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ARTICLE

Networks of international knowledge flows: new layers in innovation systems

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ABSTRACT

Innovation systems, as dynamic structures, tend to become progressively more globalized, reflecting the presence of a greater intensity of cross-border flows. This process is related to the emergence of a Global Innovation System (GIS). Our research investigates this structural transformation by focusing on international knowledge flows (IKFs). To integrate this investigation with the previous literature on national innovation systems (NISs), we examine international knowledge flows connecting institutions (firms, universities, research institutes, hospitals) from different NISs. Among possible IKF types, we focus on those created by patent citations - of other patents or scientific articles - and scientific coauthorships. We represent the institutions and the IKFs they create as networks where the nodes are the institutions and the links connecting these nodes are the IKFs. We organize the network in three layers according to the type of IKF that connects the institutions: scientific collaboration, patent citation or article citation in patents. We have divided this paper into five sections. The first presents our theoretical background. The second discusses the characteristics and properties of complex networks and complex systems, as well as some characteristics of multilayer networks, a concept used as an analytical tool to develop the empirical analysis. The third addresses the data and methodology. The fourth section analyses the structure of the three network layers, their entanglement and multiplex properties, and the institutions connecting them. The fifth and conclusive section discusses how those findings improve the understanding of an emerging GIS.

KEYWORDS | International knowledge flows; Innovation systems; Networks of networks

1. Introduction

As dynamic structures, innovation systems tend to become progressively more globalized, reflecting the presence of a greater intensity of cross-border flows, linking agents and institutions distributed throughout different countries. This process is related to the emergence of a Global Innovation System (GIS).

Our research investigates this structural change by focusing on international knowledge flows (IKFs). To integrate this investigation with the previous literature on national innovation systems (NISs), we discuss international knowledge flows connecting institutions (firms, universities, research institutes, hospitals) from different NSIs. Among possible IKF types, we focus on those created by patent citations - of other patents or scientific articles - and scientific coauthorships.

To build an analytical framework to address this structural change, Binz and Truffer (2017, p. 1287-1288) introduce an insightful suggestion of a multiscalar approach to innovation systems, with the global dimension as a new layer. Our paper is based upon this suggestion of a multiscalar approach to innovation systems, viewing the global dimension as a new layer and endeavoring to extend its reach.

Our theoretical framework (BRITTO; RIBEIRO; ALBUQUERQUE, 2021b) was elaborated combining earlier insights of pioneering works on innovation systems (FREEMAN, 1982; NELSON, 1993) - that highlighted the role of international movements of people, machines and knowledge in the initial development of national systems in the United States, Germany and Japan – and empirical evidence collected in three previous papers (RIBEIRO et al., 2014, 2018; BRITTO; RIBEIRO; ALBUQUERQUE, 2021a) – that investigated different networks showing the intensity and growth of international flows. Structural changes in capitalism – growth of transnational firms, the production value chains that they orchestrate, new technologies of information and communication, the formation of national systems of innovation in all continents – led to the growth of international knowledge flows, a phenomenon so intense that create a new structural transformation: the emergence of an international layer in innovation systems. This new layer does not erase the national, sectoral, regional or local systems, but changes the hierarchy among them, opens new challenges and opportunities, rearranging their roles.

We represent the institutions and the IKFs they create as networks where the nodes are the institutions and the links connecting these nodes are the IKFs. We organize the network in three layers according to the type of IKF that connects the institutions: scientific collaboration, patent citation or article citation in patents. In previous analysis, we approach each of those layers singly (RIBEIRO et al., 2014, 2018; BRITTO; RIBEIRO; ALBUQUERQUE, 2021a) to identify their structure and organization. We find evidence of their relation to self-organized systems, components of complex systems. Now, in this paper, we investigate how those three layers overlap and entangle, determining a network of networks (RIBEIRO et al., 2022).

