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Opening entrepreneurial ecosystem's black box: the power of networks in African low-income countries

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Abstract

What makes one type of entrepreneurial ecosystem (EE) more conducive to entrepreneurial dynamics than another? EE research is a hot topic, and considerable progress has been made as regards its elements, network, and actors' components. However, some scholars regret the absence of an empirical analysis of EE as a whole to understand how EE configuration operates. To introduce this perspective, we propose an unexplored inter-organizational ties analysis among all EE actors, at a country-level scale. Based on the network theory perspective, we conduct an exploratory research in five low-income African countries, using innovative research methods (the quantitative graph theory, web scraping, the fuzzy-set qualitative comparative analysis) to understand the organizational patterns in these EEs, and their impact on entrepreneurial outcomes. At the core of this perspective lie inter-organizational ties measures of closeness, cohesiveness, and inter-connectedness, which are key causal conditions for high entrepreneurial dynamics levels and rates in low-income countries. This research underlines the importance of EE network attributes to facilitate the easy distribution of entrepreneurial nurturing components to entrepreneurs. It also highlights the importance of ease of information and knowledge flow, as well as a strong collaborative and coopetitive environment to make an EE more conducive to entrepreneurial dynamics.

Keywords Entrepreneurial ecosystem · Network theory · Quantitative graph theory · fsQCA · Big data · Africa · Entrepreneurial dynamics

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Introduction

Since Van De Ven (1993)'s paper on "infrastructure for entrepreneurship," and Isenberg (2010)'s seminal work, the analysis of entrepreneurial ecosystem (EE) has become a popular research topic (Velt et al., 2020). EE is a "set of interdependent actors and factors coordinated in such a way that they enable productive Entrepreneurship" (Stam, 2015). It underlines the inter-organizational nature of EE, and—by design—a field of research meant to "explain entrepreneurial activities" (Cantner et al., 2020). Even as the knowledge of EE has improved drastically, several core topics remain under-explored; scholars criticized the EE concept (Acs et al., 2016; Cunningham et al., 2019), pointing at "superficial generalisations" research (Stam & Spigel, 2016), regretting the inconsistency in terms of social science-oriented methods (O'Connor et al., 2018) and the lack of a "clear analytical framework that makes explicit what is cause and what is effect in an EE" (Alvedalena & Boschmaa, 2017). This might be explained by a theoretical and empirical research (Cao & Shi, 2020; Cavallo et al., 2019) void at a meso-level of analysis, and a lack of research on structural and organizational patterns among the EE elements at a full EE scale. Such analysis would explain how EE-specific organizational configuration weighs on the effective distribution of its resources, and is a causality of entrepreneurial dynamics.

In order to address these criticisms, we have to take into account the composition of EEs, their inter-dependencies, and, especially, understand the properties of EE interactions at a global level. EE comprise interacting elements (Stam & van de Ven, 2019) that are diverse in their roles and nature: physical infrastructure, demand, intermediaries, talent, knowledge, leadership, or finance (Isenberg, 2010). If the system theory (Daniel et al., 2018) and the complexity theory (Roundy et al., 2018) are classically evoked to modelize EEs, it appears interesting to consider a core aspect of EE: the network theory.

The network theory is regularly highlighted (Purbasari et al., 2020a) and induced in most EE definitions (Malecki, 2018), but it has never been empirically mobilized to understand what arises at an EE whole scale. We propose to improve on such research. As EEs comprise organizations, to understand their interactions, we are led to research their inter-organizational ties (Gaonkar & Mele, 2019; Granovetter, 1985; Tatarynowicz et al., 2016; Xu et al., 2019). We chose the quantitative graph theory (QGT) (Dehmer et al., 2017), an innovative method for EEs, in order to analyze its actors' dyadic ties. Indeed, this method allows us to identify EE network properties (Auschra et al., 2019; Barnes, 1969), and better understand EE effectiveness in resource distribution to entrepreneurs. As the use of this method in the context of EE is new, we decided to realize an exploratory empirical analysis.

