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Exploring spatial network structures in entrepreneurial ecosystems: a network and clustering analysis of global venture funding flows

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Abstract This study examines the interconnectedness of entrepreneurial ecosystems (EEs) through a comprehensive geospatial network analysis of global investment flows. Addressing the critical need to explore EEs beyond their local boundaries, we investigate how EEs interact across regional, national, and international levels. Utilizing data from Crunchbase, which details 556,612 investment interactions among 5488 city-regions globally from 2000 to 2022, our analysis employs network topology analysis and hierarchical clustering to elicit similarities and differences in the financial interconnectedness. Our findings reveal significant variability in how EEs are connected, with distinct patterns emerging among clusters. We highlight the role of external linkages in shaping the structure EEs, challenging the inward-focused perspective commonly held in current literature. Notably, our research uncovers the extensive

reach and complexity of EEs' financial interactions, illustrating both concentrated and dispersed network embeddedness. The study contributes to the entrepreneurial ecosystem literature in three ways. First, we extend the analysis of EEs to consider their spatial interconnectedness and complex network structures. Second, we introduce network topology analysis as a robust method for understanding the complexities of EE connectivity. And third, through hierarchical clustering of EEs by their network metrics, we show that EE vary greatly in their relational structures. These insights not only enrich our understanding of EEs but also inform policy implications, suggesting avenues for fostering stronger, more resilient entrepreneurial environments through strategic network facilitation and international cooperation.

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Plain English Summary This study looks at how entrepreneurial ecosystems (EEs) connect with each other globally by analyzing investment flows from all over the world. We go beyond just looking at local interactions to understand how EEs interact on regional, national, and international levels. We used data from Crunchbase, which includes details on 556,612 investments across 5,488 city-regions from the year 2000 to 2022. Our approach involves using network topology analysis and hierarchical clustering to figure out how these financial connections vary among EEs. Our results show there is a lot of variation in how these ecosystems connect, and we found

specific patterns in how they link up. We point out that external connections—how EEs link with the outside world—greatly shape their structure. This adds to the the common focus on just looking at what happens inside an EE, which is what most studies usually examine. Our findings reveal that EEs have complex and widespread financial interactions, showing both close-knit and far-reaching connections. We add to the understanding of EEs in three main ways. First, we expand the study of EEs to include how they connect across different places and through complex networks. Second, we introduce network topology analysis as a detailed method to understand the complexities of how EEs connect. Third, by grouping EEs based on how they connect, shown through hierarchical clustering, we highlight that EEs vary greatly in their relational structure. These insights not only deepen our understanding of EEs but also suggest ways to help develop stronger and more connected entrepreneurial environments through better planning and international cooperation.

Keywords Entrepreneurial ecosystems · Economic geography · Spatial network analysis · Longitudinal study · Evolutionary economics · Complex adaptive systems

JEL Classification L26 · R12 · C55 · O52 · R58 · F63 · R11

1 Introduction

Entrepreneurial ecosystems (EE) can be understood as geographic locations in which a “set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship” (Stam, 2015, p. 1765). The proper relational and interactive organization of the system elements is crucial in spurring entrepreneurial activity and the overall success of the system over time (Spigel, 2017; Spigel & Harrison, 2018). Prior EE research often highlights the availability as well as interaction of their elements (e.g., financial capital, knowledge, support, entrepreneurs) *within* a particular (geographic) area (Brown & Mason, 2017; Malecki, 2018; Spigel & Harrison, 2018). However, less attention has been paid to EE *exogenous* linkages, and how they are interconnected with one another (Bouncken & Kraus, 2022; Fischer et al., 2022;

Schäfer, 2021). Entrepreneurial ecosystems are not isolated phenomena. They have crucial relationships with their outside world and are connected beyond their direct territorial scope shaping a unique exogenous network that provides resources and determines the nature and evolution of the ecosystem (Cho et al., 2022; Mack & Mayer, 2016; Malecki, 2011; O’Connor & Audretsch, 2023; Theodoraki & Catanzaro, 2022).

One stream of research, recently termed the “spatial axis” (Theodoraki & Catanzaro, 2022), highlights this geographically dispersed and interconnected nature of EEs. The spatial dimension of EEs is often implicitly assumed without taking into account the development of (trans)national connections between EEs and overlooking the importance of their borders and scale (Cantner et al., 2021; Schäfer & Henn, 2018). Some scholars have acknowledged how both an EE’s geographic reach can vary significantly (Perugini, 2023) and reconceptualize the EE as supposedly having “bridging” properties that emphasize the spatial importance (Lange & Schmidt, 2021). Some scholars argue, as EEs mature (or scale-up) they tend to shift from inward-looking towards being outside-oriented, thus expanding their geographic connections over time (Brown & Mason, 2017). However, a recent longitudinal case-study by Kap-turkiewicz (2022) suggests a more complex dynamic as, in general, EEs tend to become more outward oriented as they mature but this can vary strongly based on sectoral orientations, institutional contexts or prior path-dependencies (Audretsch & Belitski, 2017; Spigel & Harrison, 2018) and, in the long-term, inward-outward orientation might balance. Theodoraki and Catanzaro (2022) suggest that we would expect an EE to have more international connectedness if it is embedded in small and geographically proximate contexts (and vice versa). Furthermore, some scholars point out that EEs investment patterns significantly vary from region to region and especially those within emerging economies show distinct patterns compared to developed countries (Cao & Shi, 2021).

So, we ask the question: *How are entrepreneurial ecosystems interconnected with their regional, national and international environment as well as with one another?*

To explore this question, we employ complex spatial network analysis (CSNA) (Anderson & Dragičević, 2020). Complex spatial networks are a special form of networks because (1) they are embedded in physical

space containing a metric attribute usually in the form of Euclidean distance in a two-dimensional space (e.g., kilometric distance on the globe) (Barthelemy, 2022; Barthélemy, 2011) and (2) ties can represent social structures (trade relationships). In general, networks function as important architecture through which capital, knowledge, and influence are channeled across various levels—from local to global scales—in and out of any EE. CSNA is widely used in disciplines like geography or physics (Anderson & Dragičević, 2020; Barthélemy, 2011; Boschma & Frenken, 2010; Glücker, 2007; Sorenson, 2018).

