply chains outside), but it is (implicitly) assumed that the actors remain within the system. However, to capture the impact of actor mobility beyond the boundaries of entrepreneurial ecosystems, we need to treat entrepreneurial ecosystems as open systems that can attract actors from outside, but also experience actors moving outside. Such an open system view can accommodate talent flows between systems (Basile et al., 2019), including for example diaspora entrepreneurship (Saxenian, 2007; Andonova et al., 2020) and immigrant entrepreneurship (Azoulay et al., 2022). This open systems view also provides an adequate starting point for understanding global versus regional entrepreneurial ecosystems (Audretsch & Belitski,2021), and inter-ecosystem links more broadly (Wurth et al., 2023).

Figure 1. Isolated, closed and open systems



In this paper we conceptualize entrepreneurial ecosystems as complex open systems, which allows us to consider the multidimensional and interdependent nature of entrepreneurial ecosystems and to examine emergence within economies and effects on other economies. Emergence is primarily approached with creation mechanisms that explain why some places nurture more productive entrepreneurship than others. This is a central aspect of the entrepreneurial ecosystem approach (Stam, 2015; Audretsch & Belitski, 2017; Stam & Van der Ven, 2021; Leendertse et al., 2022), which provides a more appropriate model to study entrepreneurship and its inherent uncertainty (Knight, 1921) and out-of-equilibrium dynamics (Schumpeter 1934) than general equilibrium models (Lucas, 1978).

2.2 Creation mechanisms within entrepreneurial ecosystems

A central argument in the entrepreneurship literature is that there is a distinct set of local conditions (e.g., shared norms, entrenched culture, enabling infrastructures, fear of failure, social connections) that enable the creation of new firms (Fritsch and Wyrwich, 2017; Sorenson, 2017; Wyrwich et al., 2019). This "creation mechanism" explains how the qualities of (regional) entrepreneurial ecosystems influence the prevalence of (different types of) entrepreneurial activities. These studies focus on entrepreneurial activity in specific industries in particular regions (Glaeser & Kerr, 2009; Buenstorf & Klepper, 2010; Frenken et al., 2015) or on specific elements of the entrepreneurial ecosystem, for example, finance (Michelacci & Silva, 2007; Samila & Sorenson, 2011), culture (Fritsch & Wyrwich, 2014; Falck et al, 2017), demographics (Bönte et al. 2009), social capital (Bauernschuster et al., 2010), agglomeration economies (Glaeser et al., 2010), or the overall quality of entrepreneurial ecosystems and their entrepreneurial outcomes (Guzman & Stern 2020; Stam & Van de Ven 2021; Leendertse et al. 2022). Significant heterogeneity in the quality of entrepreneurial ecosystems (Glaeser et al., 2010; Chatterji et al., 2014) leads to a highly uneven spatial distribution of entrepreneurship across cities, regions, and countries (Qian et al., 2013; Stam & Van de Ven 2021; Leendertse et al. 2022), which is a driver of spatially uneven economic growth and development (Glaeser et al., 2015; Audretsch & Belitski, 2021). This creation mechanism is also at the heart of models of endogenous regional growth (Coffey & Polese, 1984), and the knowledge spillover theory of entrepreneurship (Morris et al., 2023).

2.3 Attraction and supply mechanisms between entrepreneurial ecosystems

Building upon and going beyond the current literature, we propose that the quality of entrepreneurial ecosystems not only enables local startups (creation mechanism), but is also essential for attracting and supplying non-local founders. Entrepreneurial ecosystems can be seen as open systems that attract and supply entrepreneurial actors outside the system (see

Figure 1). Not only is the quality of the entrepreneurial ecosystem at the destination critical to understanding the mobility of (potential) founders, but also the quality of the entrepreneurial ecosystem at the place of origin, which can act as a supplier for non-local founders. Many entrepreneurs stay in their region of origin, but a significant group of entrepreneurs also migrate between countries (Azoulay et al. 2022) and regions (Reuschke & Van Ham, 2013). This raises the question of whether the creation mechanism is sufficient to understand the uneven spatial distribution of entrepreneurship. To what extent do high-quality entrepreneurial ecosystems not only nurture local founders (the creation mechanism) but also attract non-local founders? Despite recent attention to the geographic mobility of startups (Bryan & Guzman, 2023; Guzman, 2024), there is limited evidence on the flows of (potential) founders and the relationship with geographic contexts (see Anelli et al., 2019; Bonaventura et al., 2020). We need more insight into the attraction mechanisms that explain why some regions attract more (potential) founders than others. There may also be conditions that explain where entrepreneurs are (partially) nurtured and migrate to other places: supply mechanisms. The latter illustrates an escalator mechanism when (prospective) entrepreneurs move from good to better entrepreneurial ecosystems. An example of this is the dominance of California (USA) as an attraction point for startups from the Tel Aviv (Israel) area (Conti & Guzman, 2023), indicating both an attraction mechanism (of the qualities of the California economy) and a supply mechanism (based on the qualities of the Tel Aviv economy).

The attraction of global cities as catalysts for innovation is a relatively well-documented phenomenon (see Bettencourt et al., 2007; Verginer & Riccaboni, 2021, Belderbos et al., 2022), but the other local dynamics of entrepreneurship have not been adequately studied. Similarly, interregional migration has been shown to be an important driver of labor market and professional network development. This has implications for both source regions (brain drain) and destination regions (brain gain), with the innovation capacity of migrants and natives potentially complementing each other (Bosetti et al., 2015; Faggian et al., 2017; Basile et al., 2019). Younger and more highly educated people are more likely to move longer distances and might therefore be more attracted to high-quality entrepreneurial ecosystems than older and less educated people (see Anelli et al., 2019). This may be highly relevant for young founders, who are attracted to creative and vibrant environments that provide better conditions for exploring and exploiting breakthrough ideas (Acemoglu et al., 2014; Bratti & Conti, 2018).

Gravity models provide a method to better understand interregional flows of (potential) founders (see Lewer & Van den Berg, 2008). Two insights from economic gravity models may be relevant here. First, a negative effect of distance between two regions is expected: the farther two regions are from each other, the lower the flows of (potential) founders between them. The second and perhaps less intuitive insight from gravity models is that the greater the economic activity in a given region, the less the distance between two regions is a barrier to the exchange of goods, services or human capital. This explains, for example, the relatively large flows of people, goods, and services between the world cities of London and New York, despite the considerable distance between them (Deruddder & Taylor, 2005). Applying this to entrepreneurial ecosystems raises the question of whether people leave regions with a very low-quality entrepreneurial ecosystem by necessity, as evidenced by the large historical emigration from the Mezzogiorno (southern Italy; Hirschman 1970), or whether migrants are more likely to come from regions with relatively high levels of economic activity and a relatively high-quality entrepreneurial ecosystem (Conti & Guzman, 2023).

3. Methodology and data collection

3.1 Measuring entrepreneurial ecosystems

One cannot qualify entrepreneurial ecosystems by measuring only their entrepreneurial outputs. This would lead to a tautology in which high-quality entrepreneurial ecosystems are classified based on their outputs, and that regions with a high prevalence of entrepreneurship are classified as high-quality entrepreneurial ecosystems. Such a tautology would be misleading for both scholars and policymakers in identifying the most important conditions for entrepreneurship-led economic development (Stam, 2015). Recently, this gap has been addressed by providing metrics for entrepreneurial ecosystems that are able to capture the granularity, interconnectedness, and systemic nature of entrepreneurial economies (Stam & Van der Ven, 2021; Leendertse et al., 2022). In this paper, we build on the entrepreneurial ecosystem approach (Stam, 2015; Acs et al., 2017; Stam & Spigel, 2018; Stam & Van der Ven, 2021; Leendertse et al., 2022). We also operationalize ten key elements of entrepreneurial ecosystems at two levels: institutional arrangements *(Formal Institutions*, *Culture*, and *Networks*) and resource endowments (*Physical Infrastructure, Finance, Leadership, Talent, New Knowledge, Demand and Intermediate Services*). Considering the large differences between territories in terms of the quality of their entrepreneurial ecosystem and the level of entrepreneurial performance, we chose the European Union level NUTS3 and analyzed 105 Italian NUTS3 regions[1] (cf. Iacobucci & Perugini, 2021; Perugini, 2023). The metrics at this territorial level were collected from different data sources: ISTAT, Italian Chambers of Commerce, EUROSTAT, mainly from 2015 to 2019 (except for travel time to urban nodes, which was reported for 2013). For five elements (Formal Institutions, Culture, Networks, Leadership, and Intermediate Services), we take average values, as their structural nature

[1] Since the last territorial reclassification by ISTAT, Italian NUTS 3 level are currently represented by 111 regions. However, six regions belonging to Sardinia (Carbonia-Iglesias, Medio Campidano, Ogliastra, Olbia-Tempio and Sud Sardegna) and one region from Apulia (Barletta-Andria-Trani) have been excluded for their absence from many of the indicators used to build the Entrepreneurial Ecosystem index.

makes them less variable over time[2]. In Table 1, we describe the data used to construct each element[3].

Table 1. The building blocks of the entrepreneurial ecosystem index

Element	**Measures**
Formal Institutions	The institutional quality index developed by Nifo and Vecchione (2014) based on 5 groups of elementary indexes (evaluating corruption, governance, regulation, law enforcement, and social participation).
Culture	New firm formation rate (excluding the sole proprietorship firms), which reflects how common it is to create independent new business activity in a certain territory (Stam, 2013).
Networks	The number of Network Contracts between firms ("Rete Contratto"), established by Italian Law 33/2009 that represent an agreement tool that gives the possibility to firms to share one or more objectives and a common program, without creating a new legal entity (Leoncini et al., 2020). This policy tool has been mainly adopted by SMEs and therefore can be used as a proxy of connectedness degree within regions.
Physical Infrastructure	A composite indicator of three measures: a) travel time to urban centres, b) average speed in the NUTS3 regional capital, and c) percentage of the population with a broadband subscription. The first two indicators have been intended as proxies of accessibility to measure the opportunity cost in terms of time, while the last one has been considered as a fundamental territorial prerequisite for businesses that highly rely on digital infrastructure to birth and prosper.
Finance	Exploiting information on the innovative source of financing (Venture capitalist, Project Finance and Crowdfunding) from the permanent census by ISTAT (2018), we constructed a proxy for local financial development (cf. Michelacci & Silva, 2007).
Leadership	Leadership is still scarcely measured at the territorial level, despite its increasing importance to understanding path creation dynamics (Grillitsch & Sotarauta, 2020). Thanks to the availability of the CORDIS database, which contains information on the Research and Innovation Program Horizon2020 projects and participants, we follow Leendertse et al. (2022) in considering Italian participants that take the role of project coordinator. In this way we measure the capacity of the territories to coordinate and attract sources of innovation.
Talent	This is an important measure to understand the human capital that can nurture the ecosystem. We build a composite indicator, considering the level of education of people (percentage of graduates and Ph.D.) and the engagement of firms in training activities to acquire new skills and competencies.
New Knowledge	The contribution of the ecosystem in terms of research and innovation, measured with intramural expenditure on activities related to R&D.
Demand	The potential internal market of the ecosystems measured with GDP per capita

[2] The decision to combine data from different years is primarily driven by the availability of certain data for specific years. To maintain a structure similar to the entrepreneurial ecosystem index by Leendertse et al. (2022), we aimed to retain the same data structure and, whenever possible, gather the same indicators to construct dimensions of the entrepreneurial ecosystem index. The choice to calculate the average of certain indicators is based on their more "structural" nature, as they are expected to demonstrate low variability and change gradually over time (a common practice in index construction). This approach helps minimize noise and the potential impact of outliers, resulting in a more stable measure of long-term trends. However, combining data from different years may introduce comparability issues, as different years may be associated with specific events that have varying impacts compared to other periods. To ensure the reliability of our data, we conducted a correlation analysis between our averaged values at the NUTS-2 level and the values by Leendertse et al. (2022). We found a correlation of 83% between the index values, indicating a high level of reliability.

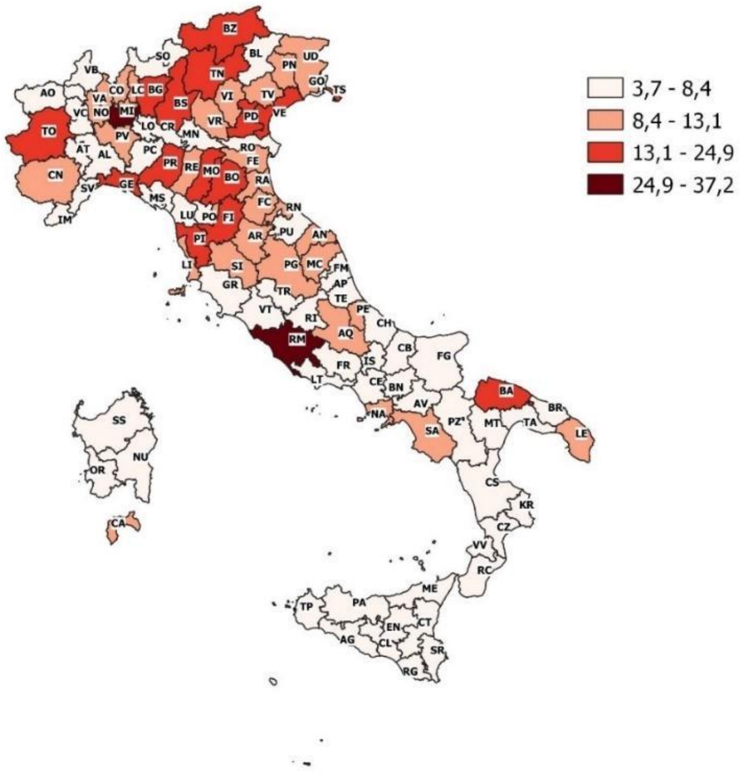
[3] For the data sources we used see Table A.1 in the Appendix.