To avoid a high noise effect of external elements in the understanding of the EE impact on entrepreneurial dynamics, we chose low resource environments. In ecosystems, everything matters. If an important factor is reduced (in our case resources), the other elements, such as the efficiency of inter-organizational ties, reveal the properties that influence related entrepreneurial dynamics. Research on causes of entrepreneurial dynamics reveals interesting results in the lowest resources environments. Indications that low knowledge and resources stimulate international entrepreneurship (Baier-Fuentes et al., 2020) are interesting, as well as indications of existing higher efficiency EE in low-incomes countries (Dionisio et al., 2021). Such evidence suggests that in low-resource environments, EE plays a more significant role to stimulate entrepreneurial dynamics compared to high-resource environments, where the relative abundance of resources attenuates the importance of a well-performing EE. Research acknowledges that a low-resource environment undermines entrepreneurial dynamics (Muñoz et al., 2020), underlining a positive effect on necessity entrepreneurship and a negative effect on opportunistic entrepreneurship. However, these studies do not capture the EE configurational causes of those entrepreneurial dynamic variances in the low-income countries group. In this group we can see an unexplained and significant Total early-stage Entrepreneurial Activity (TEA) level and evolution variance (Tran, 2018) among low-income countries. For this reason, we chose to run this research in a continent where we can find similar and comparable low-income countries: Africa.

We propose to open new perspectives on EE under a network theory standpoint, by measuring inter-organizational ties between its actors using QGT methods, in the context of select low-income countries in Africa, especially Morocco, Tunisia, Burkina Faso, Senegal, and Madagascar. The analysis of the causality of EE outcomes in a reduced number of countries is evaluated through a fuzzy-set qualitative comparative analysis (fsQCA). By doing so, we provide a new understanding of the power of network within the entrepreneurial ecosystem, and how its network attributes stimulate or undermine related entrepreneurial dynamics. One would consider that, in a sense, we open “the black box” of EE, and so, new points of view in this field of research (van Gelderen et al., 2021).

Theoretical background and hypothesis

The under-explored entrepreneurial ecosystem under social science perspective

A rising number of scholars point out that EE literature lacks “rigorous social science research” perspectives (Audretsch et al., 2018; Stam & Spigel, 2016). Recent empirical studies explored micro-level of the analysis scale approach, for example, with a network theory micro-level of analysis on incubators (van Rijnsoever, 2020), entrepreneur network-oriented perspective (Tiba et al., 2020), structural perspective at a local micro-level scale (Scheidgen, 2020), network perspective at a local micro-level scale (Purbasari et al., 2020b), network-oriented triple-helix approach at a local scale (Purbasari et al., 2020a), and mix-method to capture local evaluation of antecedents and outcomes (Muñoz et al., 2020). These micro-level analyses address local or small groups of actors, but none addresses the analysis of EE at a country level, or the analysis of inter-organizational ties of all EE actors or elements.

Some scholars propose a research canvas in network adjacent fields of research (Shipilov & Gawer, 2020), but it is not actually mobilized in EE research. Nevertheless, the network theory research canvas suggests an interesting question in the

EE research field: how can one EE produce more entrepreneurial dynamics than another?

Inter-organizational ties within entrepreneurial ecosystems

The inter-organizational ties stream of research, established by William Evan (1965), saw interesting research in trust measurement (Seppänen et al., 2007), relations between network structure and innovation attitude (Ferraro & Iovanella, 2016), configurations (Wooten & Sacco, 2017), and network formation (Gaonkar & Mele, 2019), all suggesting that inter-organizational network configuration has a significant impact on performance. Inter-organizational ties in EE are place-centric (Autio et al., 2018; Kuebart & Ibert, 2019), suggesting that physical distance plays a key role in its effectiveness. However, the issue of network distance has not yet been addressed, despite the fact that network closeness appears to be key in an EE (Purbasari et al., 2020b). This opens an inter-organizational perspective in EE research.

EE is a complex phenomenon. Scholars highlight its multi-level characteristic (Theodoraki & Messeghem, 2017), complexity (Phillips & Ritala, 2019), and its underlying various forms of cooperation (Purbasari et al., 2020a; Xu et al., 2019). Nevertheless, in EEs, inter-organizational ties (Dagnino et al., 2016; Tatarynowicz et al., 2016; Belso-Martínez et al., 2020; Shipilov & Gawer, 2020) appear to be a key research element to evaluate the efficiency of entrepreneurial support, especially regarding the "central role of alignment between structure and process" (Krishnan et al., 2020). The outputs of multiple dyads can be combined into a "broader innovative whole" (Davis, 2016), which can explain EE outcomes variances.