This paper presents and analyzes 17,240,834 international knowledge links (data from 2017) that form new layers of innovation systems. These 17,240,834 international links may be disaggregated into three basic networks. First, 15,920,875 international links connecting authors of scientific papers - a university-led network. Second, 1,249,320 international links connecting inventors of patents that cite foreign patents - a firm-led network. And third, 70,639 international links connecting patent-holding inventors that cite foreign papers - a second firm-led network. These three international layers overlap and interconnect, forming an international network of networks. The contribution of this paper is the identification and preliminary analysis of this overlapping and interconnection – empirical evidence for the identification of the present phase in a tentative typology of a transition towards a global innovation system (BRITTO; RIBEIRO; ALBUQUERQUE, 2021b, p. 270-273).

There are four specific themes that we propose to investigate: 1) Is there a network of international, cross-border knowledge flows – based on data from scientific collaboration, patent citation or article citation in patents - connecting institutions (firms, universities) of different countries? 2) How are the different layers of this network structured and entangled? 3) Is this network a complex and self-organized system with specific features? 4) What are the critical institutions inserted in this network? After this analysis, we return to our theoretical framework, examining how those empirical findings and answers contribute to our analysis of the emergence of a GIS.

We organized this paper into six sections. The first presents our theoretical background. The second discusses the characteristics and properties of complex networks and complex systems. The third discusses some characteristics of multilayer networks, a concept used as an analytical tool to develop the empirical analysis. The fourth addresses the data and methodology. The fifth section analyses the structure of the three network layers, their entanglement and multiplex properties, and the institutions connecting them. The sixth and conclusive section discusses how those findings improve our understanding of an emerging GIS.

1.1 A theoretical background: the role of international knowledge flows

The emergence of a global innovation system is an important and ongoing structural change (BRITTO; RIBEIRO; ALBUQUERQUE, 2021b). Driven by the growth of transnational corporations, by the international nature of science and by changes in information and communication technologies, the development of new and international layers in innovation systems has been investigated by a growing literature (BINZ; TRUFFER, 2017).

GIS transforms innovation systems, creating a new hierarchy involving previous levels: national, regional, local and sectoral systems. Our contribution to this literature is focused on investigations of one component of this emerging GIS: the layers formed by knowledge flows and their internationalization (SOETE; VERSPAGEN; WEEL, 2010, p. 1176). As in other levels of innovation systems, knowledge flows integrate the operations of their basic institutions: firms, universities, hospitals and other formative institutions interact in many forms. In this sense, knowledge flows are important institutional connectors. The theoretical framework articulating international knowledge flows and GIS underpins our empirical investigation, providing evidence about their interaction.

At least since Nelson's (1959) and Arrow's (1971) classic papers, which dealt with the properties of basic research and information, including information disclosure in patents, knowledge flows have been discussed in the economics of innovation. Griliches (1979) introduces an elaboration on spillovers, stressing that "real knowledge spillovers"... "are the ideas borrowed by research teams of industry *i* from the research results of industry *j*" (GRILICHES, 1979, p. 104). Later, Griliches further elaborated on what we should genuinely consider as knowledge spillovers. According to Hall, Jacques and Pierre (2010, p. 1063), Griliches (1992) is a pioneer in distinguishing two types of spillovers: "rent spillovers and knowledge spillovers".

The focus on IKFs and the institutions related to them is based on a large literature, illustrated by the reference that Jaffe, Trajtenberg and Fogarty (2000, p. 215) make to Griliches (1979): "At least since Zvi Griliches's (1979) seminal paper on measuring the contributions of R&D to economic growth, economists have been attempting to quantify the extent and impact of knowledge spillovers". Griliches (1992, p. S39), in turn, writes that "Jaffe (1986, 1988) comes closest in looking for the second type of spillovers, the disembodied kind". These authors are relevant references in a vast literature on knowledge flows that involve different features of this important topic of innovation dynamics, summarized in the following subsections.

Knowledge flow presupposes at least two institutions: one generating new knowledge and the other with a very peculiar and challenging capacity to learn – reflecting an absorptive capability (COHEN; LEVINTHAL, 1989, 1990). In other words, a knowledge flow assumes that an institution is at one end of the flow innovating and another institution is at the other end either innovating or learning – implementing one of the "two faces" of R&D. Aghion and Jaravel

(2015, p. 535), evaluating the contribution of Cohen and Levinthal, discuss the integration between this concept of absorptive capacity and knowledge spillovers in general, as they evaluate "that imitation (or 'technological adaptation') is as much an investment as frontier R&D".