Intermediate Services	Identifies the presence of business services that can nurture the activity of startups, sustaining them in consulting activities across different levels (e.g., legal, financial, strategical).[4] As a proxy, we use the percentage of firms in knowledge-intensive market services in line with Leendertse et al. (2022).

To allow better interpretation of our results (more robust to outliers), we set an upper bound on the maximum values (four times the standard deviation). We then standardize the composite indicators (Physical Infrastructure and Talent), normalize the ten items by dividing them by their mean (to facilitate interregional comparison), and finally compose an Italian entrepreneurial ecosystem index in an additive manner. The results show a high degree of interconnectedness between the elements and their aggregate measure (the correlation is 0.42 on average, see Appendix; cf. Leendertse et al., 2022). Looking at the performance of the regions, the highest values of the Italian entrepreneurial ecosystem index are spatially concentrated in the north of Italy (with few exceptions such as Rome and Bari), while the lowest values are found in the southernmost regions and islands. Not surprisingly, Milan and Rome achieve the highest entrepreneurial ecosystem index values (37.2 and 33.3, respectively), followed by Bologna (see Figure 2 and Table A.2 in the Appendix).

[4] The entrepreneurial ecosystem index by Leendertse et al. (2022) also included the number of incubators. However, we decided not to include this information in our analysis, since most of the Italian NUTS3 regions do not have incubators (about 74%).

Figure 2. The entrepreneurial ecosystem index of Italian regions[5]



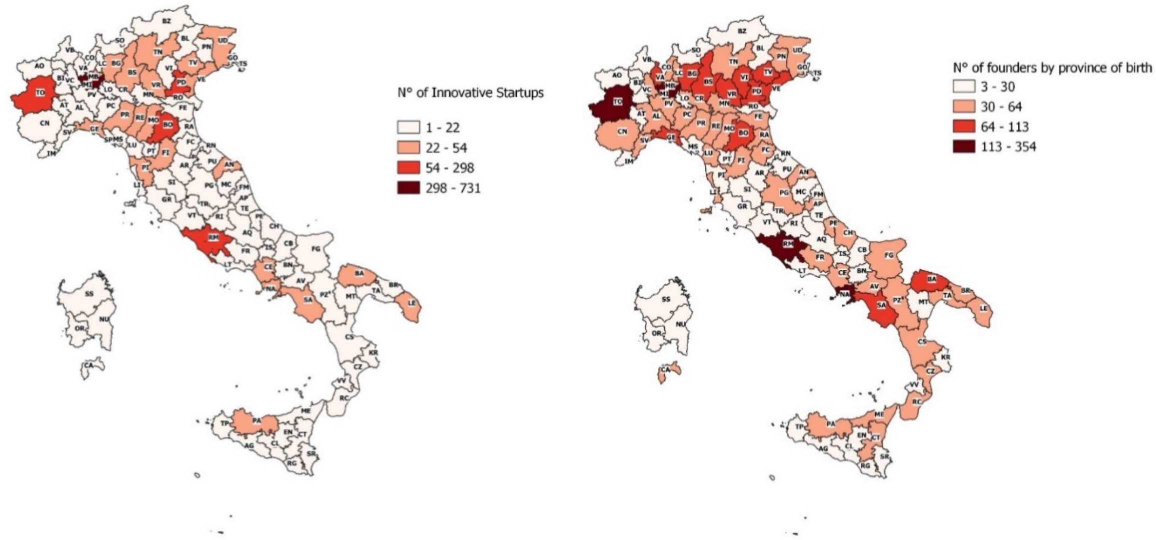
[5] Intervals for all geographic maps were calculated using Jenks Natural Breaks, which have the advantage of reducing variance within groups and therefore represent the most similar elements together.

3.2 Non-local innovative startups

In our analysis, we focus on innovative startups defined by a new policy to promote entrepreneurship in Italy, the so-called Start Up Act (Decree Law 179/2021). This policy aims to increase the prevalence of innovative startups and bridge the gap with other, more innovative OECD countries (Biancalani et al., 2022; Grilli et al., 2023). We selected from the Italian Chambers of Commerce database all innovative startups founded between 2016 and 2019. From this initial sample (7,529 innovative startups; see Figure 3), we search ORBIS for the innovative startups with available information on the founders. We found 4,838 firms with 9,737 founders (see Figure 3). Since we are interested in the role of entrepreneurial ecosystems as suppliers and attractors of founders, we focus on non-local founders of innovative startups. If we exclude founders born in the same region NUTS3 where the startup was founded, we arrive at 5,004 non-local founders (51.4% of all founders) out of 2,779 innovative startups (57.5% of all firms). When we consider innovative startups consisting only of non-local co-founder(s) the number drops to 2,743 founders spread across 1,660 firms (34.3% of all innovative startups). Our dataset includes information on the birthplace of the founder and the location of the startup's founding, but no information on possible movements between these two events. We address this database limitation by looking at aggregate flows of founders rather than considering individual choices. We deepen this caveat by extending the link between entrepreneurial ecosystem elements and the emergence of productive entrepreneurship to consider non-local founders as the end product of the dyadic interconnection between different ecosystems. By selecting only non-local startups – i.e. startups composed by non-local founders – we reduce the likelihood of including shadow cases such as daily commuting.

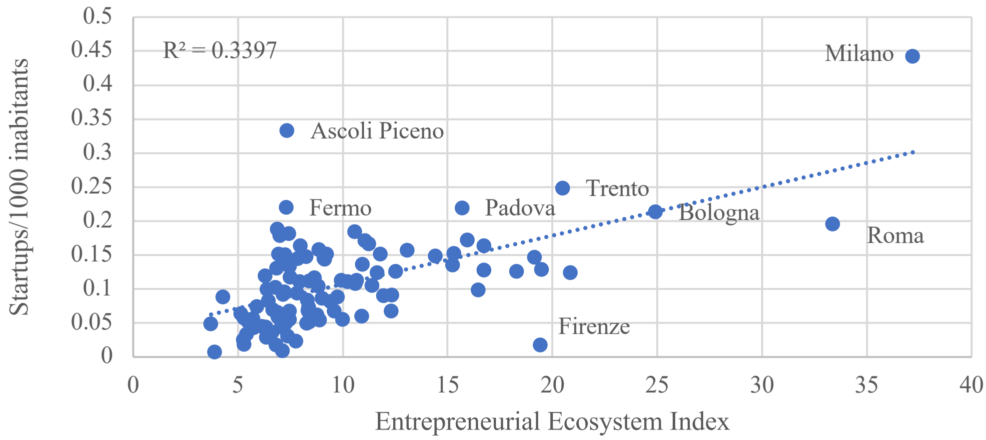
To gain further insight into the potential career paths of founders, we manually examined the LinkedIn profiles of a random sample of 100 founders from our database. Social media have recently been used to track the mobility of entrepreneurs (Butler et al., 2020). This research was conducted with the goal of gaining additional insight into the underlying micro-processes of interregional macro-flows, and we find an interesting tree of possibilities presented in section 4. This qualitative analysis, even though it only considers education and work experience, provides useful insights into the different stages that precede the creation of startups.

Figure 3. Innovative startups and non-local founders in Italian regions



We test the robustness of the Italian entrepreneurial ecosystem index with the presence of innovative startups, based on the assumption that there should be a positive relationship between the quality of the entrepreneurial ecosystem and this measure of productive entrepreneurship (Baumol 1990). The results show a strong and positive relationship between the entrepreneurial ecosystem index and the prevalence of innovative startups in Italian regions: a 5-point increase in the quality of the entrepreneurial ecosystem, as measured by the Italian entrepreneurial ecosystem index, tends to lead to an increase of 0.05 innovative startups per 1,000 inhabitants (see Figure 4). Negative outliers (with a much lower prevalence of innovative startups than expected) are Florence and Rome, while Milan is a positive outlier.

Figure 4. The relationship between the entrepreneurial ecosystem index and innovative startups per capita in Italian regions



In the second step of the descriptive analysis, we analyze the interregional flows to understand the relationship between the innovative startups and non-local founders shown in Figure 3. More specifically, we consider the network where the nodes are Italian NUTS3 regions and directed links are drawn between the region where the non-local founder was born and the region where the startup was founded, setting the network direction in that order. The weights of the links are the number of non-local founders moving from the region of origin to the region where the startup was founded.

As a measure of network centrality, we used the PageRank algorithm, which is useful for revealing influential nodes beyond their directed connections. The decision to rely on PageRank is due to its suitability to describe directed mobility networks that involve more than one possible movement. Originally, PageRank was used to determine the importance of web pages based on the links received from other web pages (Page et al., 1999). In a nutshell, it assumes individuals as “random surfers” who repeat the action to browse different websites. In this study, we analogously measure the probability of a “random surfer” of a given agent born in a region *j* moving to another region to create a startup. Technically, this is an iterative algorithm that assigns each node a probability of being connected to the other nodes of a network by summing all the incoming links of a node *j* and dividing by the count of outgoing links spanning from nodes i through n. The approach presented here can be identified as a variant of eigenvector centrality for directed networks (Page et al., 1999). The PageRank formula is as follows:

$$PR(prov_j) = (1-d) + d(PR(prov_{\,i})/C(prov_{\,i}) \cdots PR(prov_{\,n})/C(prov_{\,n})) \qquad (1)$$

Where *PR* stands for PageRank, *d* for dumping factor[6], and *C* for outbound links (interregional movement of non-local founders). The sum of all PageRanks of the network (excluding the self-ties relationship) must be equal to one. The results show Milan, Rome, Turin and Bologna in the first places and Crotone, Imperia and Nuoro in the last places of the ranking (see Table A.2 in the Appendix).

Figure 5 shows the inter-regional mobility network of non-local founders. We embedded the PageRank estimate and the networks of non-local startup founders into a geographic layout using Gephi software. The size of the node is proportional to its PageRank centrality and the thickness of the links varies according to their intensity. Dark green links represent the dyadic links with high mobility (90-105), light green with medium-high (45-60), orange with medium intensity (21-40) and yellow with low intensity (10-20 links). Milan stands out as the most central region, attracting the most non-local founders from many different regions (even from other large regions such as Rome and Turin). It is also worth noting that a large part of the links originating from Milan lead to high-quality entrepreneurial economies in the surrounding area, such as Monza-Brianza and Brescia. It turns out that the entrepreneurial ecosystem index is strongly correlated with the PageRank centrality of NUTS3

[6] The dumping factor gives the probability that the random walk will continue at each step of the computation. The optimal value is usually set at 0.85 (Page et al., 1999). We calculated PageRank centrality using Gephi, a specialized software for network analysis.

regions in the network of movements of non-local founders between areas (see Figure 6). This suggests that high-quality entrepreneurial ecosystems attract more non-local founders.

Figure 5. The inter-regional mobility network of non-local founders

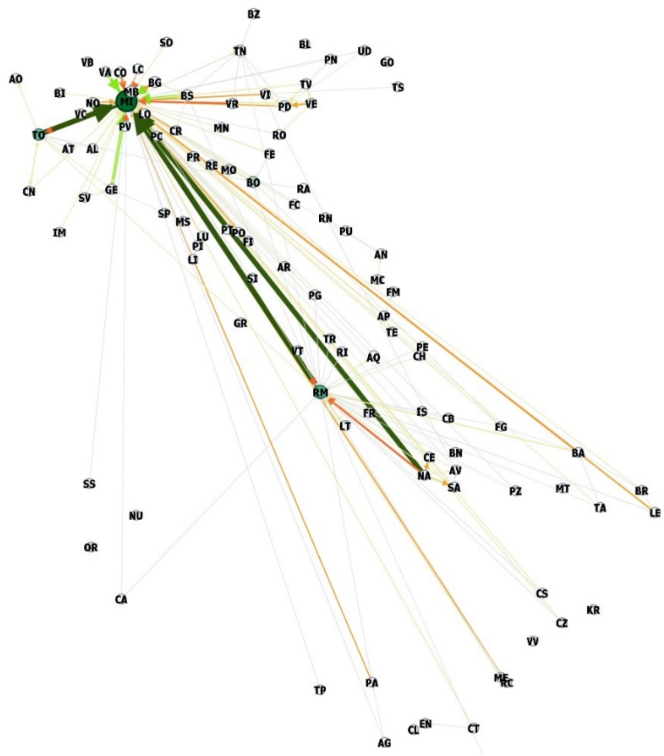
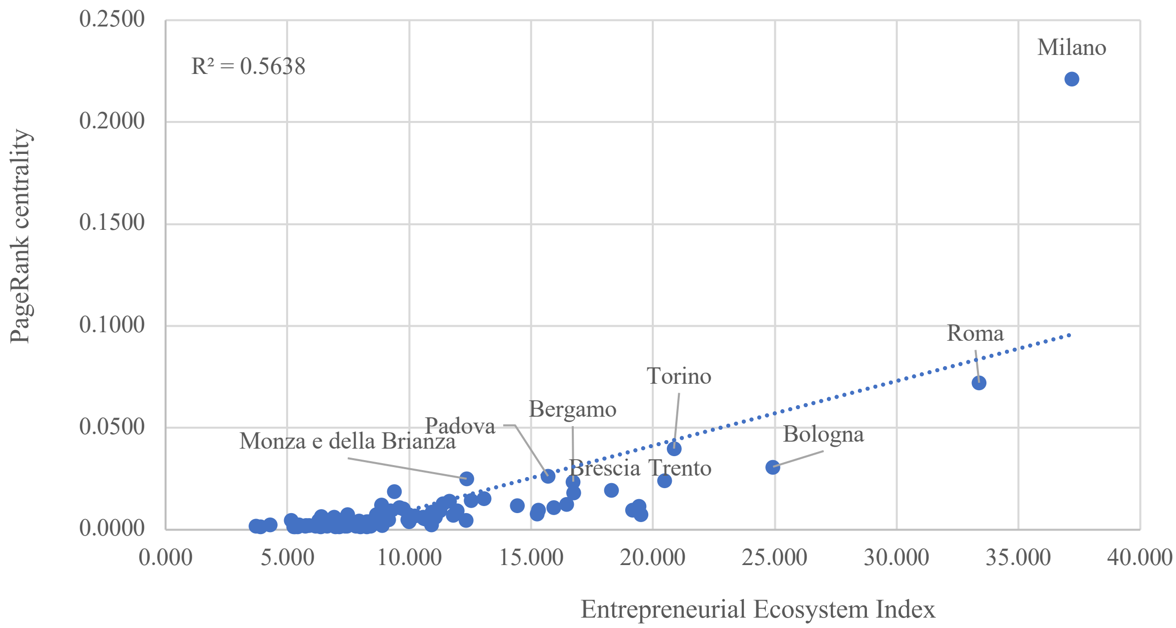


Figure 6. Correlation PageRank centrality and entrepreneurial ecosystem index



To further explore this potential relationship, we divide NUTS3 regions into four quartiles according to the entrepreneurial ecosystem index scores in Table 2.