Entrepreneurial ecosystem spillover measurement

The "creation of new business is seen as a key factor to reach economic goals at regional and national levels" (Micozzi, 2020). There are various entrepreneurial dynamics measurement methods (Mathews & Zander, 2007) mainly at a national level (Sternberg et al., 2019), such as the Global Entrepreneurship Monitor's (GEM) TEA, and the motivation index, which evaluate the opportunity entrepreneurship level. Moreover, the GEM provides a multi-factor econometric-oriented evaluation of EEs at a country level. The World Bank Group Entrepreneurship Survey (WBGES) proposes entry density measurement. The "GEM data may represent the potential supply of entrepreneurs, whereas the World Bank data may represent the actual rate of entrepreneurship" (Acs et al., 2008). Therefore, Research designates the TEA level and rate (TEA evolution on time basis) as the preferred metric to evaluate EE's attributes' impact on its outcomes.

Network theory measurements applied to entrepreneurial ecosystems

Some studies apply the network theory at a micro-level of analysis, but never on a larger scale. Recent research on the network and ecosystem theories (Shipilov & Gawer, 2020) has offered an interesting perspective on the elaboration of an EE research canvas (Theodoraki et al., 2018). As the network theory relies massively on the graph theory, the recent development of the QGT (Dehmer et al., 2017) and associated methods, measurements, and tools provide fresh empirical research perspectives. The provided analytic methods facilitate the grasping of EE's global properties through its network attributes based on its actors' dyadic ties. There are three groups of interesting attributes: cohesiveness, inter-connectedness, and closeness, which capture different dimensions of the EE configuration.

Entrepreneurial ecosystem cohesiveness

Two measures provide a network's cohesiveness information: centrality and density. Locally addressed research on actor roles (Purbasari et al., 2020b) reveals the importance of these measures for understanding how information and knowledge spread impact an ecosystem outcome. They are extremely important in the context of EE (Agarwal et al., 2007; Audretsch & Belitski, 2020; Kuebart & Ibert, 2019) as they are strongly related to its innovation and productivity capabilities. Centrality measures indicate the cohesiveness level of a network (Borgatti & Everett, 2006). An EE that has high cohesiveness provides an entrepreneur a high degree of information on its resources and actors, which leads to a positive impact on the outcomes. It benefits the autonomy of the entrepreneurs and the effectiveness and speed of their entrepreneurial process. Therefore, we predict that a high level of cohesiveness is a causal condition for a high level and high rate of entrepreneurial dynamics.

Hypothesis 1a : EE actors-ties high cohesiveness is a causal condition for high TEA level.

Hypothesis 1b : EE actors-ties high cohesiveness is a causal condition for high TEA rate.

Entrepreneurial ecosystem inter-connectedness

The inter-connectedness measure is based on the average weight measure, which calculates the average number of ties of each actor in a network. This indicates the degree to which a network provides multiple paths possibilities to entrepreneurs who have to travel across the EE to collect a resource. As an addition, we completed this measure with the rate of actors that have at least one tie, as we see that some EE actors seem isolated, with no partnerships. We predict that high inter-connectedness levels are a causal condition for high entrepreneurial dynamics level and rate.

Hypothesis 2a : EE actors-ties' high inter-connectedness is a causal condition for high TEA level.

Hypothesis 2b : EE actors-ties' high inter-connectedness is a causal condition for high TEA rate.

Entrepreneurial ecosystem closeness

A third set of measures, the distance measures, with the average shortest path, clustering coefficient, and mean distance, is also highly useful to evaluate a network. It allows us to evaluate the connectedness and connectivity (Barnes, 1969) between network actors, and, consequently, the intensity of various forms of collaborations (Xu et al., 2019) across the EE. This information is important to appreciate the distribution capability of entrepreneurial nurturing components. Short distance measure means proximity, and we reversed those measures to provide a proximity factor. We predict that a high level of closeness is a causal condition for high entrepreneurial dynamics level and rate.

Hypothesis 3a : EE actors-ties' high closeness is a causal condition for high TEA level.

Hypothesis 3b : EE actors-ties' high closeness is a causal condition for high TEA rate.