We analyze the network of EE financial resource providers (Brown & Mason, 2017)—i.e., venture capital, business angels but also governments or corporations—because finance is “at the heart of the ecosystem” (Stam, 2015, p. 1766). The relationship between spatial effects and financial investment patterns has been hotly debated, although with mixed conclusions to what extent geographic proximity is a decisive factor (Chen et al., 2010; Fritsch & Schilder, 2008; Harrison et al., 2020; Lindgaard Christensen, 2007). However, this debate circulates mainly on venture capital firms which is not the sole focus of our study. We are interested in the structural composition of an EE’s exogenous linkages. Hence, financial investment networks are a vehicle of knowledge transfer and regional development (Ferrary & Granovetter, 2009). In that sense, we use investments as proxy for connectedness and consider a variety of investor types to model EE financial interconnectivity. Understanding EEs (investment) networks becomes ever more important in fostering innovation, promoting entrepreneurial activity, and driving regional economic growth (Boschma & Frenken, 2010; Fernandes & Ferreira, 2022).

Our exploratory approach takes an elaborate perspective on the regional, national, and international connectedness of EEs, focusing on aggregated investment flows between city-regions. Leveraging data on funding rounds from Crunchbase, a renowned database for tracking information on entrepreneurial ventures, we determined 556,612 single investments between 5488 city-regions on a global scale that were made between 2000 and 2022. We create the worldwide complex spatial investment network and employ topology analysis as well as hierarchical clustering on a selection of EEs to elicit patterns and differences of their interconnectedness. Our contribution

to the literature is threefold. First, we go beyond the inward focus on EEs research and investigate the spatial spread of their reach on a large scale. Second, we introduce complex network topology analysis as a suitable and promising tool for research on EEs connectivity both on a relational as well as spatial scale. And third, we cluster EEs based on their network properties as well as relational structure, and contrast this with startup output rates.

Our paper proceeds as follows. Section 2 provides a brief overview of relevant theoretical literature concerning the role of spatial and complexity dynamics of EEs. Section 3 introduces network topology analysis with regard to EEs. Section 4 gives an overview of our methodology, the dataset we established and used, as well as more details on our analytical approach. Section 5 then presents our findings, giving an overview and comparison of the various structural network patterns and the most striking findings from our clustering analysis. Section 6 discusses the findings and implications for literature and policy practice and ends with a conclusionary remark before Sect. 7 then rounds up some concluding remarks.

2 Entrepreneurial ecosystems and exogenous linkages

2.1 EEs and their interconnections

EEs have their roots in regional innovation systems (RIS) and industrial cluster (IC) literature (Acs et al., 2017), and in all three research streams an active debate persists about what exactly constitutes the “boundaries” of the system or cluster. There is consensus about the system being “open” on various levels and one of these is of spatial scope. This openness results in overlapping and ambiguous structures that, at their core, still allow for robust interactions and networks with agents beyond the system’s border (Edquist, 2006; Asheim et al., 2011). Consequently, and accelerated by globalization, there is a continuous exchange of ideas, information, capital, individuals, and cultural dynamics. This exchange means cities and regions have become deeply intertwined in global networks (Amin, 2004). The idea that EEs are not isolated entities but are open to external influences is gaining traction in academic research, taking the long-proposed open, interactive, interdependent and

evolving characteristics finally seriously (Audretsch et al., 2019; Cao & Shi, 2021; Volkmann et al., 2021; Theodoraki & Catanzaro, 2022). Schäfer and Henn (2018) uncovered inter-regional ties based on bi-directional human capital flows. Their findings reveal that persistent migration of skilled workers and “future entrepreneurs” profoundly impact both home and domestic EEs. Similarly, Prokop and Thompson (2023) emphasized the importance of EEs’ interconnections and based on academic spinoff generation, their analysis indicates that the more interconnected an EE is, the higher its rate of entrepreneurial activity. However, connectivity is mostly about intra-system linkages, neglecting how important inter-system connections can be for ecosystem life-cycles and adaptive dynamics (Auerswald & Dani, 2017; Mack & Mayer’s, 2016; Cantner et al., 2021; Colombelli et al., 2019) and the spatial spread of their connections with other ecosystems can uncover much insight about the stage or path of a particular EE (Brown & Mason, 2017). This is beginning to change. Cho et al (2022) emphasized the importance of space in the success of EE, as it constantly “draws new knowledge from a variety of sources often situated outside its geographical boundaries “ (p. 12).

2.2 Spatial and complexity dynamics of EE interconnections

Investigating and understanding the geospatial interconnectedness of EEs necessarily involve factors of network dynamics of complex adaptive systems (CAS). CAS constantly exchange and dissipate resources (e.g., financial capital) and the initial conditions or influences of these resources may determine a non-linear evolution. Thus, system dynamics such as feedback loops enable the EE to build up, strengthen and vary its activity (Haarhaus et al., 2020; Roundy et al., 2018; Spigel & Harrison, 2018). Often, exchange in CAS happens through particular network dynamics on a structural and spatial dimension that are organized in a *core-periphery* layout where strong connectivity in the core is contrasted by looser connections and dispersion in the periphery (Barthélemy, 2011; Balland et al., 2013; Borgatti & Everett, 2000). The importance of networks and their geographic features for EEs has been pointed out by economic geographers for quite a while. What type of networks exist, in what way they are organized or structured, what actors and agents are connected

and how changes occur over time, is a lively debate (Boschma & Frenken, 2010; Sorenson, 2006). Extra-local interconnectedness can increase innovation performance in peripheral city-regions (Balland & Boschma, 2021; Barzotto et al., 2019; Fiţjar & Rodríguez-Pose, 2011) and the particularities of their networks, such as their positioning or and embeddedness, can play a major role for innovative activity (Yao et al., 2020).

3 Complex spatial network topology

Networks of complex systems are often embedded in space (Barthélemy, 2011). While researching the network aspects of EEs has sparked increasingly prominent ground among scholars (for a review see Fernandes & Ferreira, 2022), studies that *actually* employ techniques from network and quantitative graph analysis are very rare. Notable exceptions are Prokop and Thompson (2023) and Ancona et al (2023). Networks function as the fundamental architecture through which resources, knowledge, and influence are channeled across various levels in and out of the ecosystem. At a macro level, the interactions between different EEs exemplify the significance of network analysis in understanding and enhancing the global landscape and patterns of EE (Barthélemy, 2011; Boschma & Frenken, 2010).