Table 2. Flows of founders between regions divided into four quantiles by entrepreneurial ecosystem index (EEI) values.

Origin (birth)/destination	**High EEI**	**Medium-high EEI**	**Medium-low EEI**	**Low EEI**	**Total**
High EEI	1865	362	141	137	2505
Medium-high EEI	860	134	64	35	1093
Medium-low EEI	486	99	68	43	696
Low EEI	519	84	44	63	710
Total	3730	679	317	278	5004

Most non-local founders (1,865) move from high quality entrepreneurial ecosystems to other high-quality entrepreneurial ecosystems. This is mainly due to the large number of moves from Rome to Milan. Second, there is little movement between low, medium-low, and medium-high quality entrepreneurial ecosystems. Third, the high-quality entrepreneurial ecosystems have a positive net balance. Finally, there is still a significant group of founders who have moved from high-quality entrepreneurial ecosystems to nearby medium-high (e.g. Milan to Brescia) and medium-low quality entrepreneurial ecosystems (e.g. Milan to Lecco).

3.3 Econometric Strategy

To measure the inter-regional geographic mobility of (prospective) entrepreneurs, we relied on an econometric strategy widely used in migration studies to estimate bilateral flows. At this stage, we included data on the region of origin (the birthplace of the founder) and the region of destination (the location of the startup). Since we trace the movements of non-local founders between Italian NUTS3 regions, we decided to rely on a specific stream of literature that analyses domestic migration flows (Biagi et al., 2011; Poot et al., 2016; Piras, 2017; Beine et al., 2020) with a focus on entrepreneurial mobility (for a similar approach, see Engel & Heneric, 2013). As in the case of trade and finance, the methodological starting point of this literature is a gravity model. This model, originating in physics, to explain the attraction between two objects (proportional to their mass and inversely proportional to their distance) has been applied to explain the different effects of "forces" in the origin and destination regions in determining migration flows. The empirical specification of a gravity equation applied to the decision to choose a region other than the birthplace to start a business can be estimated with the following terms:

$$ln\left(SF_{ij}\right) = \beta_0 + \beta_1 \, ln \, ln\left(Fd_i\right) + \beta_2 \, ln \, ln\left(Fo_j\right) - \beta_3 \, ln\left(R_{ij}\right) + \eta_{ij} \qquad (2)$$

Where SF_{ij} are the founders flows from the region of birth i to the place of destination j, function of: Fd_i, the “destination factors” (in our case the Entrepreneurial Ecosystem Index of destination with the addition of the population density and GDP per capita at destination as control), Fo_j “origin factors” (in our case the Entrepreneurial Ecosystem Index of origin, controlling for the population density and GDP per capita) and R_{ij} represent the vector of distances (in our case driving hours between regions and regional contiguity). C represents the constant term, $\beta_1, \beta_2, \beta_3$ the elasticities terms linking destination and origin regions and η_{ij} represents the error term.

The log transformation of the gravity equation has two major weaknesses (Silva & Tenreyro, 2006):

1) it does not allow for zeros (i.e., the absence of movements between two regions i and j);
2) in the presence of heteroskedasticity, the errors are correlated with the covariates, leading to inconsistent estimates.

A standard approach to dealing with missing movements had been to remove zeros, estimating the log-linear form with OLS. However, if we consider the case of two regions (*i,j*) that both have low "gravitational" force (low entrepreneurial ecosystem index value), the result is a value of zero, i.e., no decision by a (potential) founder to move from region *i* to *j* and create a non-local startup. This information can be considered coherent with the structural characteristics of the regions and is therefore essential to keep zeros to avoid sample selection bias (Persyn & Torfs, 2016).[7]

To preserve the integrity of the sample and avoid problems with heteroskedasticity, we follow the approach of Silva and Tenreyro (2006) and estimate the gravity equations in a multiplicative form using a PPML model[8]. PPML is a count model particularly suited to zero-inflated models and is consistent with fixed effects, a desirable property for testing the impact of the entrepreneurial index (Fally, 2015). Given this, the specification (and for the properties of log and exp) equation 2 becomes

[7] In our case, considering the possible set of dyadic observations (105x104=10,920) the presence of zeros is dominant and excluding them would reduce the sample to 1,113 observations.
[8] The term "Pseudo" is attributed to the fact that PPML works regardless the data distribution (Silva & Tenreyro, 2006).

$$SF_{ij} = exp[\beta_0 + \beta_1 \, ln \, ln \, (Fd_i) + \beta_2 \, ln \, ln \, (Fo_j) - \beta_3 \, ln \, (R_{ij})]\eta_{ij} \quad (3)$$

Following Silva and Tenreyro (2011), we rescale our dependent variables to avoid PPML convergence problems. We consider different model versions with different definitions of non-local startup founders moving from i to j (SF_{ij}). To avoid spurious effects from the contribution of local founders to startups, we only consider non-local startups in our baseline model. Therefore, we only count the movements of non-local founders who launched non-local startups. We test our model for a broader set of non-local founders as a robustness check. In an alternative setting, we consider all non-local founders. This is equivalent to considering the contribution to most Italian startups that have at least one non-local founder. As an intermediate case, we also consider movements to found a startup where the majority of founders are non-local. To further investigate the importance of the Entrepreneurial Ecosystem Index in our gravity model, we use the LASSO PPML post-estimation techniques (Breinlich et al., 2021).

Apart from the impact of the Entrepreneurial Ecosystem Index, we also controlled for factors that have been previously identified as enabling conditions for startups. First, population density (population by km^2) serves as a proxy for urbanization economies and market size (Piras, 2017; Sato et al., 2012). Second, we control for geographic distances between regions NUTS3 by computing distances between centroids of regions NUTS3 as a matrix of driving hours using the free API of https://openrouteservice.org/ and geocoding with R (for a similar approach, see Cavallo et al., 2020). Third, we include a dummy variable of contiguity between NUTS3 regions to test whether a common boundary can reduce movements between regions, as described in the previous section. Fourth, we include GDP per capita, a standard measure for testing the attraction between two areas in gravity models (Tinbergen, 1962). Whenever we include GDP per capita as a control in a regression, we omit the GDP component from the entrepreneurial ecosystem index (Demand element). Fifth, we include the number of STEM students per 1000 inhabitants to control for the presence of educational clusters in science and engineering subjects, which tend to be a very important "catchment effect" for founders of innovative startups (see Anelli et al., 2019).

Sixth, we add a NUTS2 dummy variable to test for possible institutional and spatial patterns (Bonaccorsi et al., 2014). Table 3 presents the descriptive statistics for the variables we include in our model. The correlation table is available in the Appendix.

Table 3. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Non-local founders	10,920	.251	1.482	0	62
Pop. density (ln)	10,920	1	1.405	.141	9.556
Driving time (ln)	10,920	1.681	.766	-.916	3.109
NUTS3 Contiguity	10,920	.043	.203	0	1
GDP p.c. (ln)	10,920	-.038	.278	-.567	.72
STEM/pop.	10,920	.04	.041	0	.234
EEI (ln)	10,920	2.084	.445	1.143	3.56
EEI (ln, w/o demand)	10,920	2.201	.422	1.313	3.616

3.4 Qualitative analysis

To better interpret our macro-level findings on the interregional flows of founders of non-local startups and to validate the structure of our data, we analyze a subsample of non-local founders using LinkedIn data on their biographies. We manually searched LinkedIn profiles of non-local founders up to theoretical saturation (Patton, 1990) to infer potential mobility patterns. The manual search is less error-prone and feasible given the general limitation of scraping and crawling LinkedIn data using APIs.

We obtained information for 100 entrepreneurs (having scraped over 300 startups in alphabetical order), the lower bound for a statistically significant sample. We then replicated the matrix representing the flows of founders between entrepreneurial ecosystems (considering their level of quality divided into four quantiles by entrepreneurial ecosystem index values - low, medium-low, medium-high and high -see Table 2) also with the collected LinkedIn data to check if the two structures were similar. In general, we found very similar percentage data by category. To have more robust evidence, we conduct a t-test on the difference between the average of the LinkedIn sub-sample and our ORBIS sample, considering the value of the entrepreneurial ecosystem index across the 4 quantiles. We performed 12 t-tests testing 6 flow relationships (37,5% on the total), considering the entrepreneurial ecosystem of origin and destination for the cases where we have more than 2 observations in the LinkedIn sample. From our analysis, only 2 cases[9] out of 12 showed show statistical differences in the means.

4. Results

We first analyze regional level data with gravity models, to test for entrepreneurial ecosystem attraction and supply mechanisms. This is followed by an in-depth micro-level analysis of the career paths of 100 non-local founders from the main sample.

4.1 Econometric estimation

Our gravity model tests the supply and attraction mechanisms, focusing on the role of the quality of the entrepreneurial ecosystem at origin and destination to explain the mobility pattern of non-local founders of startups in Italy. Table 4 summarizes our results. Models 2 and 3 strongly support the claim that the quality of the entrepreneurial ecosystem is crucial to attract non-local startups. We also find a positive and significant role of the quality of the founders' entrepreneurial ecosystem of origin (supply mechanism). This effect is less pronounced than for the quality of the destination entrepreneurial ecosystem in which the startup is founded, confirming the escalator mechanism described earlier.

[9] Namely: a) founders born in medium-low quality ecosystems and founders active in high-quality ecosystems - only for entrepreneurial ecosystems of origin; b) founders born in high-quality ecosystems and founders active in low-quality ecosystems - only for entrepreneurial ecosystems of origin.

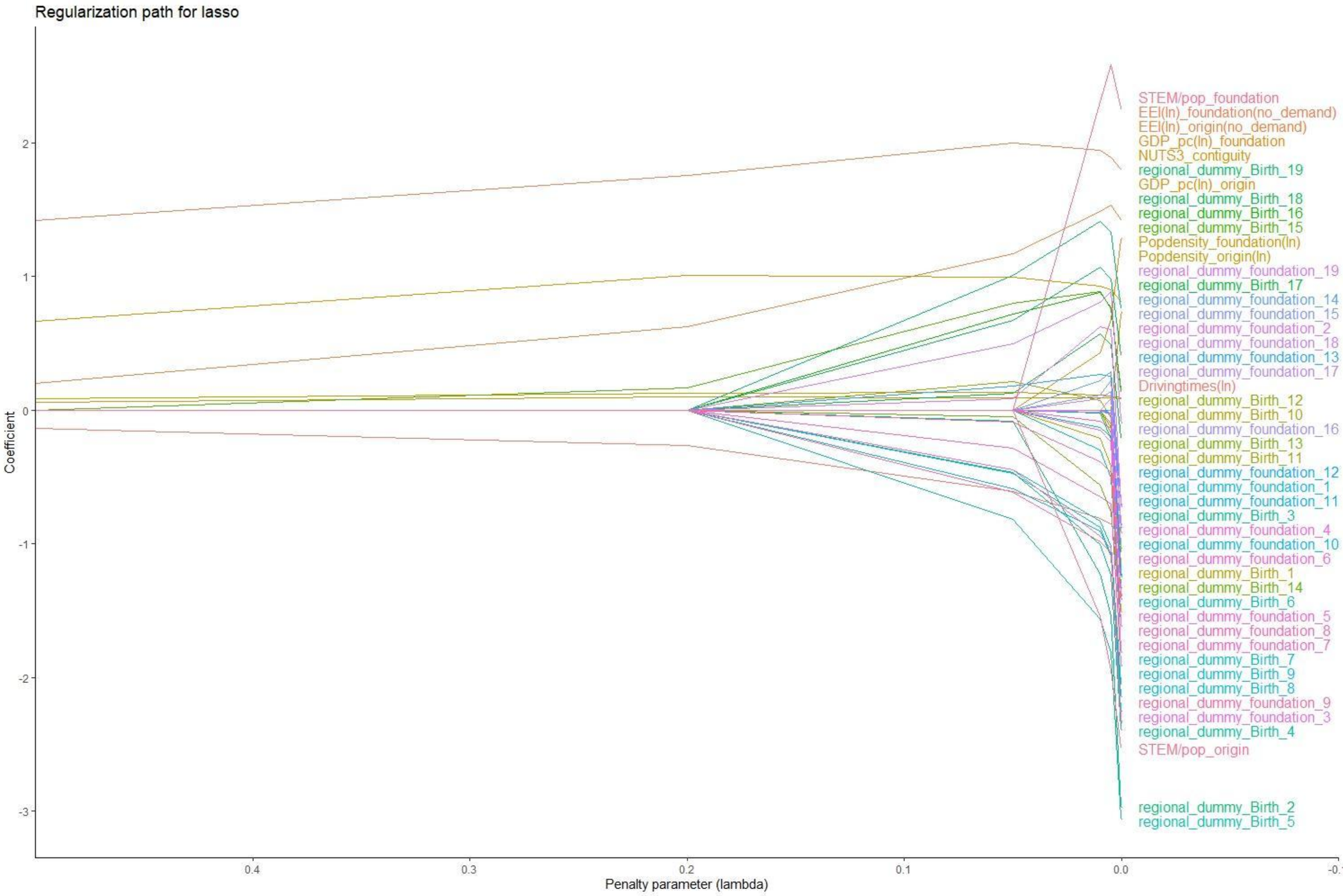
Table 4. Gravity model of interregional flows of non-local startups (all founders are non-local) between Italian regions