Data and methods

EE actors in 5 African low-income countries: Morocco, Madagascar, Burkina Faso, Senegal, and Tunisia

We decided to apply this methodological approach to an unexplored but stimulating context: Africa. We chose, as a case study sample, five culturally similar low-income countries, presenting important TEA gaps (-6,46% to 115%) (GEM, 2019)[1]: Morocco, Madagascar, Burkina Faso, Senegal and Tunisia. These countries present other similarities too: French occupation history, similar institutional structures, and cultural similarities (Donaldson, 2020).

Research design and protocol

We designed a new research protocol to perform a rigorous and relevant analysis of the EE of each of these countries, and to conduct a comparative analysis between them. We defined 10 methodological steps: (1) draw the complete list

[1] https://www.gemconsortium.org/report/gem-2019-2020-global-report

of EE actors within each country; (2) verify that list and identify the appropriate online media that contains the most EE actors' information; (3) clean the actors' list and prepare sub-set lists for automated treatment; (4) identify the dyadic data source and identify web CSS codes to run a web scraping loop; (5) run the web scraping loop and verify the result; (6) run a data pretreatment protocol to identify dyadic associations; (7) identify the central actor and the number of interconnected actors; (8) run the various R specialized packages to extract measures, plots, and statistics; (9) build a country comparative table from extracted measures; and (10) run an fsQCA data calibration and an fsQCA statistics protocol.

Steps 1 to 3

To identify all the EE actors (incubators, accelerators, fablabs, institutions, business angels, etc.) we decided to mobilize economic services from French and German embassies to identify the proper source(s) to list the EE actors. We verified the robustness and accuracy of the given repositories of actors by checking social networks and web pages of each actor, corrected typographical errors in their names, and removed some actors that appeared not to belong to EE, such as accountants or communication agencies. The final list presents a total of 472 actors: 141 for Morocco; 50 for Madagascar; 62 for Burkina Faso; 56 for Senegal; and 163 for Tunisia.

Steps 4 to 5

Thereafter, we needed to analyze ties between actors, and for this, we used online media coverage. EE actors advertise their partnerships and ties through press releases; journalists directly report them, making media coverage relevant for detecting positive dyadic associations. They indicate strong and positive inter-organizational ties, as none of the actors would publicly communicate an existing negative or weak tie, or the end of a partnership. Other forms of communication, such as social network posts, embed noisy messages or negative ties, making these sources of information irrelevant. Partnerships among EE actors are neither always contractually formalized, nor reported in existing EE repositories. This makes press releases the only available and the most significant secondary data source to track positive, and known, inter-organizational ties among EE actors. To identify EE actors' inter-organizational ties, we used big-data from online media coverage (Von Bloh et al., 2019) in the targeted country's top economic online journals, employing web scraping.

We chose the open-source R Studio software packages[2] to run web scraping protocols, and various network measures, plots, and analyses. To operate this protocol, we developed a genuine R code of 800+lines to run the web scraping loop and treatments, and QGT calculations, plots and statistics. In order to develop the code, we prepared a cleaned list of actors, as well as identified the target HTML page web structure to operate and target the web scraping method.

[2] Main R packages used: rvest, ggraph, netrankr, tnet, and CINNA.

Steps 6 to 9

We analyzed the network properties of the EE. We used the QGT measurements to quantify structural information of networks (Dehmer et al., 2017), as well as various forms of comparative analyses, based on isomorphism-based measures, graph edit distance, iterative graph similarity methods, string-based measures, and graph kernels. Its characterization for determining the complexity of a given network can be obtained through distance-based graph measures, degree-based measures, eigenvalue-based measures, or information-theoretic measures. For this exploratory research, we chose to extract cohesiveness, inter-connectedness, and closeness measurements. This research, using the QGT, provides five countries nine sets of results, each measure having specific explanations (Table 2) related to EE outcomes casualties.

Step 10

After modelizing the five EEs through network theory-related methods, it becomes possible to compare them to understand what is going on. The appropriate method to compare a limited number of cases is the qualitative comparative analysis (QCA) method (Ragin, 1987). It can provide an interesting causality analysis of EE measures on its outcomes. However, for this exploratory research, QCA does not fit to run this attribute-base comparative analysis (Kraus et al., 2018). Contrastingly, the fsQCA is suitable to reach this goal, and has been successfully used in EE research in Africa (Beynon et al., 2020). In order to perform the fsQCA, we first created a data calibration matrix, and prepared our dataset. Using the fsQCA's truth table, we obtained the potential causal configurations. We used the fsqca[3] software for the calculations (Beynon et al., 2021).