A network is a set of nodes and edges, whereas the former delineates any entity (e.g., an entrepreneurial city-region in our case) with a list of specific attributes, and the latter determines their connectivity based on the direction and weight of the link (in our case, how many investments were made from one node to another) (Borgatti & Everett, 2000; Borgatti et al., 2009). Complex spatial networks add some additional properties because nodes and edges are embedded in physical space containing a metric attribute usually in the form of Euclidean distance (e.g., kilometric distance on the globe) (Barthélemy, 2011). In the case of financial linkages between EEs, the nodes are bound to a geographic location (determined by coordinates) yet the edges are non-planar insofar that they are not (purely) physically constrained, and able to cross each other frequently (contrary to planar systems; e.g., a railroad or highway system where edges cannot easily cross each other) (Ducruet & Beaugritte, 2014). The *degree* of a network’s node refers to the number of ties it has. In the present study, it reflects the *count*

of investments (irrespective of the monetary amount invested) for a given city-region. Important are further *in-* and *out-degree*, the total count of investments flowing into the city-region or out of it, respectively. As investment ties are directed links, the count and type of degree matters: A city-region might receive more investments ($\text{in-degree} > \text{out-degree}$) or distribute more investments ($\text{in-degree} < \text{out-degree}$). Level and ratio of degree are important, as any city-region is not automatically an EE and the exogenous connections of any EE are not with *only* EEs. The degree (and the importance) of a city-region crucially influences the network structure where hubs are often formed through preferential attachment (new nodes get linked to existing high-degree nodes) and closure (nodes link to a node they share a node with) which makes the network denser; and both are important factors in innovation networks (Boschma & Frenken, 2010; Glückler, 2007).

We analyze *network topology* to understand the composition of the networks. Topology in network analysis refers to the arrangement of nodes and edges and depicts the structural layout of the network (Borgatti & Everett, 2000; Borgatti et al., 2009). Network topology analysis has been an integral part of research on regional innovation systems and complementary to a pure componential assessment on spatial innovation (Grant and Baden-Fuller 1995, 2004; Pyka and Küppers 2002; Pyka 2002). For example, Vermeulen and Pyka (2018) simulated the network topology of innovative regions with respect to spatial distribution and found that networks showing “gatekeepers” were particularly innovative; so were those who, generally, had increased triadic connections patterns. Others indicate that on a global level “gatekeepers” can significantly alter a region’s innovativeness by mediating knowledge and closing structural holes (Burt, 2014; Spencer, 2003; Breschi & Lenzi, 2015).

In network topology there are various ways of analyzing a network’s structure and relational organization. On a micro scale, specific node properties (degree, betweenness, eccentricity) are considered whereas on a macro-level averaged and global network metrics (size, diameter, assortativity) are referenced. In the meso-scale specific nodes may be grouped according to community structures based on similar connectivity behavior or on the role they play within the network (e.g., because of specific properties). Further, a network’s

topology can be assessed in terms of a core-periphery structure, where nodes are densely interconnected in the core but in the periphery are rather sparsely connected with each other, or only with the core (Borgatti & Everett, 2000; Newman et al., 2011; Elliott et al., 2020; Csermely et al., 2013). There are several network metrics and concepts relevant for analyzing a network’s structural characteristics that play a significant role to assess a network’s topological layout (Maggioni et al., 2011; Dorogovtsev & Mendes, 2002). Metrics to assess topology of networks have been used in regional innovation (see, e.g., Galaso, 2018) and complex financial network studies before (e.g., Forte, 2020). Additionally, we calculated several ratio metrics of the edges properties. For example, we assessed *tie strength* (Granovetter, 1973) by labelling any connection that occurs only once between a given pair of nodes a “weak tie,” and otherwise “strong tie,”¹ and any reciprocal connections as well as their geographic origin.

4 Method

We investigate the (inter)regional connectedness of EEs by analyzing global investment flows between city-regions. Despite debates on EEs’ boundaries, we use cities as proxies, acknowledging their relevance both academically and practically (Audretsch & Belitski, 2017; Feld, 2020; Florida et al., 2020). We consider various EE-agents such as venture capitalists, business angels, and government funds, assuming any city-region investing or receiving investment also has entrepreneurial activity to a specific extent. This approach provides a comprehensive view of investment flows, suited to the complexity of EEs.

We gathered data from Crunchbase on investments made globally from 2000 to 2022, covering all finance types.² Based on the meta-information about the investor’s and investee’s location, we obtained the coordinates of every investment. To increase accuracy and meaningfulness, we combined our data with the GHS

¹ We are aware that this approach is rather arbitrarily chosen. However, there is no single or easy definition of a weak or strong tie and for our explorative analysis we only use it as distinction.

² Although we do have data for 2023, we excluded it from the analysis as it would distort results because the year is not over and data is, therefore, incomplete.

global settlement layer and grouped our data according to its classification of urban centers.³ If the coordinates were not within an urban center, the original location was retained. We also excluded any investments made *within* any of the city-regions to specifically obtain *only inter-city* investments connections. In total we analyze 556,612 investments between 5488 urban centers on a global scale that were made between 2000 and 2022 in 178 countries in 14 world sub regions.⁴

Our exploratory approach is then twofold. We establish the global investment network of all investments and depict and analyze the connectedness of a few particular EEs. This allows for a unique perspective on the (inter-)connectedness of EEs. Second, calculating and using various global network integration metrics, we select EEs with a degree over 100 and get a worldwide selection of 596 EEs. We then performed an extensive hierarchical clustering based on several relational properties. Table 1 provides a descriptive overview of the initial dataset as well as the constructed global network.

5 Findings

5.1 Topological structures of EEs' external linkages

How do EEs connect? Based on the global network, we “zoomed in” on Europe for visual purposes by plotting the network of all investment connections that are outgoing from and incoming to Europe. This allows us to inspect how EEs are embedded in their specific world region. Figure 1 depicts a selection of European EEs European network embeddedness. The graphs show all investment connections flowing in or out of Europe. Highlighted (in blue) are all direct connections. Node shapes display their geographic area with respect to the focal EE (i.e., in the case of Paris, “national” refers to ties within France). We can observe that EEs vary strongly

in the way they integrate into the global network. Some EEs boundaries are characterized by strong connections to the periphery and by linking up with the core of the network through nodes they share with other EEs. Occasionally, EEs maintain unique segments of the periphery focused on specific geographic areas. For example, Paris possesses a distinct set of national ties not shared with others, whereas London's unique links are geographically more widespread.

Not every connection involves another EE; some may link to a peripheral location that is otherwise unconnected. This structural attribute is shaped by the nature of tie formation: weak ties (a unique connection between two nodes) are conducive to the creation of a separate peripheral segment as they can indicate untapped investment opportunities or an EE's expansion in reach or sectoral diversity. Simultaneously, weak ties are often essential for initial integration into the global network. If an EE appears less integrated, this could be attributed to contextual characteristics or its level of maturity. The visual topology analysis reveals a multitude of relational configurations and structural patterns. To further explore the visual findings, we employed hierarchical clustering as quantitative tool.