	Non-local startups		
	(1)	(2)	(3)
	b/se	b/se	b/se
EEI (ln), foundation		**2.4448*****	**1.8029*****
		(0.0922)	(0.1351)
EEI (ln), origin		**1.6418*****	**1.4249*****
		(0.1214)	(0.1787)
Pop. density (ln), foundation	0.4319***	0.1056***	0.0927***
	(0.0296)	(0.0195)	(0.0199)
Pop. density (ln), origin	0.2527***	0.0912*	0.0834*
	(0.0348)	(0.0359)	(0.0376)
Driving time (ln)	-0.8959***	-0.9583***	-0.9616***
	(0.0980)	(0.0777)	(0.0770)
Contiguity, NUTS3	0.7240***	0.8052***	0.8081***
	(0.1807)	(0.1327)	(0.1344)
GDP p.c. (ln), foundation			1.2849***
			(0.3575)
GDP p.c. (ln), origin			0.7344
			(0.5050)
STEM/pop., foundation			2.2450*
			(0.9988)
STEM/pop., origin			-2.5260**
			(0.9010)
Constant	-0.4485	-8.2167***	-5.6698***
	(0.3878)	(0.4489)	(0.5969)
NUTS2 dummy	YES	YES	YES
N	10,920	10,920	10,920
R^2	0.202	0.559	0.561
Pseudo Log-likelihood	-5372.9567	-3970.2291	-3951.1587
VIF max	1.23	1.39	3.18

The robustness of the effect of the quality of the entrepreneurial ecosystem of origin and destination is confirmed in model 3 with the control variables GDP and the presence of STEM graduates, which could to some extent mitigate the effect of the quality of the entrepreneurial ecosystem. As expected, density plays a positive and significant role as a proxy for urbanization economy in the origin and destination regions, with a lower significance level for region of origin in the full version of model (3). The negative values of travel times underscore the influence of spatial distance, as also evidenced by the positive influence of NUTS3 regional contiguity in all 3 models. GDP per capita is significant in the target region and serves as a proxy for regional prosperity, but is not significant as a push mechanism, which could help interpret startup flows as less dependent on general economic conditions. The effect of STEM graduates is interesting as it negatively affects the entrepreneurial ecosystem of the region of origin: the scarcity of graduates in STEM subjects can be interpreted as a factor limiting moves from source regions, while a high prevalence of STEM students in the start-up region has a clear attraction effect. We test for the presence of multicollinearity problems by running a VIF test and finding values between 1.23 and 3.18, well below the threshold recommended in the literature (10 and 5 in the most parsimonious settings).

To analyze the role of the entrepreneurial ecosystem index in our gravity model, we use the LASSO PPML postestimation techniques following the approach developed by Breinlich et al. (2021). LASSO is used in model selection to identify λ-values at which variables are excluded from the model. For each λ-value, the set of non-zero coefficients is determined: the higher λ is, the smaller the set of variables with non-zero coefficients. For a long list of variables (as in our case for the presence of NUTS2 dummies), typically some variables are removed at a certain threshold λ value.

Figure 7. PPML LASSO of model 3



The results (see figure 7 and Table A4 in the appendix) confirm that entrepreneurial ecosystem index of destination and origin are both within the threshold of non-zero coefficients (considering λ cross-validation rule[10]), respectively occupying 1 and 3 positions in the coefficient rank. This suggests that the quality of entrepreneurial ecosystems is an essential part of the gravity model of non-local founder movements.

[10] For model 3: λ Cross-validation rule that minimizes RMSE = 0.3 with seed set at the value of 5,000 (see table A5 in the appendix). We test the robustness of the findings also with a stricter variant than the Cross Validation method, the plug-in method (Belloni et al., 2012), which automatically computes the optimal penalty threshold (for details see the penppml R package developed by Breinlich and colleagues, available at this link:here). Also in this case the entrepreneurial ecosystem index of destination and origin are both included within the lists of non-zero coefficients.

To support our results, we provide the results of the gravity model with alternative definitions for nonlocal founders in Table 5. Models 4 and 5 account for all movements of non-local founders, including founders who co-found a startup with local founders. Models 6 and 7, on the other hand, restrict the analysis to the case where the majority of founders are non-locals. All results of the baseline model regarding the quality of the entrepreneurial ecosystem are confirmed. Among the control variables, it is noticeable that population density and STEM in the region of origin are no longer significant when we include all non-local founders in model 5. In this model, only controls at the destination remain significant, while the role of the quality of the entrepreneurial ecosystem in the region of origin remains positive and largely significant.

Table 5. Robustness check: alternative definitions of non-local innovative startups

	at least 1 founder non-local		majority of founders non-local	
	(4) b/se	(5) b/se	(6) b/se	(7) b/se
EEI (ln), foundation	**2.6188*****	**1.9497*****	**2.5655*****	**1.8901*****
	(0.0876)	(0.1125)	(0.0887)	(0.1166)
EEI (ln), origin	**1.6988*****	**1.3919*****	**1.6795*****	**1.3985*****
	(0.1207)	(0.1693)	(0.1197)	(0.1663)
Pop. density (ln), foundation	0.0829***	0.0679***	0.0900***	0.0759***
	(0.0180)	(0.0182)	(0.0184)	(0.0187)
Pop. density (ln), origin	0.0694	0.0610	0.0708	0.0630
	(0.0379)	(0.0400)	(0.0377)	(0.0397)
Driving time (ln)	-0.9722***	-0.9786***	-0.9809***	-0.9871***
	(0.0716)	(0.0706)	(0.0733)	(0.0723)
Contiguity, NUTS3	0.8278***	0.8272***	0.8063***	0.8048***
	(0.1238)	(0.1254)	(0.1255)	(0.1266)
GDP p.c. (ln), foundation		1.3342***		1.3215***
		(0.3278)		(0.3300)
GDP p.c. (ln), origin		0.9044		0.8368
		(0.4919)		(0.4900)
STEM/pop., foundation		2.5093**		2.7487***
		(0.7836)		(0.8266)
STEM/pop., origin		-1.5776		-1.7058*
		(0.8076)		(0.8033)
Constant	-8.2685***	-5.4973***	-8.1884***	-5.4916***
	(0.4303)	(0.5341)	(0.4347)	(0.5450)
NUTS2 dummy	YES	YES	YES	YES
N	10,920	10,920	10,920	10,920
r2	0.593	0.598	0.597	0.603
Pseudo Log-likelihood	-5660.4268	-5627.6903	-5397.2146	-5365.515
VIF max	1.39	3.18	1.39	3.18

To further improve the reliability of our results, we test two additional versions of the models. First, we exclude regional mobility within NUTS2 (between NUTS3 regions within the same NUTS2) to reduce the likelihood of impact of daily commuting shadow cases. Second, we exclude the Milan region as the main attraction point for non-local start-ups. In both cases, the results of the model are still valid and show positive and significant effects of the entrepreneurial ecosystem of the region of origin and destination.

To separate general attractiveness from "entrepreneurial ecosystem attractiveness" as an additional robustness check, we consider the interregional migration flows of the general population as another control variable for the interregional migration flows of non-local founders (see Table A6 in the Appendix). As expected, interregional migration flows have a strong and positive effect on the mobility patterns of non-local founders in all the models we consider. However, the positive effects of the quality of the entrepreneurial ecosystem at origin and destination remain.

4.2 Qualitative insights in the career paths of non-local founders

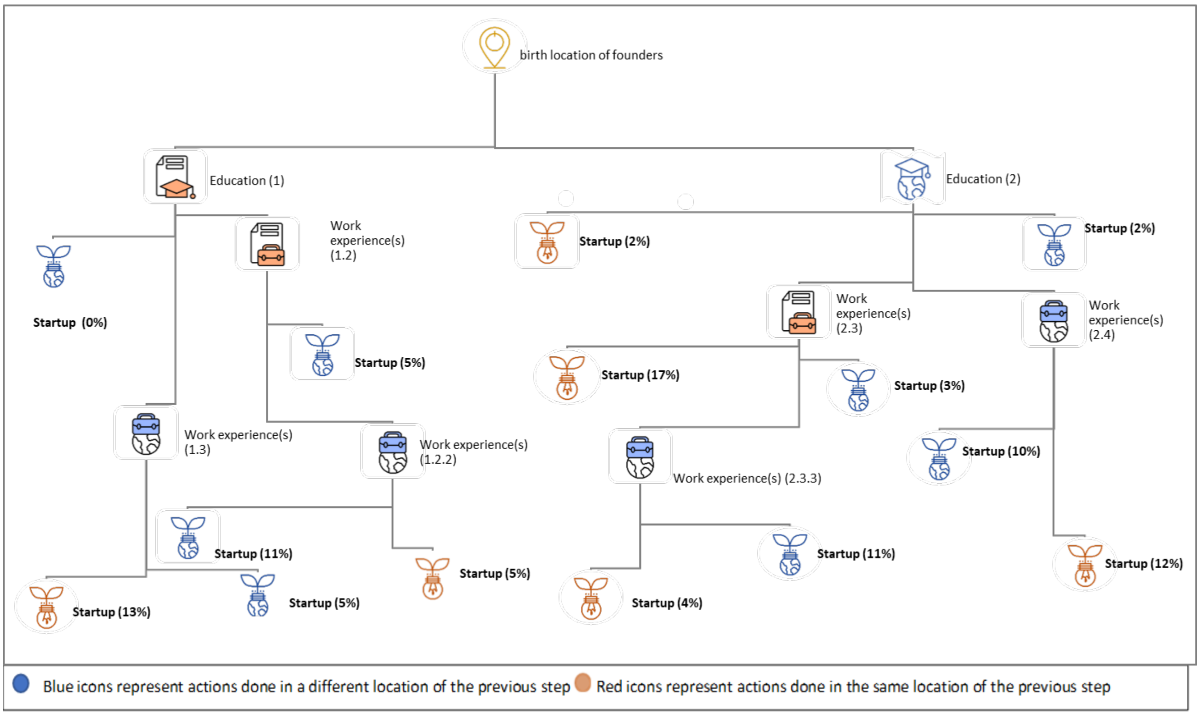
The creation of a startup can take place in different sequences and steps (cf. Stam, 2007). Figure 8 summarizes the potential career paths of the non-local founder preceding the creation of the startup, identified with a decision tree. We identify 14 pathways preceding the creation of a startup, taking into account education and work experience. The majority of the non-local founders (61%) followed the path in the right of the tree (education in a different place) (cf. Baltzopoulos & Broström, 2013), while 39% of the non-local founders followed the path in the left part of the tree (education in the same place of birth). These paths show that the non-local founders start their business most often after leaving the home region for educational or work career reasons. Only 5% of the non-local founders appear to have left their region of origin to start a business in another region. This confirms the stylized fact in the geography of entrepreneurship that most entrepreneurs start a business in the region where they live (have been educated) and/or work (Stam, 2007), albeit not necessarily the region in which they were born. Several paths precede the creation of non-local startups, and the entrepreneurial trajectory may vary depending on age and career path. Young founders are more likely to start a non-local business after moving for educational reasons, while middle-aged founders are likely to have gone through several career stages, possibly in different regions, before starting a business.

Two examples of well-known American entrepreneurs can be cited to illustrate this point: Marc Andreessen (co-founder of Netscape) and Michael Mauldin (co-founder of Lycos). Marc Andreessen was born in Iowa and grew up in Wisconsin before moving to Illinois for his education (Education 2). After his education, he moved to California to work (Work Experience 2.4) and stayed in California to found Mosaic (later renamed Netscape) (startup in same location as Work Experience, with non-local founder: 12% of Italian startups in our sample). Michael Mauldin was born and raised in Texas, where he also earned his bachelor's and master's degrees, but moved to Pennsylvania for his doctorate (Education 2), where he later founded Lycos (startup in the same location as Education, with non-local founder: 2% of Italian startups in our sample). The fact that Lycos moved to Massachusetts within 2 years of its founding does not matter, as we only consider the founding location. Such interregional moves by young firms are extremely rare (see Stam, 2007).