The introduction of absorptive capacity in these flows defines the intensity of spillover: "the more knowledge is codified, and the higher is the absorptive capacity of other firms, the more knowledge spillover will take place" (HALL; JACQUES; PIERRE, 2010, p. 1065).

Absorptive capacity is a crucial concept for our research because it shows that there must be at least two institutions in each knowledge flow, either in knowledge-creating or knowledge-diffusing flows. This approach is vital to explain the unit of analysis of our research: the international knowledge link connecting two institutions.

Jaffe, Trajtenberg and Henderson (1993, p. 578) opened a new line of investigation on this subject, as they found that "knowledge flows do sometimes leave a paper trail, in the form of citation in patents". These citations contribute to understanding two sets of agents: those who generate knowledge - patent owners (or patent assignees of cited patents) - and those who can learn and use the information of that accumulated stock of knowledge to promote technological innovation, leaving traces of this use in citing patents - the patent assignee of the citing patent. These knowledge flows also span cross-national boundaries: Jaffe, Trajtenberg and Henderson (1993) highlighted that Grossman and Helpman (1991) "consider explicitly international knowledge spillovers".[1]

Coe and Helpman (1995) pioneered the topic of "international R&D spillovers". Griliches (1979, 1992) was a relevant reference for them. Although Coe and Helpman (1995) do not include Cohen and Levinthal (1989, 1990) in their references, they may have an implicit or indirect dialog with them as they introduce domestic R&D stock in their analysis, which we may interpret as an aggregate measure of absorptive capacity, a tool for the use of international R&D spillovers.

1 See Grossman and Helpman (1991, p. 165-171), section 6.5 on "international knowledge flows".

For Coe and Helpman (1995, p. 860), "own R&D enhances a country's benefits from foreign technical advances, and the better a country takes advantage of technological advances in the rest of the world, the more productive it becomes."

Branstetter (1998) presents a review of the literature on international knowledge spillovers. The first paper of Jaffe and collaborators on international flows mentions two previous references on "technological flows" - Teece (1977) and Coe and Helpman (1995) (JAFFE; TRAJTENBERG, 1999, p. 106). Resuming Griliches's distinction, Jaffe and Trajtenberg (1999, p. 106) stress that "[k]nowledge spillovers are much harder to measure than technology transfer, precisely because they tend to be disembodied". Jaffe and Trajtenberg (1999) pioneered patent citations to track international knowledge flows.

The connection between the literature on international knowledge spillovers and absorptive capacity is essential, as suggested by Cohen and Levinthal (1989, p. 569, footnote 1): in this pioneering paper, they mention this relationship as the international diffusion of knowledge generated by agricultural research depended upon the existence of institutions to absorb them, as Evenson and Kislev (1973) had shown. Aghion and Jaravel (2015) explore other aspects of a potential dialog among the authors discussing international knowledge (or R&D) spillovers and absorptive capacity. This dialogue defines the choice of our basic unit of analysis – International Knowledge Flows (IKLs) connecting institutions as their nodes.

This vast literature on knowledge flows may be summarized by some significant flows described by relevant papers. Table 1 presents six types of knowledge flows, describing their nature, traceability, and related papers. All these flows have been analyzed, including the international dimension – an essential feature for our analysis. Table 1 shows selected international knowledge flows related to knowledge creation or diffusion, including codified and tacit knowledge, as well as scientific and technological knowledge – all essential knowledge flows for innovation systems.