5.2 Cluster analysis

Are there identifiable patterns in how entrepreneurial ecosystems (EEs) interconnect? Our analysis now shifts to clustering analysis. Based on all EEs with a degree of greater than 100, we calculated several metrics and ratios (see Table 1) for each single EE. We then standardized the variables to implement multi-dimensional scaling—a common method to reduce data to fit a two-dimensional space while retaining statistical differences. We performed hierarchical using Euclidean distance and Ward's method for linkage. We assessed the clustering quality by computing the mean silhouette score, Dunn index, and Calinski-Harabasz index as well as ANOVA as statistical test. We found 15 clusters to be optimal: Despite the modest mean silhouette score of 0.35 and a Dunn index of 0.033, and a Calinski-Harabasz index of 367.7 this suggests a reasonably coherent cluster structure, particularly given the complex nature of the real-world data. ANOVA tests confirmed significant differences for both dimension 1 ($F(14, 500) = 374.3, p < 2e - 16$)

³ The GHS Global Settlement is an EU-funded research project observing the human presence on the planet. Its data bases have been widely used in research <https://www.frontiersin.org/journals/environmental-science/articles/10.3389/fenvs.2022.1003862/full>

⁴ We focus on the time period 2000–2022 as some EEs do not display well earlier on the investment landscape. Further, although data is available, we excluded 2023 due to the incompleteness of data and possible distortion of results.

Table 1 Overview and descriptive stats of initial dataset and global network transformation

Initial dataset	Value	Mean/median/Min/Max	Distinct count	Most common value
Total Investments	556,612			
Investment Year		2016/2018/2000/2022		
Investee Country			178	“USA”
Investee Urban Center			5367	“San Francisco Bay Area, USA”
Investee World Region			5	“Americas”
Investee World Sub Region			19	“Northern America”
Investor Country			150	“USA”
Investor Urban Center			2445	“San Francisco Bay Area, USA”
Investor World Region			5	“Americas”
Investor World Sub Region			19	“Northern America”
Network metrics (total)	Value			
Reciprocity	0.56			
Density	0.02			
Diameter	7.00			
Total Nodes	5492			
Total Edges	556,612			
Mean Coreness	108.39			
Transitivity	0.14			
Modularity	0.35			
Assortativity	0.08			
Node metrics (averages)	Mean	Standard deviation		
Degree	96	977		
Eccentricity	4.22	0.44		
Eigenvector	0.0030	0.0288		
Page Rank	0.0003	0.0019		
Local Clustering Coef	0.50	0.41		
Coreness	18.34	115.07		
National Ties	27.41	219.04		
International Ties	68.36	796.54		
Reciprocal Connection	4.93	28.64		
Weak Ties	9.02	28.32		
Strong Ties	7.43	37.33		
Total Ties	16.45	65.14		

and dimension 2 ($F(14, 500)=360$, $p < 2e-16$), establishing that our clusters are meaningfully distinct.

Figure 2a and b illustrate these 15 clusters comprising all 515 EEs mapped onto a two-dimensional space. Table 2 presents the aggregated characteristics and metrics for each cluster. The segmentation reveals considerable diversity in network metrics, reflecting various patterns of connectivity and integration across EEs.

Clusters 1 through 15 exhibit a wide range of average startup outputs, from as low as 49 in Cluster 1 to 11,612 in Cluster 15. We emphasize that our methodological approach cannot—and does not aim to—establish any causal claims. It should be noted that our examination focuses on a highly skewed, scale-free network, in some real-world instances a rare phenomenon (Broido & Clauset, 2019). Thus, most

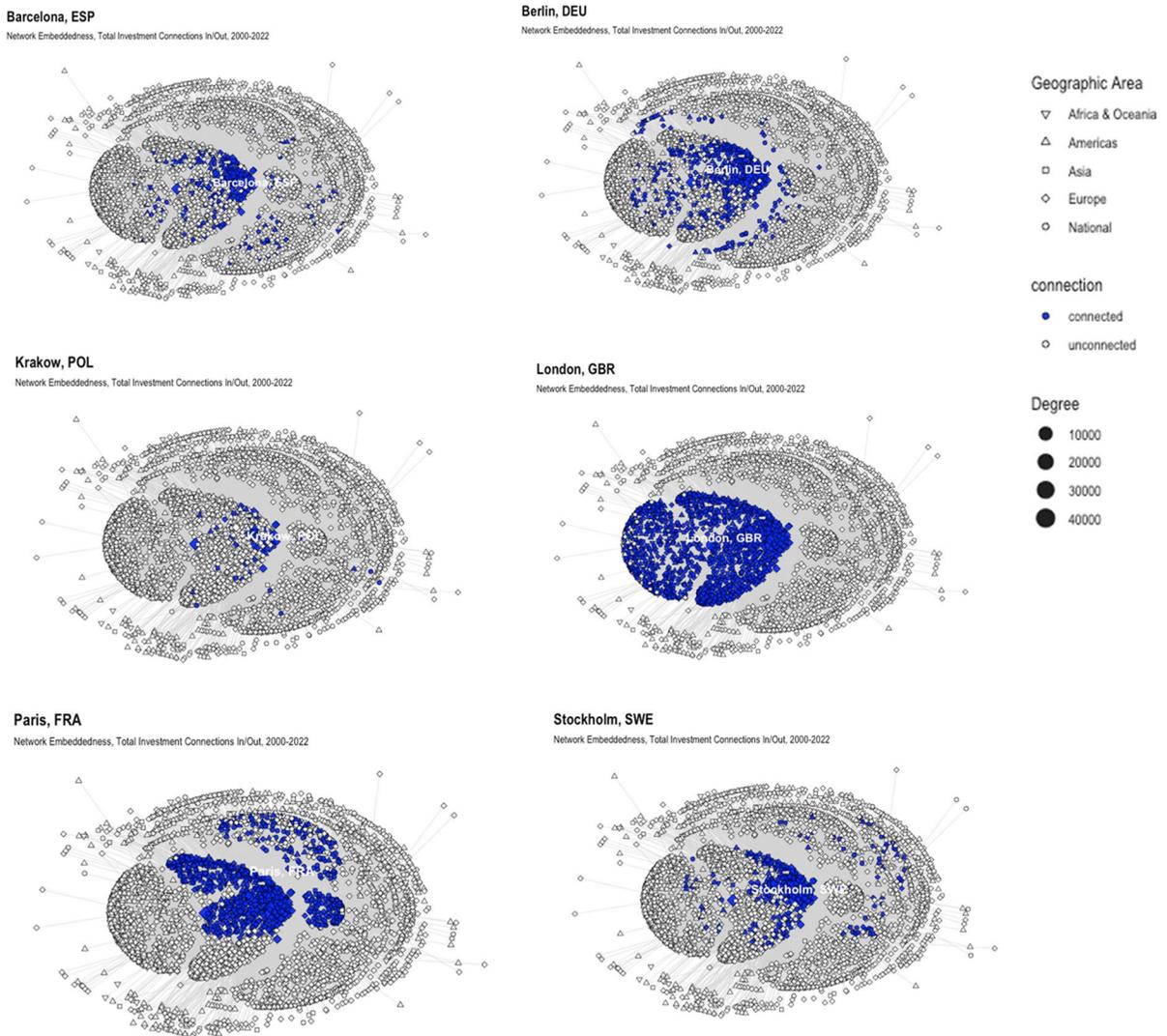


Fig. 1 Network embeddedness of selected EEs within Europe

metrics are expected to vary enormously and clustering can reveal further insights into EEs' differences in their composition and how they compare.