We also give two examples from our LinkedIn sample to illustrate the possible sequences. The first was born and raised in Sassari (Sardinia) and moved to Pisa (Tuscany) to pursue a university degree in physics (Education 2). Then he moved professionally to Milan (R&D department) (Work experience 2.4), then to Berlin and San Francisco (in a similar function), and after 15 years he founded his company in the Monza-Brianza region (specialized in

Graphene Photonics) (startup in other region as Work experience, with non-local founder: 10% of Italian startups in our sample). The second was born in Taranto and graduated in Modena with a university degree in Pharmacy (Education 2). Then she moved to Venice for new work experience (Work experience 2.4). After 3 years of experience as a researcher, she founded her company in the Treviso area (specialized in food health and nutritional analysis) (startup in other region as Work experience, with non-local founder: 10% of Italian startups in our sample).

Figure 8. Sequence analysis by education and work career stages



Source: Authors' elaboration using resources from Flaticon.com. Base Icons taken from: Ultimatearm, Freepik and Eucalyp.

5. Discussion

This study has provided several new insights for understanding entrepreneurial ecosystems. First, we have discussed the too narrow view of (explicitly or implicitly) theorizing entrepreneurial ecosystems as closed systems. Our study contributes to the existing literature on entrepreneurial ecosystems by analyzing entrepreneurial ecosystems as complex open systems and paves the way for future research on this topic that responds to the limitations of analyzing entrepreneurial ecosystems as closed systems (Brown & Mason, 2017; Schäfer & Henn, 2018; Fredin & Lidén, 2020; Lange & Schmidt, 2021).

Second, non-local founders are not a marginal phenomenon, but make-up the majority of the founders of innovative startups in our Italian sample, and likely in other contexts as well, and should be taken seriously in the explanation of the prevalence of productive entrepreneurship in different places. In order to do so, we have theoretically articulated and empirically tested two (attraction and supply) mechanisms explaining the flows of entrepreneurial talent between entrepreneurial ecosystems, and in that way theorized entrepreneurial ecosystems as open systems, as nodes in macro-networks of regions.

Our empirical tests show the relevance of these two mechanisms to explain the prevalence of productive entrepreneurship in Italian regions, with not only taking into account the quality of the region in which the startup was created, but also the quality of the entrepreneurial ecosystem in which the (non-local) founder was born. Once entrepreneurial ecosystems are conceptualized as nodes in macro-networks, and measured accordingly, an escalator mechanism is discovered, through which (prospective) entrepreneurs move from good to better entrepreneurial ecosystems. We demonstrate the benefits of a network view of entrepreneurial ecosystem interconnectedness, which improves our explanations of how the quality of entrepreneurial ecosystems affects productive entrepreneurship, not only by local founders, but also by non-local founders, and not only the attraction of non-local founders, but also the supply of non-local founders. This provides a whole new avenue of research into how inter-ecosystem links affect flows of resources, including entrepreneurial talent, and how this sets in motion cumulative causation over time (cf. Myrdal 1957), which needs to be analysed in future research.

6. Conclusions

This paper aimed to provide new insights into the role of entrepreneurial ecosystems as enablers, attractors, and suppliers of entrepreneurial talent. For this we answered the question: To what extent and how does the quality of origin and destination entrepreneurial ecosystems explain the prevalence of non-local startups? We developed an entrepreneurial ecosystem index to measure the quality of local entrepreneurial ecosystems in Italy and showed that it is positively correlated with the subsequent prevalence of startups and network centrality. We used the result of this test as a starting point for the analysis of attraction and supply mechanisms in relation to the quality of destination and origin entrepreneurial ecosystem in relation to the prevalence of non-local startups. It turned out that the majority of startups had at least one non-local founder, suggesting that (even in Italy) there is not a strong local orientation of founders with respect to the region of origin.

The results of the econometric and machine learning analyses point out positive effects of the quality of both destination and origin entrepreneurial ecosystems of non-local founders against a number of control variables (density, geographic distances, GDP, and STEM graduates). There appear to be both attraction and supply mechanisms at work affecting the entrepreneurial ecosystem in the destination and origin regions. Non-local founders come from relatively high-quality entrepreneurial ecosystems and start new firms in even higher quality entrepreneurial ecosystems. Regions with lower-quality entrepreneurial ecosystems are not only less likely to create local startups, but also less likely to “supply” aspiring entrepreneurs to higher-quality entrepreneurial ecosystems.

Policy implications

This paper provides policy insights for entrepreneurship-led economic development. The recent economics of entrepreneurship literature has shown that policy for an entrepreneurial economy is more likely to be effective than entrepreneurship policy, as policy can better improve entrepreneurial ecosystems to enable productive entrepreneurship than target particular (potential) entrepreneurs (Audretsch & Thurik, 2001; Thurik et al., 2013; Stam, 2015). To date, most studies and policies have assumed that entrepreneurship is essentially a local phenomenon. Our study does not question the value of local contexts for entrepreneurship, but provides new, more nuanced insights about the role and connectedness of local contexts. We show that improving the entrepreneurial ecosystem is a double-edged sword: on the one hand, it stimulates the creation of startups; on the other hand, it also seems to increase the outflow of (potential) founders. Improving the quality of entrepreneurial ecosystems is likely to stimulate the creation of startups in all regions, but may also increase the inflow of non-local founders to the highest quality entrepreneurial ecosystems, which could lead to a large increase in entrepreneurial activity in a few regions with the highest quality entrepreneurial ecosystems. Positive sorting into migration, with migrant entrepreneurs realizing more successful businesses, could even strengthen this cumulative causation (see Conti & Guzman, 2023). This could partly explain the non-linear relationship between the quality of entrepreneurial ecosystems and entrepreneurial outputs (Leendertse et al., 2022; Van Dijk et al., 2024). Cumulative causation could be beneficial for the economy as a whole, and in particular for the regional entrepreneurial ecosystems with the highest quality (in Italy mainly Milan), but at the expense of regions with a high, but not the highest, quality of entrepreneurial ecosystem (in Italy mainly Turin, Rome and Naples). Thus, the results of our analyses suggest that increasing the quality of the entrepreneurial ecosystem leads to higher levels of local entrepreneurship, but also to non-local startups entering higher quality entrepreneurial ecosystems. This can lead to a "winner take all" situation (cf. Chattergoon & Kerr, 2022) that improves national welfare more than welfare in the region of origin.

Research agenda

We need more longitudinal and granular data on individual careers and regional economies to better understand the dynamic and net effects of the creation, supply, and attraction mechanisms. This will provide insight into the mechanisms causing increases in the quality of entrepreneurial ecosystems over time, including feedback effects (see Wurth et al., 2023). This could also provide insight into the net effects of founders leaving their region of origin (Anelli et al., 2019) and the increased access of remaining entrepreneurs to knowledge accumulated in these destination regions (Agrawal et al., 2011) or even the return of diaspora entrepreneurs (Saxenian, 2007; Andonova et al. 2020). Follow-up studies could analyze international migration and provide insights into escalator mechanisms and "winner take all" effects at the international level. At the micro level, there is a need for more insights into the decision-making mechanisms of (potential) founders over time and the performance of their businesses (see Guzman, 2024). This could be done using data that allows us to track the personal history of founders from birth to startup creation, with the help of multi-stage location choice models. Nevertheless, the process of startup location choice is more complex to model than traditional individual decisions because it is composed of the personal and professional motivations of the founders of startups. To fully understand the micro-level mechanisms and the resulting macro effects, longitudinal data on individuals, especially on their education, work, and location decisions, as well as on their firms, are needed in combination with data on their environment.

References

Acemoglu, D., Akcigit, U., & Celik, M. A. (2014). *Young, restless and creative: Openness to disruption and creative innovations* (No. w19894). National Bureau of Economic Research.

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

Agrawal, A., Kapur, D., McHale, J., & Oettl, A. (2011). Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. *Journal of Urban Economics*, 69(1), 43-55.

Andonova, V., Perez-Lopez, J. A., & Schmutzler, J. (2020). The role of diaspora in entrepreneurial ecosystems and national innovation systems. In: *Entrepreneurial Ecosystems Meet Innovation Systems* (pp. 61-83). Edward Elgar Publishing.

Anelli, M., Basso, G., Ippedico, G., & Peri, G. (2019). Youth drain, entrepreneurship and innovation. *National Bureau of Economic Research*.

Audretsch, D. B., & Belitski, M. (2017). Entrepreneurial ecosystems in cities: establishing the framework conditions. *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.

Azoulay, P., Jones, B. F., Kim, J. D., & Miranda, J. (2022) Immigration and Entrepreneurship in the United States. *American Economic Review: Insights*, 4(1): 71-88.

Baltzopoulos, A., & Broström, A. (2013). Attractors of entrepreneurial activity: Universities, regions and alumni entrepreneurs. *Regional Studies*, 47(6), 934-949.

Basile, R., Girardi, A., Mantuano, M., & Russo, G. (2019). Interregional migration of human capital and unemployment dynamics: evidence from Italian provinces. *German Economic Review*, *20*(4), e385-e414.

Bauernschuster, S., Falck, O., & Heblich, S. (2010). Social capital access and entrepreneurship. *Journal of Economic Behavior & Organization*, 76(3), 821-833.

Baumol, W. J. (1990) Entrepreneurship: Productive, unproductive, and destructive, *Journal of Political Economy*, 98(5), pp. 893–921.

Beine, M., Delogu, M., & Ragot, L. (2020). The role of fees in foreign education: evidence from Italy. *Journal of Economic Geography*, *20*(2), 571-600.

Belloni, A., Chen, D., Chernozhukov, V., & Hansen, C. (2012). Sparse models and methods for optimal instruments with an application to eminent domain. *Econometrica*, 80(6), 2369-2429.

Bettencourt, L. M., Lobo, J., & Strumsky, D. (2007). Invention in the city: Increasing returns to patenting as a scaling function of metropolitan size. *Research Policy* 36(1), 107-120.

Biagi, B., Faggian, A., & McCann, P. (2011). Long and short distance migration in Italy: the role of economic, social and environmental characteristics. *Spatial Economic Analysis*, *6*(1), 111-131.

Biancalani, F., Czarnitzki, D. & Riccaboni, M. (2022) The Italian Start Up Act: a microeconometric program evaluation. *Small Business Economics* 58, 1699–1720. https://doi.org/10.1007/s11187-021-00468-7

Bonaccorsi, A., Colombo, M. G., Guerini, M., & Rossi-Lamastra, C. (2014). The impact of local and external university knowledge on the creation of knowledge-intensive firms: Evidence from the Italian case. *Small Business Economics*, *43*(2), 261-287.

Bonaventura, M., Ciotti, V., Panzarasa, P., Liverani, S., Lacasa, L., & Latora, V. (2020). Predicting success in the worldwide start-up network. *Scientific reports*, *10*(1), 1-6.

Bonifazi, C., Heins, F., & Tucci, E. (2017). Italy: internal migration in a low-mobility country. In *Internal Migration in the Developed World* (pp. 242-262). Routledge.

Bönte, W., Falck, O., & Heblich, S. (2009). The impact of regional age structure on entrepreneurship. *Economic Geography*, 85(3), 269-287.

Bosetti, V., Cattaneo, C., & Verdolini, E. (2015). Migration of skilled workers and innovation: A European perspective. *Journal of International Economics*, *96*(2), 311-322.

Bratti, M. & Conti, C., (2018). Immigration, Population Diversity and Innovation of Italian regions, *Regional Studies*, vol. 52(7), pages 934-947.

Breinlich, H., Corradi, V., Rocha, N., Ruta, M., Santos Silva, J.M.C., & Zylkin, T., (2021) "Machine Learning in International Trade Research – Evaluating the Impact of Trade Agreements", World Bank Group –Development Research Group & Macroeconomics, Trade and Investment Global Practice Policy Research Working Paper 9629.

Buenstorf, G., & Klepper, S. (2010). Why does entry cluster geographically? Evidence from the US tire industry. *Journal of Urban Economics*, 68(2), 103-114.

Brown, R., & Mason, C. (2017). Looking inside the spiky bits: a critical review and conceptualisation of entrepreneurial ecosystems. *Small Business Economics*, *49*(1), 11-30.

Bryan, K. & Guzman, J., (2023). Entrepreneurial Migration. *Review of Economics and Statistics*. forthcoming (available at SSRN: https://ssrn.com/abstract=3914010.)

Butler, J. S., Garg, R., & Stephens, B. (2020). Social networks, funding, and regional advantages in technology entrepreneurship: An empirical analysis. *Information Systems Research*, *31*(1), 198-216.

Chattergoon, B., & Kerr, W. R. (2022). Winner takes all? Tech clusters, population centers, and the spatial transformation of US invention. *Research Policy*, 51(2), 104418.

Chatterji, A., Glaeser, E., & Kerr, W. (2014). Clusters of entrepreneurship and innovation. *Innovation policy and the economy*, 14(1), 129-166.

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.

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.

Coffey, W. J., & Polese, M. (1984). The concept of local development: a stages model of endogenous regional growth. *Papers in Regional Science*, 55(1), 1-12.