This research design, applied to the five selected low-income countries, led to some interesting results that we present in the following section.

Results

We web scrapped each national top online economic journal for a total of 54,060 articles citing at least one of the 472 listed actors, representing inter-organizational ties announcements from 2014 to 2020. Counting the co-occurrence of those actors in articles allowed establishing dyadic associations and elaborating the QGT graph matrices, network plots, and measures. Using bottom-line network measures, we drove a comparative analysis using fsQCA methods to identify how the EE network impacts its outcomes in these countries.

[3] http://www.socsci.uci.edu/~cragin/fsQCA/software.shtml

Table 1 Country level EE network and outcomes measures

		Morocco	Madagascar	Burkina Faso	Senegal	Tunisia
	Actors (a)	141	50	62	56	163
	Articles (ar)	16,588	6,863	2,388	4,653	23,568
	Nodes (N)	85	19	7	19	75
	Vertices (M)	970	25	4	85	411
Cohesiveness	Density (d)	0.34	0.16	0.67	0.81	0.3
	Centrality (c)	0.46	0.41	1	0.69	0.38
	Cohesiveness factor (c*d)	0.16	0.07	0.67	0.56	0.11
Inter-connectedness	Inter-connectivity (N/a)	0.6	0.38	0.11	0.34	0.46
	Average weight (aw)	4	7	2	3	4
Closeness	Average shortest path (asp)	1.99	3.08	1.5	1.56	2.07
	Clustering coefficient (cc)	0.44	0.14	0	0.47	0.35
	Mean distance (md)	1.99	3.08	1.5	1.56	2.07
	Proximity factor _((1-asp)*(1-md))	0.25	0.11	0.44	0.41	0.23
Outcome	TEA level 2018 (ta)	6.65	20.74	29.75	38.55	4.78
	TEA level 2019 (tb)	11.4	19.4	33.53	40.28	10.3
	TEA rate 18_19 (tb/ta)-1	0.71	-0.06	0.13	0.04	1.15

Country level network measures

Extracted measures from our protocol provided interesting metrics on the expected dimensions (Table 1), each one having a specific meaning (Table 2, Measure). They represent the various cohesiveness (centrality and density), inter-connectedness (average weight and inter-connected actors' ratio), and closeness measures (reverse average shortest path and mean distance, and clustering coefficient). We reported the known TEA levels for the five selected countries from the country profile page of the GEM website.

The first interesting result is the inter-connectivity ratio, presenting the proportion of actors reporting inter-organizational ties.

fsQCA data calibration

Those sets of measures (cohesiveness, inter-connectedness, closeness) have not yet been mobilized in the EE field of research; we do not have measurement benchmarks to compare our results to existing ones. Based on a Boolean approach, owing to the limited number of studied countries, and the relative contrast of those measurements, we built the following data calibration matrix, except for the outcome

Table 2 The fsQCA data calibration

Abbreviation	Concept	Measure	Crossover point	Qualitative threshold calibration
D	Density	Global cohesiveness of the EE	0.6	[1] for full membership > = 0.6 [0.5] crossover point 0.6 [0] for non-membership < 0.6
C	Centrality	Global cohesiveness of the EE around the central actor	0.5	[1] for full membership > = 0.5 [0.5] crossover point 0.5 [0] for non-membership < 0.5
Aw	Average weight	Average number of inter-connections between EE actors, indicating a collaboration activity rate	4	[1] for full membership > = 4 [0.5] crossover point 4 [0] for non-membership < 4
Asp	Average short path	Average number of actors to pass through to cross the EE, indicating the ease for an entrepreneur to navigate through the EE	2	[1] for full membership > = 2 [0.5] crossover point 2 [0] for non-membership < 2
Cc	Clustering coefficient	The coefficient of grouping and agglomeration of EE actors, presenting potential sub-communities within the EE	0.4	[1] for full membership > = 0.4 [0.5] crossover point 0.4 [0] for non-membership < 0.4
Md	Mean distance	Is the summa of all shortest paths between actor couples divided for the total number of actor couples, providing a complementary asp measure	2	[1] for full membership > = 2 [0.5] crossover point 2 [0] for non-membership < 2
Inter_r	Inter-connectivity rate between EE actors	Rate of inter-connected actors (N) among the total EE actors population (a): (N/a), indicating the spread of EE partnership activity	0.4	[1] for full membership > = 0.4 [0.5] crossover point 0.4 [0] for non-membership < 0.4
cohe_f	Centrality and density measures factor, as indication of information and knowledge spread, and network cohesiveness	Centrality (c) and Density (d) mean: (c*d)	0.5	[1] for full membership > = 0.5 [0.5] crossover point 0.5 [0] for non-membership < 0.7
prox_f	Reverse distance measures is an indication of EE actors' proximity rate	Proximity of actors factor: ((1-asp)*(1-md))	0.4	[1] for full membership > = 0.4 [0.5] crossover point 0.4 [0] for non-membership < 0.4