While we contrast the cluster's properties with their average startup output, it is crucial to note that our methodological framework neither asserts nor aims to establish causal relationships. Our analysis primarily addresses a highly skewed, scale-free network, typical of real-world scenarios. Consequently, most metrics are anticipated to vary enormously, thus allowing clustering to offer deeper insights into the disparities in composition and comparative analysis of EEs.

Clusters 1 through 15 display a broad spectrum of average startup outputs, ranging from as low as 49 in Cluster 1 to 11,612 in Cluster 15, which intriguingly seems generally independent of the number of distinct EEs, regions, or the most frequent countries. Interestingly, some clusters are similar in their levels of startup output but not necessarily in their relational characteristics. This observation extends across EEs from both developed and emerging economies, each exhibiting either weak or strong integration in the global investment network.

When considering degree levels, it is hardly surprising that higher values correlate with greater

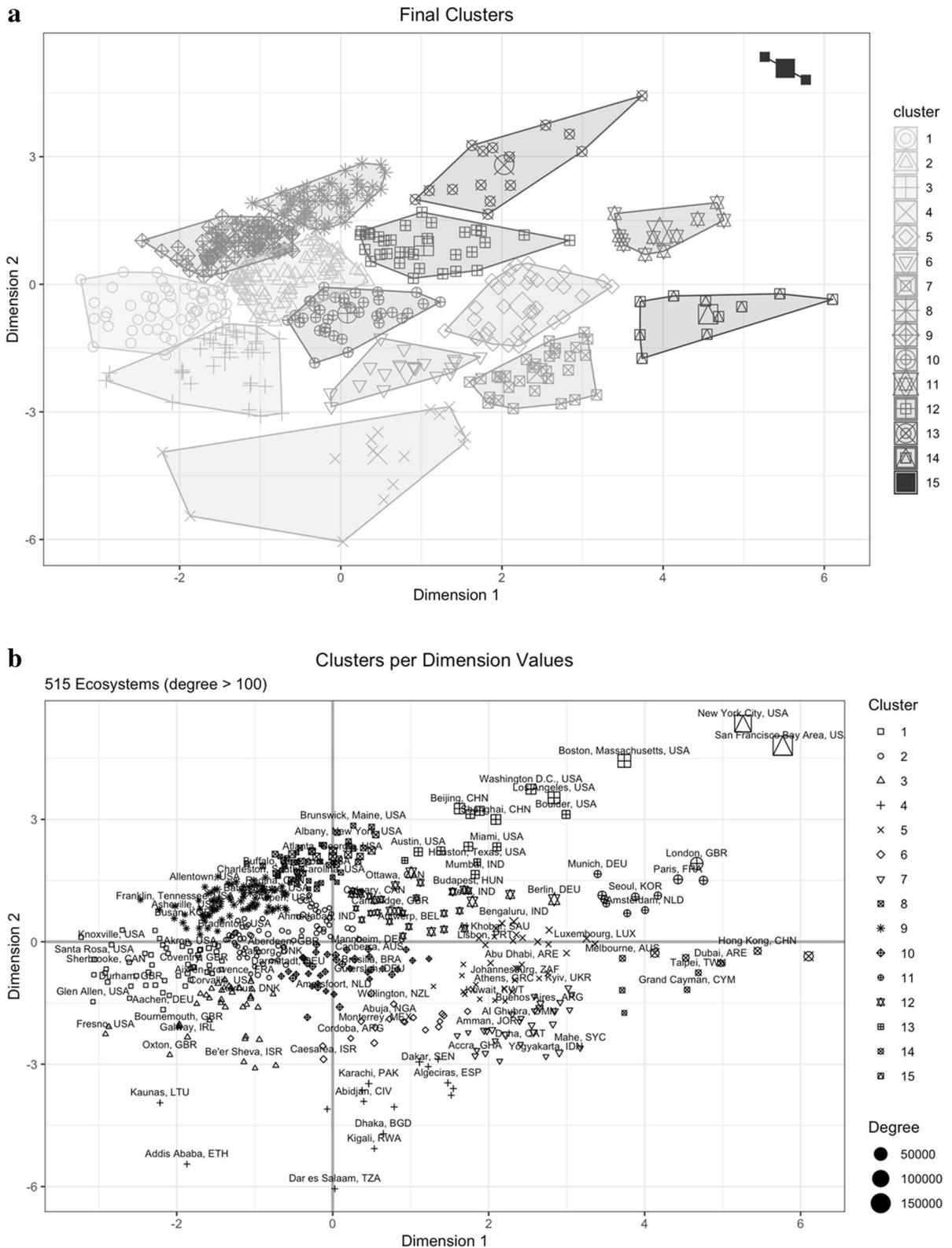


Fig. 2 **a** Two-dimensional cluster visualizations. **b** Two-dimensional cluster visualizations with selected EE labels