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.

Colombo, M. G., Dagnino, G. B., Lehmann, E. E., & Salmador, M. (2019). The governance of entrepreneurial ecosystems. *Small Business Economics*, *52*(2), 419-428.

Conti, A., & Guzman, J. A. (2023). What is the US comparative advantage in entrepreneurship? Evidence from Israeli migration to the United States. *Review of Economics and Statistics*, 105 (3): 528-544.

Daniel, L. J., De Villiers Scheepers, M. J., Miles, M. P., & de Klerk, S. (2022). Understanding entrepreneurial ecosystems using complex adaptive systems theory: Getting the big picture for economic development, practice, and policy. *Entrepreneurship & Regional Development*, 34(9-10), 911-934.

Derudder, B., & Taylor, P. (2005). The cliquishness of world cities. *Global Networks*, 5(1), 71-91.

Engel, D., & Heneric, O. (2013). Localization of knowledge and entrepreneurs' mobility: the case of Germany's biotechnology industry. *Jahrbuch für Regionalwissenschaft*, *33*(2), 173-192.

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.

Falck, O., Gold, R., & Heblich, S. (2017). Lifting the iron curtain: school-age education and entrepreneurial intentions. *Journal of Economic Geography*, 17(5), 1111-1148.

Fally, T. (2015). Structural gravity and fixed effects. *Journal of International Economics*, *97*(1), 76-85.

Frenken, K., Cefis, E., & Stam, E. (2015). Industrial dynamics and clusters: a survey. *Regional Studies*, 49(1), 10-27.

Fredin, S., & Lidén, A. (2020). Entrepreneurial ecosystems: towards a systemic approach to entrepreneurship?. *Geografisk Tidsskrift-Danish Journal of Geography*, *120*(2), 87-97.

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. (2017). The effect of entrepreneurship on economic development—an empirical analysis using regional entrepreneurship culture. *Journal of Economic Geography*, *17*(1), 157-189.

GEM (2021) *Global Entrepreneurship Monitor Report 2020*.

Glaeser, E. L., & Kerr, W. R. (2009). Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain? *Journal of Economics & Management Strategy*, 18(3), 623-663.

Glaeser, E. L., Kerr, W. R., & Ponzetto, G. A. (2010). Clusters of entrepreneurship. *Journal of Urban Economics*, 67(1), 150-168.

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.

Grilli, L., Mrkajic, B. & Giraudo, E. (2023). Industrial policy, innovative entrepreneurship, and the human capital of founders. *Small Business Economics,* 60(2), 707-728. https://doi.org/10.1007/s11187-022-00611-y

Grillitsch, M. & Sotarauta, M. (2020). Trinity of change agency, regional development paths and opportunity spaces. *Progress in Human Geography*, 44(4), 704-723..

Guzman, J. (2024). Go west young firm: The impact of startup migration on the performance of migrants. *Management Science*, 70(7), 4824-4846.

Guzman, J., & Stern, S. (2020). The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 US States, 1988–2014. *American Economic Journal: Economic Policy*, 12(4), 212-43.

Hilton, B., Sood, A. P., & Evans, T. S. (2020). Predictive limitations of spatial interaction models: a non-Gaussian analysis. *Scientific Reports*, *10*(1), 1-10.

Hirschman, A. O. (1970). Exit, voice, and loyalty: Responses to decline in firms, organizations, and states. *Harvard University Press*.

Holland, J. H. (2006). Studying complex adaptive systems. *Journal of systems science and complexity*, *19*(1), 1-8.

Iacobucci, D., & Perugini, F. (2021). Entrepreneurial ecosystems and economic resilience at local level. *Entrepreneurship & Regional Development*, 1-28.

Italian Ministry of Economic Development - MISE (2019), *The Italian Startup Act Italy's policy framework to support innovative startups – executive summary*, Directorate General for Industrial Policy, Competitiveness and SMEs.

Knight, F.H. (1921). *Risk, Uncertainty and Profit*. New York: Houghton Mifflin.

Lange, B., & Schmidt, S. (2021). Entrepreneurial ecosystems as a bridging concept? A conceptual contribution to the debate on entrepreneurship and regional development. *Growth and Change*, *52*(2), 790-807.

Larsson, J. P., Wennberg, K., Wiklund, J., & Wright, M. (2017). Location choices of graduate entrepreneurs. *Research Policy*, 46(8), 1490-1504.

Leendertse, J., Schrijvers, M., & Stam, E. (2022). Measure twice, cut once: Entrepreneurial ecosystem metrics. *Research Policy*, 51(9) https://doi.org/10.1016/j.respol.2021.104336

Leoncini, R., Vecchiato, G., & Zamparini, L. (2020). Triggering cooperation among firms: an empirical assessment of the Italian Network Contract Law. *Economia Politica*, *37*(2), 357-380.

Lewer, J. J., & Van den Berg, H. (2008). A gravity model of immigration. *Economics Letters*, 99(1), 164-167.

Lucas, R. E. (1978). On the Size Distribution of Business Firms. *Bell Journal of Economics,* 9(3): 508–523

Maggioni, M. A., Uberti, T. E., & Usai, S. (2011). Treating patents as relational data: knowledge transfers and spillovers across Italian provinces. *Industry and Innovation*, *18*(1), 39-67.

Mason, C. M., & Harrison, R. T. (2006). After the exit: Acquisitions, entrepreneurial recycling and regional economic development. *Regional Studies*, 40(1), 55-73.

Michelacci, C., & Silva, O. (2007). Why so many local entrepreneurs? *Review of Economics and Statistics*, 89(4), 615-633.

Morris, A. K., Fiedler, A., & Audretsch, D. B. (2023). Enablers of knowledge spillover entrepreneurship in entrepreneurial ecosystems: synthesis and future directions. *Journal of Technology Transfer*, 1-25.

Myrdal, G. (1957). *Economic theory and underdeveloped regions*. London: Gerald Duckworth.

Nifo, A., & Vecchione, G. (2014). Do institutions play a role in skilled migration? The case of Italy. *Regional Studies*, *48*(10), 1628-1649.

Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). *The PageRank citation ranking: Bringing order to the web.* Stanford InfoLab.

Persyn, D., & Torfs, W. (2016). A gravity equation for commuting with an application to estimating regional border effects in Belgium. *Journal of Economic Geography*, *16*(1), 155-175.

Perugini, F. (2023). Space–time analysis of entrepreneurial ecosystems. *Journal of Technology Transfer*, 48, 240–291.

Piras, R. (2017). A long-run analysis of push and pull factors of internal migration in Italy. Estimation of a gravity model with human capital using homogeneous and heterogeneous approaches. *Papers in Regional Science*, *96*(3), 571-602.

Poot, J., Alimi, O., Cameron, M. P., & Maré, D. C. (2016). The gravity model of migration: the successful comeback of an ageing superstar in regional science. *Investigaciones Regionales= Journal of Regional Research*, (36), 63-68.

Qian, H., Acs, Z. J., & Stough, R. R. (2013). Regional systems of entrepreneurship: the nexus of human capital, knowledge and new firm formation. *Journal of Economic Geography*, *13*(4), 559-587.

Qian, H., & Acs, Z. J. (2023). Entrepreneurial ecosystems and economic development policy. *Economic Development Quarterly*, 37(1), 96-102.

Reuschke, D., & Van Ham, M. (2013). Testing the 'residential rootedness' hypothesis of self-employment for Germany and the UK. *Environment and Planning A*, 45(5), 1219-1239.

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.

Samila, S., & Sorenson, O. (2011). Venture capital, entrepreneurship, and economic growth. *Review of Economics and Statistics*, 93(1), 338-349.

Sato, Y., Tabuchi, T., & Yamamoto, K. (2012). Market size and entrepreneurship. *Journal of Economic Geography*, *12*(6), 1139-1166.

Saxenian, A. (2007). *The new argonauts: Regional advantage in a global economy*. Harvard University Press.

Schäfer, S., & Henn, S. (2018). The evolution of entrepreneurial ecosystems and the critical role of migrants. A phase-model based on a study of IT startups in the Greater Tel Aviv Area. *Cambridge Journal of Regions, Economy and Society*, *11*(2), 317-333.

Schumpeter, J. A. (1934). *The Theory of Economic Development*. Cambridge, MA: Harvard University Press

Silva, J. S., & Tenreyro, S. (2006). The log of gravity. *Review of Economics and statistics*, *88*(4), 641-658.

Silva, J. S., & Tenreyro, S. (2011). Poisson: Some convergence issues. *The Stata Journal*, *11*(2), 207-212.

Simon, H. A. (1962). The Architecture of Complexity. *Proceedings of the American Philosophical Society*, *106*(6), 467-482.

Sorenson, O. (2017). Regional ecologies of entrepreneurship. *Journal of Economic Geography*, *17*(5), 959-974.

Stam, E. (2007). Why butterflies don‘t leave: Locational behavior of entrepreneurial firms. *Economic Geography*, 83(1), 27-50.

Stam, E. (2013). Knowledge and entrepreneurial employees: A country-level analysis. *Small Business Economics*, *41*(4), 887-898.

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: *The SAGE Handbook of Small Business and Entrepreneurship*, SAGE: Thousand Oaks. pp. 407-422

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

Theodoraki, C., & Catanzaro, A. (2022). Widening the borders of entrepreneurial ecosystem through the international lens. *Journal of Technology Transfer*, *47*(2), 383-406.

Tinbergen, J., (1962). *Shaping the World Economy*, New York: The Twentieth Century Fund.

Van Dijk, J., Leendertse, J., Stam, E., & Van Rijnsoever, F. (2024). The entrepreneurial ecosystem clock keeps on ticking–Regional persistence of high-growth firms. U.S.E. Working Papers Series nr: 24-02.

Verginer, L., & Riccaboni, M. (2021). Talent goes to global cities: The world network of scientists' mobility. *Research Policy*, *50*(1), 104127.

Wyrwich, M., Sternberg, R., & Stuetzer, M. (2019). Failing role models and the formation of fear of entrepreneurial failure: A study of regional peer effects in German regions. *Journal of Economic Geography*, *19*(3), 567-588.

Wurth, B., Stam, E., & Spigel, B. (2022). Toward an entrepreneurial ecosystem research program. *Entrepreneurship Theory & Practice*, *46*(3), 729-778.

Wurth, B., Stam, E. & Spigel, B. (2023). Entrepreneurial Ecosystem Mechanisms. *Foundations and Trends® in Entrepreneurship*, 19.3: 224–345

1. Appendix

Table A1. Data sources for the entrepreneurial ecosystem index, non-local founders and control variables

Variable	Description	Source	Year(s)
FORMAL INSTITUTIONS	Institutional Quality Index based on the World Governance Indicator (WGI)	https://sites.google.com/site/institutionalqualityindex/dataset	Avg 2015-2018
ENTREPRENEURSHIP CULTURE	Number of new firms per capita (excluding the "sole proprietorship" firms). Average number of new firms in the period	ITALIAN CHAMBERS OF COMMERCE & ISTAT	Avg 2015-2019
NETWORKS	Number of contracts between firms ("rete contratto")	ITALIAN CHAMBERS OF COMMERCE - http://contrattidirete.registroimprese.it/reti/	2010-2020
PHYSICAL INFRASTRUCTURE	Travel time to urban nodes	ISTAT	2013
	Percentage of population with a broadband subscription	ISTAT	2017
	Average speed per km of public road transport in the NUTS3 regional capitals	ISTAT	2017
FINANCE	Number of firms with at least 3 employees that rely on Venture Capital Funds as a main source of financing	ISTAT	2018
	Number of firms with at least 3 employees that rely on Crowdfunding as a main source of financing	ISTAT	2018
	Number of firms with at least 3 employees that rely on project financing as a main source of financing	ISTAT	2018
LEADERSHIP	The number of coordinators on H2020 innovation projects per capita (per thousand inhabitants)	CORDIS Database	from 2014 to 2019
TALENT	Percentage of population that completed tertiary education	ISTAT	2018
	Percentage of population that obtained a PhD	ISTAT	2018
	Percentage of firms with at least 10 employees engaged in training activities (excluding the compulsory ones)	ISTAT	2018
	Percentage of firms with at least 10 employees that have invested in digital technologies	ISTAT	2018

Variable	Description	Source	Year(s)
NEW KNOWLEDGE	Percentage of firms that conduct intramural R&D activities	ISTAT	2018
DEMAND	GDP per capita (thousand value)	EUROSTAT	2017
INTERMEDIATE SERVICES	Percentage of firms in Knowledge intensive market services as share of the total business population	ITALIAN CHAMBERS OF COMMERCE	Avg 2015-2019
Non-local founders	Number of founders born outside the NUTS3 regions of startup foundation	ORBIS	2016-2019
Pop. density (ln)	Population density	ISTAT	2018
Driving time	Distances between NUTS3 regions centroids	OPENROUTESERVICE	2019
NUTS3 Contiguity	Dummy variable for shared borders	ISTAT	-
GDP p.c. (ln)	GDP per capita	EUROSTAT	2017
STEM/pop.	Number of STEM students every 1000 inhabitants	MIUR	Avg. 2016-2019
NUTS2		ISTAT	-
Migration (btw NUTS3 regions)	Internal migration between Italian NUTS3regions	ISTAT	Avg. 2016-2019