TABLE 1
Types of traceable international knowledge flows - nature, how to trace them and related literature

TYPE	NATURE	HOW TO TRACE IT	DISCUSSED BY
Scientific citation of scientific papers	Input for new knowledge and/ or diffusion of knowledge	Scientific paper citation of scientific papers	Bornmann et al. (2018), Abramo (2018)
Collaboration in science	Creation of new knowledge	Co-authorship of papers	Glänzel and Schubert (2005)
Co-invention in patents	Creation of new knowledge	Co-inventors in a patent	Breschi and Lissoni (2004)
Forward patent citations of patents	Diffusion of knowledge	Patent citation of patents	Jaffe and Trajtenberg (2002)
Backward patent citations of patents	Input for new knowledge	Patent citation of patents	Jaffe and Trajtenberg (2002)
Patent citation of scientific papers	Input for new knowledge	Patent citation of scientific papers	Narin et al. (1997)
Production and innovation activities within an MNC	Creation within MNCs	Patent inventor country different from patent assignee	Bathelt and Li (2020)

SOURCE: Authors' elaboration.

Patents are a fundamental source for tracking the four knowledge flows shown in Table 1 – patent coinventors, patent citations of patents (both backward and forward citations) and patent citations of scientific papers. Scientific papers leave traces of two knowledge flows – coauthorships and their use as knowledge inputs in patents. The structure of transnational corporations – a proxy of relationships among headquarters and their subsidiaries – reveals the tacit knowledge necessary for these corporations' productive and innovative activities.

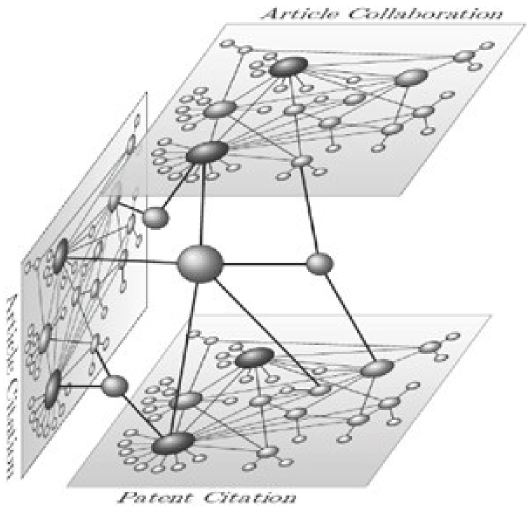
Table 1 also helps to explain why our paper tends to underestimate these international knowledge flows since, as we will show in section 2, we concentrate our investigations on four of these seven international knowledge flows (rows in Table 1). Therefore, it is possible to assume that the complexity of links and flows from which the Global Innovation System emerges is even more intense.

2. Analytical tools

2.1 Complex networks and complex systems

As we will present in greater detail in sections 4 and 5, we can represent the IKFs and the institutions that create them as a network where the nodes represent the institutions and the links connecting the nodes represent the IKFs. Each international knowledge link (IKL) – inserted in the network of the IKF - connects two institutions - nodes - from different countries (see Figure 1).

FIGURE 1
Connecting three international networks: institutions that are part of these three layers. 365 multilayer nodes (2017).



SOURCE: Authors' elaboration.

When we analyze each layer's network structure separately, we comprehend that they are scale-free networks. This kind of network has peculiar properties due to how we built them. We start the growth process with very few nodes fully connected to each other. Then, we begin adding new nodes by connecting them to an existing node in the network with a probability proportional to the number of connections the network node already has. Therefore, this preferential attachment concentrates new connections in the nodes that already have more connections and keeps poorly connected nodes with limited connections (Barabasi and Albert, 1999). The literature refers to it as Mathews' law.

This odd connection distribution leads to two fundamental properties for our future discussion in the context of the emergence of the GIS: implicit hierarchy and robustness. The hierarchy occurs because the relatively few nodes that are broadly connected to the rest of the network, hereafter hubs, will dominate these remaining nodes' dynamics and, therefore, the significant part of the network structure. Then, if we change the state of the hubs, the network state will alter as a whole. Robustness occurs if we randomly attack the network by depleting some nodes; however, the network structure will not significantly change because it is highly likely that we will only deplete poorly connected nodes. As the most critical nodes - hubs - are rather few compared to the network size, it is quite unlikely for us to pick them up randomly, depleting them, which would have a higher impact on the network dynamics (ALBERT; BARABASI, 2002).