Table 2 (continued)

Abbreviation	Concept	Measure	Crossover point	Qualitative threshold calibration
TEA level	Total early-stage Entrepreneurial Activity in 2019	Global Entrepreneurship Monitor country profile data	30	[1] for full membership > = 30 [0.5] crossover point 30 [0] for non-membership < 15
TEA rate	TEA yearly evolution levels	TEA evolution rate between 2018 and 2019	1	[1] for full membership > = 1 [0.5] crossover point 1 [0] for non-membership < 0.5

Table 3 Calibrated data

	Country	Morocco	Madagascar	Burkina Faso	Senegal	Tunisia
Cohesiveness	Density	0	0	1	1	0
	Centrality	0	0	1	1	0
	Cohesiveness	0	0	1	1	0
Inter-connectedness	Inter-connectivity	1	0	0	0	1
	Average weight	1	1	0	0	1
Closeness	Average short path	0	1	0	0	1
	Clustering coefficient	1	0	0	1	0
	Mean distance	0	1	0	0	1
	Proximity	0	0	1	1	0
Outcome	TEA level	0	0,5	0,5	1	0
	TEA rate	1	1	1	1	1

measures (Table 2). For each measure, we described its global meaning, crossover point, and qualitative threshold calibration rules in order to obtain a Boolean result.

Following this matrix, we built an algorithm to automatically calculate the calibrated data (Table 3) in order to avoid any error.

Based on this calibrated data, we first elaborated the fsQCA truth tables so as to identify five significant causal solutions: (C1) centered on a high cohesiveness

Table 4 Solution table

Attributes	Solutions	C1	C2	C3	C4	C5
Cohesiveness	Density					
(h1)	Centrality					
	Cohesiveness	◉	◉			
Inter-connectedness	Inter-connectivity			◉		◉
(h2)	Average weight			◉	◉	◉
Closeness	Average short path				○	○
(h3)	Clustering coefficient		◉	◉		
	Mean distance				○	○
	Proximity	◉	◉			
Outcome	TEA level (a)					
	Consistency	0.80*	0.80*	0.60	0.20	0.20
	Coverage	1.00**	0.67*	0.37	0.17	0.17
	TEA rate (b)					
	Consistency		0.33	1.00**	1.00**	1.00**
	Coverage		0.17	0.37	0.50	0.50

no indication: solution might be high or low

◉ High level

○ Low level

C1 & C2 solutions' consistency: 1.00**, solutions' coverage: 0.40, combined: 063

C3 & C4 & C5 solutions' consistency: 0.50, solutions' coverage: 0.33, combined: 0.13