Table 2 Cluster details

	Cluster 1	Cluster 3	Cluster 4	Cluster 6	Cluster 2	Cluster 9	Cluster 10	Cluster 7	Cluster 8	Cluster 5	Cluster 12	Cluster 14	Cluster 11	Cluster 13	Cluster 15
Dimension 1															
Mean	-2.14	-1.44	0.46	0.82	-0.70	-1.27	0.08	2.43	-0.23	2.25	1.03	4.56	3.96	2.03	5.52
Median	-2.12	-1.38	0.59	0.85	-0.74	-1.25	-0.03	2.48	-0.29	2.26	0.90	4.54	3.88	1.85	5.52
SD	0.50	0.49	1.11	0.54	0.47	0.41	0.48	0.44	0.38	0.47	0.63	0.79	0.49	0.74	0.36
Min	-3.23	-2.91	-2.21	-0.13	-1.37	-2.46	-0.66	1.60	-1.07	1.29	0.24	3.71	3.40	0.92	5.26
Max	-1.42	-0.73	1.55	1.73	0.34	-0.59	1.23	3.17	0.55	3.36	2.84	6.10	4.75	3.74	5.77
Dimension 2															
Mean	-0.57	-1.72	-4.01	-2.02	0.17	0.97	-0.68	-2.09	1.95	-0.51	0.90	-0.70	1.22	2.81	5.08
Median	-0.57	-1.52	-3.84	-1.95	0.18	0.99	-0.67	-2.16	1.95	-0.56	1.00	-0.47	1.13	3.00	5.08
SD	0.45	0.62	0.90	0.38	0.45	0.32	0.39	0.50	0.36	0.62	0.38	0.50	0.38	0.78	0.38
Min	-1.66	-3.10	-6.05	-2.88	-0.88	0.18	-1.85	-2.92	1.30	-1.45	0.14	-1.74	0.70	1.65	4.81
Max	0.29	-0.93	-2.88	-1.27	1.14	1.60	-0.07	-1.13	2.85	0.49	1.70	-0.22	1.92	4.43	5.35
Startup output	49	53	69	73	95	95	113	136	220	299	361	675	1616	2185	11,621
No. of ecosystems	52	37	16	18	76	84	38	30	60	34	32	10	11	15	2
Total degree*	190	183	267	307	410	476	461	705	1464	1810	2213	5420	11,905	17,117	128,465
In degree*	153	157	233	211	267	284	317	447	726	940	1243	2366	4621	8368	53,887
Out degree*	36	25	35	96	143	192	144	258	738	870	970	3055	7284	8749	74,579
Betweenness Centr.*	1760	1153	3037	7013	5505	4520	6871	13,296	20,905	45,939	43,424	76,272	420,488	293,582	3,054,541
Eccentricity*	4.00	4.00	4.00	4.00	3.97	3.95	4.00	3.97	3.90	3.88	3.84	3.20	3.09	3.07	3.00
Page rank*	0.00025	0.00027	0.00040	0.00040	0.00042	0.00041	0.00055	0.00064	0.00087	0.00139	0.00158	0.00292	0.00607	0.00948	0.05613
Coreness*	28.62	20.95	28.69	77.56	101.58	153.18	112.79	186.67	515.13	498.82	566.03	1672.80	2403.73	4033.20	14,998.00
Clustering Coeff.*	0.60	0.62	0.64	0.53	0.47	0.48	0.50	0.49	0.34	0.34	0.29	0.22	0.10	0.11	0.02
Avg. distance (km)	3403	4715	11,526	9551	4261	3202	6296	13,174	3464	7985	4973	15,730	7073	6053	9220
Min distance (km)*	505	1420	5069	5533	1924	1302	3592	8810	1254	4009	2670	13,143	3729	2968	7906

Table 2 (continued)

	Cluster 1	Cluster 3	Cluster 4	Cluster 6	Cluster 2	Cluster 9	Cluster 10	Cluster 7	Cluster 8	Cluster 5	Cluster 12	Cluster 14	Cluster 11	Cluster 13	Cluster 15
Max distance (km)*	5971	9445	16,309	15,866	7428	6104	11,423	20,098	5703	14,352	12,390	18,164	10,188	8567	10,533
Top 10 ecosystem items (per total degree)	Grenoble, FRA, Bordeaux, FRA, Albuquerque, USA, Santa Rosa, USA, Coventry, GBR, Nashua, USA, Eastleigh, GBR, Montpellier, FRA, France, Davis, USA, Eden Prairie, USA	Haryana, IND, Nottingham, GBR, Dresden, DEU, Galway, IRL, Lewes, USA, Oulu, FIN, Aarhus, UGA, Fort Collins, USA, Aix-en-provence, FRA, Bath, GBR	Bogota, COL, Karachi, PAK, Lahore, PAK, Dhaka, BGD, Algeciras, ESP, Kam-pala, UGA, Monte-video, URY, Dakar, SEN, Abidjan, CIV, Dar es Salaam, TZZA	Brisbane, AUS, Caesarea, ISR, Hanoi, VNM, Monterey, MEX, Mid-dletown, USA, Medellin, COL, Wellington, NZL, Guadala-jajara, MEX, Hamilton, BMU, Abuja, NGA	Lausanne, CHE, Manchester, GBR, Oxford, GBR, Las Vegas, Nevada, USA, Orlando, USA, Chengdu, CHN, Rafael, USA, Bristol, GBR, Lyon, FRA, Sacramento, USA, Rio de Janeiro, BRA	Portland, USA, Phoenix, USA, Nan-jing, CHN, Colum-bus, USA, Orlando, USA, Chengdu, CHN, Rafael, USA, Bristol, GBR, Lyon, FRA, Sacramento, USA, Rio de Janeiro, BRA	Chemai, IND, Hyderabad, IND, Kitchener, CAN, Pune, IND, Haifa, ISR, Malm, SWE, Halifax, CAN, Espoo, FIN, Gothenburg, SWE, Cork, IRL	Jakarta, IDN, Lagos, NGA, Nairobi, KEN, Buenos Aires, ARG, Kuala Lumpur, MYS, Cairo, EGY, Cape Town, ZAF, Ho Chi Minh City, VNM, Manila, PHL, Bangkok, THA	Atlanta, USA, Denver, USA, Dallas, USA, Hang-zhou, CHN, Raleigh, USA, Salt Lake City, USA, Detroit, USA, Minneapolis, USA, Baltimore, USA, Maryland, USA, St. Louis, Mis-souri, USA	Bengaluru, IND, Sao Paulo, BRA, Vancouver, CAN, Dublin, IRL, Copenhagen, DEN, Mexico City, MEX, Helsinki, FIN, Lux-embourg, LUX, Tallinn, EST, Moscow City, RUS	Berlin, DEU, San Diego (Tijuana), USA, Delhi, IND, Montreal, CAN, Barcelona, ESP, Cambridge, UK, Ottawa, CAN, Milan, ITA, Calgary, CAN, Hamburg, DEU	Singapore, SGP, Tel Aviv, ISR, Hong Kong, CHN, Sydney, AUS, Dubai, ARE, Melbourne, AUS, Taipei, TWN, Santiago, CHL, Grand Cay-man, CYM, Port Louis, MUS	London, GBR, Paris, FRA, Toronto, CAN, Tokyo, JPN, Seoul, KOR, Zurich, CHE, Brussels, BEL, Munich, DEU, Stockholm, SWE, Madrid, ESP	Boston, Massachusetts, USA, Los Angeles, USA, Beijing, CHN, Washington D.C., USA, Shanghai, CHN, Chicago, Illinois, USA, Seattle, USA, Guang-zhou, CHN, Austin, USA, Mumbai, IND	San Francisco Bay Area, USA, New York City, USA
Most frequent countries	USA, FRA, DEU, CHN	GBR, DEU, USA, CHE, FIN	PAK, BGD, CIV, COL, ETH	AUS, MEX, ARG, BMU, COL	USA, GBR, CAN, FRA, IND	USA, CHN, KOR, GBR, FRA	DEU, CAN, IND, NLD, CHE	IDN, CYP, IND, ARG, AUS	USA, JPN, CAN, KOR, USA	CHE, LUX, SAU, ARE, AUT	DEU, BEL, CAN, GBR, NLD	AUS, ARE, CHL, CYM, HKG	BEL, CAN, CHE, DEU, ESP	USA, CHN, DEU, IND	USA