Figure A1. The correlation matrix between the entrepreneurial ecosystem elements

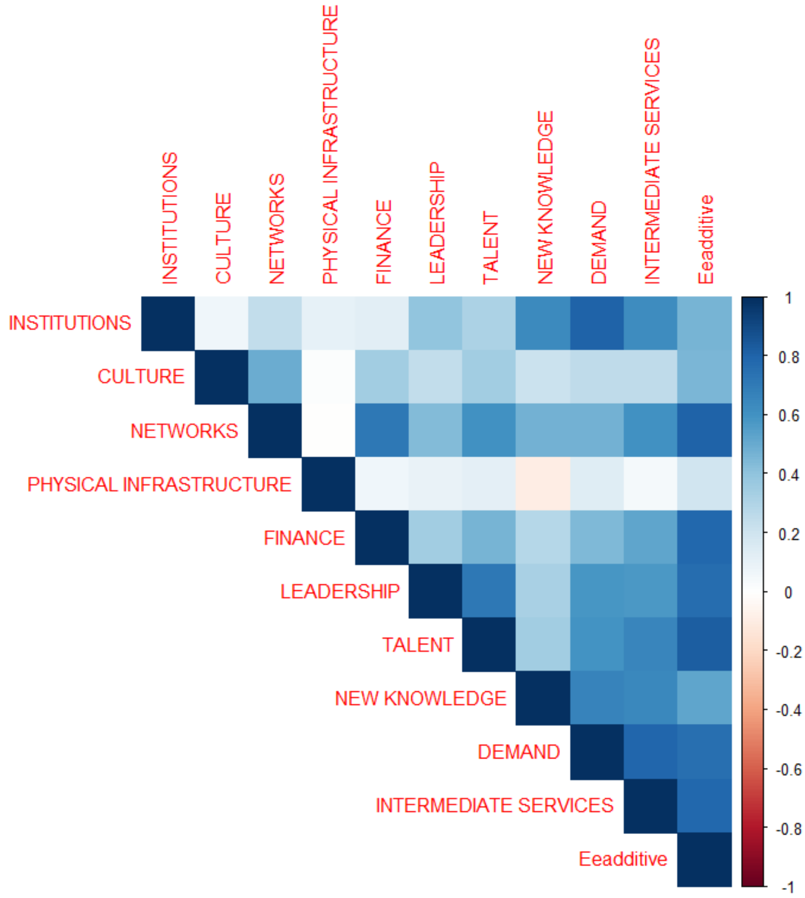


Table A2. Summary of the main features of Italian NUTS3 regions ranked by EE index: innovative startups, network centrality, and EE index

Rank	NUTS3 region	code_regione	NUTS2 Region	EE index	EE index quartile	Pagerank	Average age founders born in the region	Indegree	Outdegree	Nuber of Innovative Startups 2016-19	Innovative Startups 2016_19 (sample_all_ext)	Innovative Startups 2016_19 (sample_at_least_oneext)
1	Milano	MI	LOMBARDIA	37,20	high	0,2214	50,25	1527	354	1362	435	731
2	Roma	RM	LAZIO	33,39	high	0,0721	48,58	444	303	764	187	298
3	Bologna	BO	EMILIA-ROMAGNA	24,93	high	0,0309	47,59	180	67	204	61	92
4	Torino	TO	PIEMONTE	20,86	high	0,0398	48,87	185	233	269	47	97
5	Trento	TN	TRENTINO-ALTO ADIGE/SÜDTIROL	20,49	high	0,0242	48,11	113	37	128	35	54
6	Trieste	TS	FRIULI-VENEZIA GIULIA	19,50	high	0,0076	50,17	33	28	28	8	14
7	Firenze	FI	TOSCANA	19,43	high	0,0118	44,89	61	64	93	15	40
8	Bolzano/Bozen	BZ	TRENTINO-ALTO ADIGE/SÜDTIROL	19,16	high	0,0098	47,68	34	26	73	16	20
9	Brescia	BS	LOMBARDIA	18,29	high	0,0195	48,39	88	100	137	17	42
10	Genova	GE	LIGURIA	16,75	high	0,0183	51,31	90	113	98	14	43
11	Bergamo	BG	LOMBARDIA	16,73	high	0,0236	47,19	83	103	172	33	51
12	Venezia	VE	VENETO	16,46	high	0,0124	47,52	59	91	75	17	28
13	Pisa	PI	TOSCANA	15,93	high	0,0109	48,14	55	22	70	24	33
14	Padova	PD	VENETO	15,70	high	0,0263	47,60	144	87	204	44	78
15	Parma	PR	EMILIA-ROMAGNA	15,29	high	0,0098	49,58	48	34	65	14	24
16	Bari	BA	PUGLIA	15,25	high	0,0079	45,21	53	104	145	23	40
17	Modena	MO	EMILIA-ROMAGNA	14,43	high	0,0120	51,26	47	44	100	7	27
18	Verona	VR	VENETO	13,08	high	0,0155	45,21	74	87	137	22	38
19	Reggio nell'Emilia	RE	EMILIA-ROMAGNA	12,53	high	0,0144	51,02	69	42	61	21	32
20	Monza e della Brianza	MB	LOMBARDIA	12,35	high	0,0250	43,37	82	60	71	32	41

Ran k	NUTS3 region	code_regione	NUTS2 Region	EE index	EE index quartile	Pagerank	Average age founders born in the region	Indegree	Outdegree	Nuber of Innovative Startups 2016-19	Innovative Startups 2016_19 (sample_all_ext)	Innovative Startups 2016_19 (sample_at_least_oneext)
21	Siena	SI	TOSCANA	12,33	high	0,0047	51,47	15	15	19	8	11
22	Vicenza	VI	VENETO	11,96	high	0,0094	46,51	35	71	67	5	20
23	Pordenone	PN	FRIULI-VENEZIA GIULIA	11,81	high	0,0072	46,79	31	32	44	10	18
24	Treviso	TV	VENETO	11,65	high	0,0141	45,17	58	80	105	16	31
25	Napoli	NA	CAMPANIA	11,40	high	0,0129	47,26	73	275	301	25	47
26	Ancona	AN	MARCHE	11,26	high	0,0095	46,30	49	33	78	12	28
27	Perugia	PG	UMBRIA	11,07	medium-high	0,0064	47,24	29	45	107	11	21
28	Udine	UD	FRIULI-VENEZIA GIULIA	10,93	medium-high	0,0088	49,19	41	50	69	13	27
29	Livorno	LI	TOSCANA	10,91	medium-high	0,0025	51,03	5	32	18	4	5
30	Cagliari	CA	SARDEGNA	10,67	medium-high	0,0055	46,95	17	39	46	9	11
31	Ravenna	RA	EMILIA-ROMAGNA	10,61	medium-high	0,0057	49,19	27	35	39	10	16
32	Rimini	RN	EMILIA-ROMAGNA	10,58	medium-high	0,0062	46,26	30	22	62	14	18
33	Cuneo	CN	PIEMONTE	10,24	medium-high	0,0070	47,67	37	40	66	11	20
34	Forlì-Cesena	FC	EMILIA-ROMAGNA	9,98	medium-high	0,0042	43,68	14	34	38	7	10
35	Ferrara	FE	EMILIA-ROMAGNA	9,95	medium-high	0,0051	48,60	14	39	20	2	7
36	Pavia	PV	LOMBARDIA	9,76	medium-high	0,0103	48,49	46	60	47	10	19
37	Varese	VA	LOMBARDIA	9,61	medium-high	0,0110	47,07	33	100	55	10	19
38	Como	CO	LOMBARDIA	9,40	medium-high	0,0187	49,58	61	55	46	15	20
39	Salerno	SA	CAMPANIA	9,24	medium-high	0,0094	45,28	67	81	168	34	51
40	Macerata	MC	MARCHE	9,14	medium-high	0,0049	49,24	22	27	43	9	14
41	Pescara	PE	ABRUZZO	9,11	medium-high	0,0052	50,97	21	36	39	7	12
42	Lecco	LC	LOMBARDIA	9,02	medium-high	0,0067	48,54	14	38	30	4	7

Ran k	NUTS3 region	code_regione	NUTS2 Region	EE index	EE index quartile	Pagerank	Average age founders born in the region	Indegree	Outdegree	Nuber of Innovative Startups 2016-19	Innovative Startups 2016_19 (sample_all_ext)	Innovative Startups 2016_19 (sample_at_least_oneext)
43	Prato	PO	TOSCANA	8,88	medium-high	0,0023	44,67	7	9	12	5	6
44	L'Aquila	AQ	ABRUZZO	8,86	medium-high	0,0122	46,30	55	21	47	12	20
45	Novara	NO	PIEMONTE	8,84	medium-high	0,0087	44,53	39	40	33	11	19
46	Arezzo	AR	TOSCANA	8,79	medium-high	0,0032	55,04	9	24	18	3	5
47	Lecce	LE	PUGLIA	8,65	medium-high	0,0076	45,01	46	61	86	18	29
48	Mantova	MN	LOMBARDIA	8,42	medium-high	0,0023	47,64	4	43	22	3	4
49	Piacenza	PC	EMILIA-ROMAGNA	8,41	medium-high	0,0019	46,16	4	33	31	2	4
50	Cremona	CR	LOMBARDIA	8,37	medium-high	0,0036	48,05	13	53	26	4	8
51	Pesaro e Urbino	PU	MARCHE	8,37	medium-high	0,0041	48,03	13	28	41	6	9
52	Chieti	CH	ABRUZZO	8,36	medium-high	0,0030	46,70	11	48	23	5	7
53	Lucca	LU	TOSCANA	8,32	medium_low	0,0029	47,62	10	33	29	3	7
54	Sondrio	SO	LOMBARDIA	8,27	medium_low	0,0016	45,77	1	18	8	0	1
55	Pistoia	PT	TOSCANA	8,26	medium_low	0,0042	51,08	17	13	20	5	8
56	Foggia	FG	PUGLIA	7,99	medium_low	0,0017	47,23	4	64	37	1	3
57	Catania	CT	SICILIA	7,96	medium_low	0,0045	43,47	26	57	109	12	20
58	Avellino	AV	CAMPANIA	7,86	medium_low	0,0030	41,56	22	38	58	16	22
59	Gorizia	GO	FRIULI-VENEZIA GIULIA	7,81	medium_low	0,0018	46,33	3	12	12	3	3
60	Vercelli	VC	PIEMONTE	7,77	medium_low	0,0025	46,44	2	24	4	0	1
61	Matera	MT	BASILICATA	7,49	medium_low	0,0025	45,25	9	26	17	5	7
62	Latina	LT	LAZIO	7,48	medium_low	0,0075	44,69	27	28	38	12	15
63	Catanzaro	CZ	CALABRIA	7,47	medium_low	0,0033	47,51	13	36	44	6	11
64	La Spezia	SP	LIGURIA	7,46	medium_low	0,0019	50,48	3	22	10	2	3
65	Campobasso	CB	MOLISE	7,42	medium_low	0,0040	48,17	17	18	38	13	16

Ran k	NUTS3 region	code_regione	NUTS2 Region	EE index	EE index quartile	Pagerank	Average age founders born in the region	Indegree	Outdegree	Nuber of Innovative Startups 2016-19	Innovative Startups 2016_19 (sample_all_ext)	Innovative Startups 2016_19 (sample_at_least_oneext)
66	Trapani	TP	SICILIA	7,37	medium_low	0,0020	47,86	7	18	12	5	6
67	Ascoli Piceno	AP	MARCHE	7,35	medium_low	0,0053	48,31	25	47	69	6	15
68	Terni	TR	UMBRIA	7,33	medium_low	0,0033	46,50	8	18	32	4	6
69	Fermo	FM	MARCHE	7,31	medium_low	0,0037	38,46	16	13	16	5	8
70	Belluno	BL	VENETO	7,28	medium_low	0,0022	43,55	2	19	10	1	2
71	Teramo	TE	ABRUZZO	7,26	medium_low	0,0041	48,96	23	22	43	13	19
72	Valle d'Aosta/Vallée d'Aoste	AO	VALLE D'AOSTA/VALLÉE D'AOSTE	7,23	medium_low	0,0036	50,75	15	5	12	3	5
73	Cosenza	CS	CALABRIA	7,15	medium_low	0,0029	47,70	19	44	60	12	15
74	Asti	AT	PIEMONTE	7,12	medium_low	0,0016	49,96	1	21	2	1	1
75	Frosinone	FR	LAZIO	7,11	medium_low	0,0026	44,40	10	32	19	3	5
76	Verbano-Cusio-Ossola	VB	PIEMONTE	7,09	medium_low	0,0025	48,40	7	14	7	2	4
77	Isernia	IS	MOLISE	6,99	medium_low	0,0034	42,11	11	8	15	5	7
78	Crotone	KR	CALABRIA	6,98	medium_low	0,0015	44,92	1	10	11	1	1
79	Potenza	PZ	BASILICATA	6,95	medium_low	0,0036	50,10	18	36	50	11	15
80	Alessandria	AL	PIEMONTE	6,91	Low	0,0063	51,30	18	41	21	7	8
81	Lodi	LO	LOMBARDIA	6,90	Low	0,0060	45,75	19	25	15	4	7
82	Rovigo	RO	VENETO	6,89	Low	0,0049	47,26	23	30	41	13	17
83	Benevento	BN	CAMPANIA	6,86	Low	0,0028	48,84	10	29	36	5	9
84	Grosseto	GR	TOSCANA	6,83	Low	0,0027	49,72	5	18	4	1	2
85	Biella	BI	PIEMONTE	6,80	Low	0,0031	44,32	8	25	17	3	5
86	Sassari	SS	SARDEGNA	6,66	Low	0,0028	47,68	10	20	31	3	6
87	Massa-Carrara	MS	TOSCANA	6,63	Low	0,0020	53,13	5	15	7	0	2