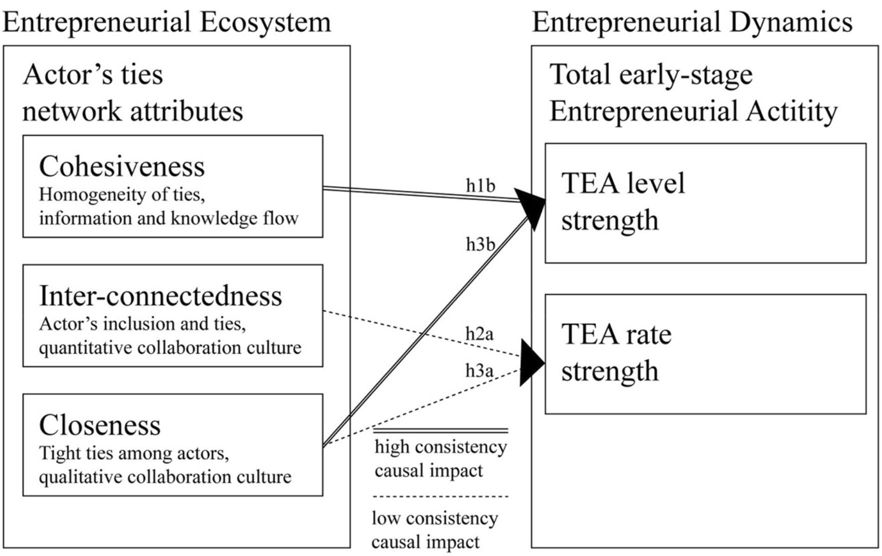

Fig. 1 The power of network in entrepreneurial ecosystem

and proximity among EE actors; (C2) with high cohesiveness, clustering coefficient, and proximity; (C3) with high inter-connectivity, average weight, and clustering coefficient; (C4) with high average weight and low average short path and mean distance; and (C5) with high inter-connectivity and average weight with low average short path and mean distance.

Based on these solutions we drove a necessary conditions analysis in order to identify the most consistent and explanatory solutions (Table 4).

When the consistency of a causal combination is less than 1, it implies that the combination incorporates one or more non-stable cases—the standard threshold being set at 0.80 for sufficient conditions (Ragin, 2008). In this study, results explain the extent to which two causal conditions (C1 and C2) lead to a high TEA. The TEA rate's solution consistency—made of C3, C4, and C5 causal conditions—is sufficient to explain its stability. The degree to which these causal conditions belong to the complete solution forms a sufficient set of causal combinations so as to produce a high TEA rate.

The various causal conditions sub-set measures are presented in three groups: cohesiveness, including centrality, density, and a cohesiveness factor; inter-connectedness including average weight and inter-connectivity ratio; and closeness, two negated measures: average short path and mean distance, a proximity factor elaborated with these two measures, and the clustering coefficient. There are two analyzed outcomes: the TEA, and its rate between 2018 and 2019. We chose this yearly rate because of the availability of the GEM data and coherence with web scrapped dyadic ties.

Findings

The causal conditions presenting a significant consistency level include C1 and C2 for the TEA level, and C3, C4, and, C5 for the TEA rate. We found that our first hypothesis was partially supported by C1 and C2 causal conditions on high TEA levels (h1a); the second hypothesis by C3, C4, and C5 solutions (h2b); and the third hypothesis by all solutions (h3a and h3b) (Fig. 1).

Solution consistency indicates the extent to which the complete solution (composed of all causal combinations) is sufficient to explain the stability, that is, the extent to which the solution is a sub-set of the observed phenomenon. In our case the C1 and C2 solution consistency coverage is 1, which indicates that all related cases have a high TEA level. Combined causal conditions C3, C4, and C5 do not provide a sufficient coverage (50% and less), but sub-set analysis indicates that combinations of inter-connectivity and average weight, and inter-connectivity alone provide a 1,00 coverage with 0,75 consistency rate, indicating that those attributes are foundations of a high TEA rate.

Discussion and conclusions

First, this study confirmed the value of the network theory perspective to open EE's black box. This first exploratory research allowed us to effectively run an empirical study in low-income countries' EEs at a whole scale. It also confirmed both the interest to mobilize the QGT (Dehmer et al., 2017) and the fsQCA methods (Kraus et al., 2018; Ragin, 2008) in low-income African countries (Beynon et al., 2020). Doing so, we emphasize the interest of using big-data (Von Bloh et al., 2019) in EE research. Our mixed-method approach, based on newly applied protocols in the EE field of research, provided interesting results that can allow us to contribute to an empirically based theoretical analysis of organizational configurations. This analysis enables us to highlight inter-organizational ties attributes, such as cohesiveness, inter-connectedness and closeness among EE actors as causal conditions for high TEA levels and rates.

Theoretical implications

Inter-organizational ties among actors make EEs in low-income countries more conducive to entrepreneurial dynamics (Fig. 1) under various conditions. High entrepreneurial dynamics levels are related to strong cohesiveness and closeness, and high entrepreneurial dynamics rates are related to strong inter-connectedness and closeness.