Table 2 (continued)

	Cluster 1	Cluster 3	Cluster 4	Cluster 6	Cluster 2	Cluster 9	Cluster 10	Cluster 7	Cluster 8	Cluster 5	Cluster 12	Cluster 14	Cluster 11	Cluster 13	Cluster 15
Most frequent sub region	Northern America, Northern Europe, Western Europe	Western Europe, Northern Europe, Northern America	Eastern Africa, Southern Asia, Central America	Australia and New Zealand, Southern Europe, Central America	Northern America, Western Europe, Northern Europe	Northern America, Eastern Asia, Northern Europe	Western Europe, Northern America, Northern Europe	Western Asia, Southern eastern Asia, Southern America	Northern America, Eastern Asia, Northern Europe	Northern Europe, Western Asia, Western Europe	Western Europe, Northern America, Southern Europe	Australia and New Zealand, Eastern Asia, Western Asia, Western Europe	Western Europe, Eastern Asia, Northern Europe	Northern America, Eastern Asia, Southern Asia	Northern America
Distinct countries	13	18	15	16	18	10	18	27	9	30	14	9	11	4	1
Ratio of international ties	0.16	0.43	0.95	0.75	0.27	0.09	0.50	0.95	0.10	0.82	0.44	0.90	0.71	0.21	0.31
Ratio of national ties	0.84	0.57	0.05	0.25	0.73	0.91	0.50	0.05	0.90	0.18	0.56	0.10	0.29	0.79	0.69
Ratio of reciprocal ties	0.27	0.22	0.21	0.31	0.35	0.37	0.34	0.38	0.39	0.40	0.39	0.43	0.45	0.49	0.51
Ratio of weak ties	0.58	0.55	0.56	0.53	0.55	0.55	0.54	0.52	0.49	0.48	0.48	0.47	0.41	0.43	0.37
Ratio of strong ties	0.42	0.45	0.44	0.47	0.45	0.45	0.46	0.48	0.51	0.52	0.52	0.53	0.59	0.57	0.63

* Average values; rounded

For better visual clarity, cluster order has been arranged according to startup output rates, from low of high. Thus, cluster numbers are not in numerical order

startup outputs. However, there are pronounced disparities in terms of in-degrees and out-degrees across different clusters. Notably, clusters with lower startup outputs tend to show greater numbers of incoming connections compared to outgoing ones. This pattern changes with the three higher startup output clusters, particularly Cluster 13, which shows an almost equal ratio between incoming and outgoing degrees.

Overall, higher centrality measures—betweenness, eccentricity, and PageRank—reflect increasing startup outputs across clusters yet notable differences exist. Clusters with relatively high betweenness do not necessarily show more startup output (e.g., Clusters 1, 6, 2, and 11). Eccentricity values (ranging between 4.0 and 3.0) vary little, suggesting no EE is truly isolated within the network. Nonetheless, a general trend of declining values correlates with increasing startup outputs. Interestingly, despite Cluster 15. PageRank values, on the other hand, appear to validate the intuitive assumption that the more central an EE is, the higher its startup output, with a notable escalation from 0.00025 to 0.05613 across clusters, demonstrating the dramatic range from relatively “unimportant” to “important” nodes.

Structural characteristics are determined by core-periphery positioning as well as (local) clustering values. Coreness values correlate with higher startup outputs, but Clusters 9 and 5 diverge from this trend. Interestingly, despite Cluster 9 having a 50% higher coreness value, it has the exact same startup output. Local clustering, the tendency of EEs to form tightly-knit small groups, drops significantly across clusters from 0.64 to 0.02, while startup output rises overall (though not in a strictly linear way). However, abrupt drops in clustering coefficients often coincide with spikes in startup rates.

Geographic distance, measured as the average distance in kilometers of every EE’s connections, shows considerable variation across clusters, ranging from 15,730 km to 3464 km, but it appears to play a less critical role in determining startup output. It seems to be more of a contextual necessity for an EE’s operations rather than a direct contributor to economic performance.

Lastly, a trend of more reciprocal ties correlating with higher startup outputs is observed. However, the significance of reciprocity may reach a threshold, as illustrated by Cluster 11, which has a reciprocity ratio only 0.02 higher than Cluster 14, yet it shows more than double the startup output. The geographic

origin of connections—whether domestic or international—varies dramatically across clusters. Cluster 9, for instance, has 91% of all connections outside national borders, whereas Cluster 1 has 84% within the country. However, although Cluster 13 has a similar ratio (79% national ties) it exhibits almost 22 times higher startup output. Moreover, while there is moderate variability in the ratios of weak to strong ties across clusters (ranging from 0.37 to 0.58 for weak ties and 0.42 to 0.63 for strong ties), the ratios of strong ties positively correlate and weak ties negatively correlate with startup output across different clusters.

6 Discussion

We investigated the global network of EEs financial ties by assessing various geospatial network metrics and statistics. Our study adds several important aspects for a deeper understanding of the exogenous linkages of EEs:

First, recently Schäfer et al. (2024) challenged EE researchers to look “beyond local boundaries.” We agree; and posit to look even further: on the network structures. Our analysis suggests that EEs tend to organize in scale-free networks where few nodes have many links and many nodes have few links.⁵ Hence, inter-EE connections create clear yet distinct core-periphery patterns where one or several hubs dominate the network. However, EEs seem weakly or strongly both integrated in as well as separated from the global network. So far, scholars have rightly so acknowledged that EEs are relationally organized (Neumeier et al., 2019; Spigel, 2017) but they are so not only within the EE but also outside of it. Thus, we should think boundaries of EEs not only in political, administrative or geographic terms, but also in their network centrality or peripherality. Networks are not per se visible, unless they are carefully established and visualized. Thus, in contrast to political or geographic boundaries, relational boundaries are “invisible” and highly dependent on the contextualizing perspective. Nevertheless, EEs do connect with their outside world which determines another boundary layer that is comprised of an extent of control over the periphery and the core. Some connections are shared, others are less

⁵ Interestingly, it is debated if scale-free networks are rare or not in real-world settings. See, e.g. Broido & Clauset (2019)

so, but overall this dual-connectivity determines the specific patterns EEs relational boundaries exhibit.