Ran k	NUTS3 region	code_regione	NUTS2 Region	EE index	EE index quartile	Pagerank	Average age founders born in the region	Indegree	Outdegree	Nuber of Innovative Startups 2016-19	Innovative Startups 2016_19 (sample_all_ext)	Innovative Startups 2016_19 (sample_at_least_oneext)
88	Messina	ME	SICILIA	6,46	Low	0,0032	48,47	12	46	43	6	10
89	Palermo	PA	SICILIA	6,39	Low	0,0068	45,57	32	60	121	15	27
90	Savona	SV	LIGURIA	6,36	Low	0,0017	49,42	2	43	7	2	2
91	Taranto	TA	PUGLIA	6,32	Low	0,0032	46,58	14	50	25	4	7
92	Caserta	CE	CAMPANIA	6,29	Low	0,0047	45,29	40	35	110	24	32
93	Viterbo	VT	LAZIO	6,16	Low	0,0018	51,67	2	16	11	2	2
94	Reggio di Calabria	RC	CALABRIA	5,90	Low	0,0022	46,01	8	63	43	2	6
95	Siracusa	SR	SICILIA	5,76	Low	0,0024	51,78	11	21	18	4	6
96	Brindisi	BR	PUGLIA	5,72	Low	0,0020	43,98	6	39	19	3	5
97	Rieti	RI	LAZIO	5,47	Low	0,0025	46,25	6	12	7	4	4
98	Nuoro	NU	SARDEGNA	5,41	Low	0,0015	48,65	1	15	7	0	1
99	Imperia	IM	LIGURIA	5,31	Low	0,0015	48,00	1	17	2	0	1
100	Ragusa	RG	SICILIA	5,29	Low	0,0018	46,13	5	13	17	4	5
101	Vibo Valentia	VV	CALABRIA	5,27	Low	0,0016	43,62	1	12	3	1	1
102	Oristano	OR	SARDEGNA	5,15	Low	0,0048	50,67	14	3	9	6	7
103	Caltanissetta	CL	SICILIA	4,29	Low	0,0026	51,50	14	17	20	8	11
104	Agrigento	AG	SICILIA	3,89	Low	0,0017	46,97	3	30	3	0	2
105	Enna	EN	SICILIA	3,72	Low	0,0020	48,20	8	15	8	2	2
/	Total	/	/	/	/	1	47,67	5004	5004	7529	1660	2779

Table A3. Correlation matrix variables gravity model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Non-local founders (all external)	1.000													
(2) Pop. density (ln), foundation	0.287	1.000												
(3) Pop. density (ln), origin	0.137	-0.010	1.000											
(4) Driving time (ln)	-0.157	-0.085	-0.084	1.000										
(5) Contiguity, NUTS3	0.187	0.002	0.002	-0.415	1.000									
(6) GDP p.c. (ln), foundation	0.201	0.232	-0.002	-0.337	0.030	1.000								
(7) GDP p.c. (ln), origin	0.049	-0.002	0.232	-0.334	0.030	-0.010	1.000							
(8) STEM/pop., foundation	0.064	0.044	-0.000	-0.032	0.018	0.153	-0.001	1.000						
(9) STEM/pop., origin	0.021	-0.000	0.044	-0.033	0.018	-0.001	0.153	-0.010	1.000					
(10) EEI (ln), foundation	0.285	0.419	-0.004	-0.230	0.024	0.732	-0.007	0.401	-0.004	1.000				
(11) EEI (ln), origin	0.118	-0.004	0.419	-0.228	0.024	-0.007	0.732	-0.004	0.401	-0.010	1.000			
(12) Interregional migration	0.596	0.218	0.220	-0.282	0.474	0.146	0.069	0.043	0.039	0.222	0.166	1.000		
(13) EEI (ln), foundation (w/o demand)	0.286	0.415	-0.004	-0.241	0.025	0.764	-0.007	0.389	-0.004	0.999	-0.010	0.221	1.000	
(14) EEI (ln), origin (w/o demand)	0.116	-0.004	0.415	-0.239	0.025	-0.007	0.764	-0.004	0.389	-0.010	0.999	0.163	-0.010	1.000

Table A4. Performance of PPML LASSO (model 3) across different lambda threshold (β penalized coefficients are reported)

id	Variable	Lambda(0.5)	Lambda(0.4)	Lambda(0.3)	Lambda(0.2)	Lambda (0.1)	Lambda (0.075)	Lambda (0.05)	Lambda (0.025)	Lambda (0.01)	Lambda (0.005)	Lambda (0.0001)
1	NUTS3_contiguity	0,668	0,761	**0,875**	1,011	1,048	1,027	0,994	0,952	0,926	0,900	0,810
2	Drivingtimes(ln)	-0,136	-0,188	**-0,229**	-0,262	-0,409	-0,501	-0,604	-0,721	-0,808	-0,850	-0,959
3	GDP_pc(ln)_origin	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,715
4	GDP_pc(ln)_foundation	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,098	0,431	0,677	1,274
5	Popdensity_foundation(ln)	0,087	0,100	**0,114**	0,128	0,134	0,134	0,131	0,129	0,113	0,105	0,093
6	Popdensity_origin (ln)	0,062	0,077	**0,094**	0,103	0,091	0,093	0,094	0,095	0,092	0,091	0,084
7	EEI(ln)_origin(no_demand)	0,202	0,332	**0,467**	0,628	0,888	1,029	1,171	1,328	1,490	1,536	1,428
8	EEI(ln)_foundation(no_demand)	1,422	1,533	**1,644**	1,757	1,881	1,929	1,997	2,005	1,942	1,889	1,804
9	STEM/pop_origin	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,248	-1,541	-1,948	-2,516
10	STEM/pop_foundation	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,422	2,310	2,584	2,260
11	regional_dummy_Birth_1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,208	-0,421	-1,497
12	regional_dummy_foundation_1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-1,207
13	regional_dummy_Birth_2	0,000	0,000	0,000	0,000	0,000	0,000	-0,082	-0,695	-1,224	-1,538	-2,954
14	regional_dummy_foundation_2	0,000	0,000	0,000	0,000	0,000	0,000	0,089	0,501	0,626	0,607	-0,690
15	regional_dummy_Birth_3	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,019	-0,218	-1,315
16	regional_dummy_foundation_3	0,000	0,000	0,000	0,000	0,000	-0,214	-0,444	-0,726	-0,942	-1,032	-2,311
17	regional_dummy_Birth_4	0,000	0,000	0,000	0,000	-0,016	-0,248	-0,465	-0,706	-1,005	-1,232	-2,378
18	regional_dummy_foundation_4	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,034	-1,354
19	regional_dummy_Birth_5	0,000	0,000	0,000	0,000	-0,094	-0,463	-0,816	-1,188	-1,564	-1,814	-3,045
20	regional_dummy_foundation_5	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,148	-0,236	-1,589
21	regional_dummy_Birth_6	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,075	-0,299	-0,503	-1,597
22	regional_dummy_foundation_6	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,082	-0,133	-1,389
23	regional_dummy_Birth_7	0,000	0,000	0,000	0,000	0,000	-0,237	-0,448	-0,652	-0,831	-1,019	-2,040
24	regional_dummy_foundation_7	0,000	0,000	0,000	0,000	-0,016	-0,148	-0,282	-0,503	-0,647	-0,702	-1,889

25	regional_dummy_Birth_8	0,000	0,000	0,000	0,000	-0,081	-0,290	-0,471	-0,659	-0,878	-1,083	-2,238
26	regional_dummy_foundation_8	0,000	0,000	0,000	0,000	0,000	0,000	-0,088	-0,226	-0,382	-0,465	-1,781
27	regional_dummy_Birth_9	0,000	0,000	0,000	0,000	-0,264	-0,440	-0,586	-0,732	-0,902	-1,089	-2,131
28	regional_dummy_foundation_9	0,000	0,000	0,000	0,000	-0,364	-0,486	-0,617	-0,813	-0,987	-1,065	-2,305
29	regional_dummy_Birth_10	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,102	-1,025
30	regional_dummy_foundation_10	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,130	-0,195	-1,365
31	regional_dummy_Birth_11	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,177	-1,149
32	regional_dummy_foundation_11	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,019	-1,221
33	regional_dummy_Birth_12	0,000	0,000	0,000	0,000	0,223	0,208	0,212	0,201	0,076	-0,055	-1,003
34	regional_dummy_foundation_12	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,004	-1,207
35	regional_dummy_Birth_13	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,131	-1,054
36	regional_dummy_foundation_13	0,000	0,000	0,000	0,000	0,000	0,029	0,179	0,263	0,266	0,255	-0,853
37	regional_dummy_Birth_14	0,000	0,000	0,000	0,000	0,000	0,000	-0,045	-0,348	-0,558	-0,759	-1,566
38	regional_dummy_foundation_14	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,059	0,220	0,289	-0,682
39	regional_dummy_Birth_15	0,000	0,000	0,000	0,164	0,658	0,715	0,803	0,898	0,891	0,757	0,144
40	regional_dummy_foundation_15	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,113	0,223	-0,694
41	regional_dummy_Birth_16	0,000	0,000	0,000	0,000	0,470	0,580	0,722	0,873	0,883	0,764	0,152
42	regional_dummy_foundation_16	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,017	0,000	-1,008
43	regional_dummy_Birth_17	0,000	0,000	0,000	0,000	0,000	0,000	0,126	0,435	0,572	0,492	-0,205
44	regional_dummy_foundation_17	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,085	0,142	-0,889
45	regional_dummy_Birth_18	0,000	0,000	0,000	0,000	0,186	0,409	0,672	0,953	1,068	0,981	0,415
46	regional_dummy_foundation_18	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,086	-0,832
47	regional_dummy_Birth_19	0,000	0,000	0,000	0,000	0,514	0,744	1,010	1,292	1,415	1,335	0,770
48	regional_dummy_foundation_19	0,000	0,000	0,000	0,000	0,102	0,305	0,494	0,667	0,808	0,885	-0,070

Table A5. Lambda Cross Validation of model 3

Lambda	**RMSE**
0.4000	90.28339
0.3000	**88.72941**
0.2000	91.55902
0.1000	101.87478
0.0750	102.67207
0.0500	104.45101
0.0250	109.44966
0.0100	112.75802
0.0050	114.72712
0.0001	116.96749
0.0000	116.98751

Table A6. Gravity models with interregional migration flows as a control variable

	all external	at least 1 external	majority external	all external UNDER45	all external OVER45
	b/se	b/se	b/se	b/se	b/se
EEI (ln), foundation	**0.8597*****	**0.9875*****	**0.9355*****	**0.8645*****	**0.8439*****
	(0.1359)	**(0.1067)**	**(0.1123)**	**(0.1833)**	**(0.1766)**
EEI (ln), origin	**0.5957*****	**0.5325*****	**0.5463*****	**0.4967****	**0.6851*****
	(0.1376)	**(0.1070)**	**(0.1109)**	**(0.1748)**	**(0.1733)**
GDP p.c. (ln), foundation	1.2061***	1.3102***	1.2768***	1.1953**	1.2229**
	(0.3431)	(0.3009)	(0.3062)	(0.4485)	(0.4315)
GDP p.c. (ln), origin	0.5259	0.7266*	0.6545	0.3510	0.6465
	(0.3941)	(0.3497)	(0.3583)	(0.4536)	(0.5043)
Pop. density (ln), foundation	0.0267	-0.0036	0.0062	0.0252	0.0281
	(0.0217)	(0.0198)	(0.0203)	(0.0266)	(0.0263)
Pop. density (ln), origin	0.0102	-0.0122	-0.0103	-0.0030	0.0215
	(0.0295)	(0.0297)	(0.0296)	(0.0274)	(0.0345)
STEM/pop., foundation	3.6712***	3.8826***	4.1031***	5.7903***	2.1370
	(0.9418)	(0.7088)	(0.7384)	(1.3358)	(1.2119)
STEM/pop., origin	-2.1205*	-1.0222	-1.1835	-1.3579	-2.8533**
	(0.8596)	(0.6268)	(0.6805)	(1.1438)	(1.1039)
Driving time (ln)	-0.4494***	-0.4416***	-0.4501***	-0.5188***	-0.4088***
	(0.0625)	(0.0534)	(0.0554)	(0.0798)	(0.0755)
Contiguity, NUTS3	-0.3545**	-0.3626***	-0.3759***	-0.3574*	-0.3653*
	(0.1143)	(0.0933)	(0.0967)	(0.1452)	(0.1488)
Interregional migration	0.7725***	0.7984***	0.7931***	0.7931***	0.7538***
	(0.0433)	(0.0361)	(0.0374)	(0.0580)	(0.0540)
NUTS2 dummies	YES	YES	YES	YES	YES
Constant	-6.0791***	-5.9684***	-5.9713***	-7.0169***	-6.5436***
	(0.5109)	(0.3989)	(0.4229)	(0.6852)	(0.6285)
N	10920	10920	10920	10920	10920
R2	0.726	0.794	0.791	0.665	0.647
Pseudo Log-likelihood	-3645.663	-5034.385	-4829.2458	-2170.100	-2511.946
VIF max	3.76	3.76	3.76	3.76	3.76