EE closeness as a foundation of high TEA

The first, and universal, causal condition for a high TEA level or rate is strong closeness among EE actors. Whatever the size of the EE, the fundamental attribute to conduct entrepreneurial dynamics is tight ties between its actors. This emphasizes the importance of a proper collaborative and coopetition mindset among EE actors, rather than a competition mindset, which would undermine related entrepreneurial dynamics, confirming recent micro-levels results (Purbasari et al., 2020a; Xu et al., 2019). The ability of an ecosystem to distribute its nurturing components significantly impacts entrepreneurial dynamics. It allows entrepreneurs to pick appropriate resources for their project. Recent research indicates that treatment design is more crucial than selection for innovative firms to achieve growth (Buffart et al., 2020), meaning that in the EE context, natural selection rather than forced selection among entrepreneurial projects produces higher entrepreneurial dynamics. However, to produce its full effect, this approach must be supported by a highly collaborative EE, which allows entrepreneurs find more accurate resources for their project, within a shorter duration. This explains why this attribute is a foundation of a high performing EE.

EE cohesiveness as a condition for high TEA level

Cohesiveness among EE actors is a causal condition for high TEA level only. It is interesting to see that it is not a causal condition for high TEA rates, meaning that related capabilities are secondary to sustain a high TEA rate. Strong cohesiveness is the sign that an EE has an average number of ties per actor that allows the overall network to be cohesive. The direct impact of such network attributes is the ease of knowledge and information flow, which is essential to sustain a high TEA level. When closeness is strong, this ease of flow offers entrepreneurs the requisite information to recognize appropriate nurturing components. Robust cohesiveness is also a sign that information and knowledge flow, and entrepreneurs' mobility, is uniform across the EE, thereby making every "corner" useful for the entrepreneur. This is a valuable asset especially for low-income low-resources countries, where optimal use of resources is essential.

EE inter-connectedness as a TEA rate stimulus

Inter-connectedness is associated with high TEA rates, when closeness is high. It indicates the high degree of partnership per actor, meaning that strong partnership intensity is a causal condition for a high TEA rate. The weakest EEs tend to be correlated to high competition between its actors, but when EE actors switch to a more collaborative or coopetitive scheme, the TEA rate improves. EE actors are supposed to provide an efficient access to people (Hui-Chen et al., 2014), resources, networking opportunities (Albourini et al., 2020), knowledge (Ratten & Rashid, 2020), and, more generally, to various EE nurturing components (Stam & van de Ven, 2019). These actors interact with each other to support entrepreneurial efforts, and consequently, their ties influence entrepreneurial dynamics and its rates. A collaborative mindset among EE actors, thus, has a spillover effect on entrepreneurial dynamics.

Managerial implications

We identified EE attributes related to high TEA levels and rates. A full presence of appropriate attributes will have a sustaining effect on related EE. Similarly, absence or mitigated presence of those attributes will produce a discontinuity effect by retarding the distribution of existing nurturing components within the EE, and reducing the mobility of entrepreneurs to execute their projects.

Policymakers willing to sustain a high TEA level will promote closeness and cohesiveness among EE actors. In order to raise TEA rates, they will promote closeness and inter-connectedness through an intensive partnership policy across the EE. This resonates with recent research on EE governance in order to promote independent, decentralized, and autonomous decision-making in EEs (Audretsch & Moog, 2020), but with clear guidance on the EE attributes so as to develop and sustain entrepreneurial dynamics at a country level. It will have a positive effect, irrespective of the available portfolio of entrepreneurial nurturing components. This study also provides useful EE indicators and EE success factors to follow. Following the actual research, it is possible to deploy an EE audit framework based on network measures, in order to identify relevant EE attributes and critical configuration patterns.

Limitations and further research

In this study, the low number of subject countries is a limitation. However, the methods deployed, which required a high investment coding for web scraping and network measurement protocol, can be now easily and quickly replicated in any given country or region. Such a campaign to expand our research cases will provide novel results to refine the EE knowledge, for instance, to qualitatively compare low-income countries with other kinds of countries. We are also limited by secondary data—we used online media big data—but which constrained this analysis; however, we do not predict finding better data sources in the immediate future. Finally, we are limited because of the spillover measures set at a national level, limiting this method to countries with only one EE.

There is a potential for future research: building a structured research canvas (Shipilov & Gawer, 2020) and exploring the definition and criteria of EE actors and entrepreneurial nurturing components, the role of the EE central actor, as well as other network measures to be sought. This research leads also to open a strategic research perspective on various ways to stimulate entrepreneurship in a given territory, may be through a resource-based view approach applied to EEs with a modularity perspective (Baldwin & Clark, 2000).

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