Second, the relational organization of EEs' financial networks also suggests there is good reason to take "the ecosystem metaphor seriously" (Kuckertz, 2019). Ecological ecosystems exist to provide life-sustaining services (Norberg, 1999) and their boundaries are crucial areas of transition, contact and separation with respect to other ecosystems. Similarly, EEs exist to provide venture-sustaining services to entrepreneurs. Our analysis shows that modelling the networks of such services (financial capital) and track where they are going to or coming from, and in what way a relational (inter)dependence exist, holds great promise for assessing ecosystem health and functioning. Ecological Network Analysis use Leontief's Input-Output-model and the distinction between internal and external compartments of the system (Suh, 2005). In complex networks, these in- and outflows occur along core-periphery patterns where we see energy—in our case financial capital—flowing in or out of the external compartment of the system from the core to the periphery, or vice versa (Csermely et al., 2013). Monitoring these flows between external and internal compartments yields insights into the balancing between compartments as well as the level of depletion nor remuneration of stock. While EEs as human-based systems function differently than ecological systems, we do believe that tracking, monitoring and adjusting the network flows can offer vital insights into the state and development of EEs.

Third, our analysis does not necessarily support the assumption that EEs' tend to be less inward oriented when they mature (Brown & Mason, 2017; Fischer et al., 2022; Malecki, 2011). EEs' exhibit a specific geographic reach (Cobben et al., 2022) but this differs drastically from region to region. Some EEs' are forced—or decide—to be outward oriented in general, presumably depending on specific contextual demands or cultural constraints. However, differences in connectedness among EE's (indicated by our clustering) are huge, and it is less a matter of inward vs. outward orientation that determines EE maturity or startup outputs but rather in what way the orientation is prevailing: Is the EE's connectedness based more or less on reciprocal, weak or strong ties? Is it part of local communities (in terms of connection pattern)? How important is it relative to neighboring EEs? Is it rather a receive or giver of investments? Questions like these are not necessarily of qualitative nature but rather structural. We should

think EEs' a lot more in terms of their connectedness and network embeddedness rather than absolute quantities—this also might reflect which EE are truly similar or different, as our clustering suggests.

Fourth, we extend the literature on EE's by tapping deeper into complexity science and add complex networks to the repertoire of EEs research scholars as other fields have long embraced (Kai Du & O'Connor, 2021). We think this is long overdue, as suggested also by Ancona et al. (2023), because one the one hand, scholars now have the computational power in every laptop to do so and, on the other hand, the interconnectedness of global business and finance should force us EE researchers to incorporate more the relational nature (Roundy et al., 2018). Complex networks are the "standard way" to model and visualize complex systems and exploring them is inescapably linked to their topological structures (Strogatz, 2001). Our analysis demonstrates that network science holds enormous potential for EE scholars to investigate non-linear dynamics and structural embeddedness of actors and factors of EEs. As our approach demonstrates, we think that, one the one hand, quantitative graph theory (Dehmer et al., 2017) offers several metrics and approaches to quantitatively assess and compare EEs and, on the other hand, that strong visualizations can capture aspects (especially for the researcher as human interpreter) that may otherwise be not clearly transmittable.

7 Concluding remarks

7.1 Limitations

Our analysis is not without limitations. The analysis is based on data sourced from Crunchbase, which, while reputable, combines professional and crowd-sourced inputs. Crowd-sourced data can sometimes introduce biases, inaccuracies, or omissions, potentially impacting the quality of the conclusions derived. The platform is US-based, and as observed, a significant proportion of the data is US-related. However, Retterath and Braun (2020) analyzed venture capital investments data bases and concluded that while non are perfect, CB is among the 3 showing the most reliable information. Given this, the generalizability of the findings to the broader global investment landscape might be limited. Regions with lesser representation in Crunchbase could have unique patterns not fully captured in

this study. Further, the dataset does not offer a complete historical perspective, given that Crunchbase was founded in 2007. Data from prior its inception is added by CB in retrospect. Also, our analysis is predominantly quantitative, potentially missing out on qualitative insights or the “why” behind observed trends.

7.2 Implications

We believe that systematically monitoring entrepreneurial ecosystems’ (EEs) investment networks can provide valuable insights into their territorial and evolutionary status. By tracking changes in position within the inter-EEs network, we can gain not only informative data but also potential indicators for action, identifying opportunities for improvement. Policymakers can utilize these insights to understand the dynamics of weak and strong ties within the network. These ties can be strategically leveraged during unprecedented crises (e.g., the war in Ukraine) that impact the entrepreneurial economy and its systems. Monitoring the geographic scope of these networks can reveal specific areas of concentrated activity within both domestic and external EEs. This information can present opportunities for strategic alignment and adaptation of business interactions. An excellent example of how network science can inform and enhance policymaking is provided by Motoyama et al. (2014) in their analysis of St. Louis.

Policymakers often attempt to replicate the “Silicon Valley” model in their own EEs and focus on hard metrics like number of unicorns or other prestigious figures to benchmark EEs against one another. However, our findings suggest that it may be more useful to compare EEs by their levels of connectedness. Our clustering analysis reveals that a diverse range of EEs exhibit similar network embeddedness. This similarity offers a fresh perspective on identifying which EEs could be models for improvement. Policymakers could consider establishing inter-EE cooperations based on their network structures, facilitating the exchange of best practices, experiences, and mutual learning. For instance, the EEs of Singapore, Tel Aviv, Hong Kong, Sydney, Dubai, Taipei, and Santiago all fall into the same cluster. Despite their different contexts and cultures, they show similar connection patterns. Enhanced cooperation in business terms among these cities could further strengthen their positions.

Our data indicates that EEs in certain regions, especially less developed ones, rely heavily on external resources. To foster self-sustained growth and reduce dependence, governments should promote stronger regional ties. Initiatives such as the EE research-based ECOSYSTEM.BUILD monitor EEs across Africa, providing tools, fostering collaboration, and encouraging exchanges among policymakers. These efforts aim to bolster regional entrepreneurial activity and establish robust, well-functioning EEs. Incorporating insights from network analysis could make these initiatives even more effective and adaptable.

7.3 Conclusion

Our explorative network analysis highlights the dynamic and multifaceted nature of EEs’ financial interconnectedness. By using network analysis and clustering we have revealed insights into the spatial and relational aspects of EEs. Our clustering of EEs based on their relational structure and global financial connectedness provides a novel understanding of their exogenous connectedness. Lastly, the findings suggest a shift in understanding EEs towards a deeper exploration and understanding of their relational boundaries akin to natural ecosystems.

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Data availability The datasets generated during and/or analyzed during the current study are not publicly available due to the requirement of an academic access to Crunchbase’s API but are, in general, available from the corresponding author on reasonable request.

Declarations

Competing interests There are no competing interests, there is nothing to declare.

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