Barabasi (2016) argues that scale-free networks are associated with self-organized systems because the preferential attachment rule rises spontaneously from an endogenous organization of the system elements and not due to an exogenous agent that calculates the connection number of each node and picks up the node that will receive a new connection. In addition, complex systems present this property of self-organization. Therefore, we can associate scale-free networks with the output of complex systems (WAGNER; LEYDESDORFF, 2005).

We can define *complex systems* as those formed by a broad set of elements interacting with each other, showing different organizations at different aggregation scales (GOLDENFELD; KADANOFF, 1999). Due to their organization, those systems spontaneously present a correlation length similar to the system size. Therefore, each element state correlates to all other system elements. This characteristic leads to a nonlinear response when the system is disturbed because a local perturbation will propagate through the systems due to the high correlation length altering the state of a significant part of the system.

Therefore, we suggest that IKFs have recently increased to such an extent that they have created a global layer that connects the different NSIs so that changes in a specific NSI propagate through the international links of the global layers to other NSIs, altering their dynamics and impacting the system behavior as a whole. At the same time, the spread of relevant knowledge tends to be strengthened with the gradual consolidation of the networks that conform to a Global Innovation System, generating important feedback effects on NISs.

2.2 Multilayer networks and network of networks

Wagner and Leydesdorff (2005) and Strandburg et al. (2009) deal with networks, and Barabási is a reference for their works. In our review of the literature on networks, Boccaletti et al. (2014) and Newman (2010) connect the works of Barabási to the notion of "monolayer networks".

"Monolayer networks", beyond regular and random networks, deal with growing networks, models that include the preferential attachment introduced by Barabási (2016), a mechanism essential to explain the emergence of power-law distributions.

These monolayer networks, as investigated by Wagner and Leydesdorff (2005) and Strandburg et al. (2009), are relevant starting points. However, the literature has moved on to more realistic and complicated structures, evolving to characterize "multilayer networks" (KIVELÄ et al., 2014).

According to Boccaletti et al. (2014),

> [m]ultilayer networks explicitly incorporate multiple channels of connectivity and constitute the natural environment to describe systems interconnected through different categories of connections. (BOCCALETTI et al., 2014, p. 5),

For Hammoud and Kramer (2020),

> the simplest definition of a multilayer network is a set of nodes, edges, and layers, where the interpretation of the layers depends on the structural characteristics of the model. (HAMMOUD; KRAMER, 2020, p. 2),

There is a profusion of models of multilayer networks - see, for example, Table 1 in Kivelä et al. (2014, p. 206-207). The combination and overlapping of networks mediated by nodes that connect different layers may be related to the concept of "multiplex networks" (Kivelä et al., 2014, p. 218-220; Domenico et al., 2013). For Wasserman and Faust (1994, p. 422), "multiplexity of relations is the tendency for two or more relations to occur together". In sum, multiplex networks are a subset of multilayer networks where we can find a set of nodes that share different types of connections (links).

These multiplex networks present a feature we can identify in the literature as "correlated multiplexity". According to Lee et al. (2014),

> [i]n real-world complex systems, however, nonrandom structure in network multiplexity can be prominent. For example, a person with many links in the friendship layer is likely also to have many links in another social network layer, being a friendly person. We termed the correlated multiplexity to refer to such a nonrandom pattern of network multiplexity. Examples of correlated multiplexity are widespread (LEE et al., 2014, p. 54-55).

Investigating this correlated multiplexity, the literature finds the most frequent pattern: positively correlated multiplexity. Lee et al. (2014, p. 55) explain that this pattern of correlated multiplexity means "that a node with a large degree in one layer likely has more links in the other layer as well".

This short review of the literature on networks helps us to investigate fundamental features of the resulting interrelationship of the layers that IKFs form.

3. Data and methodology

A procedure developed to quantify the international knowledge flows described in the previous section begins with the arrangement of two large and local databases: one covering the metadata of articles indexed on the Web of Science, which will be called ISI from here on, and another covering the metadata of patents granted by the United States Patent and Trademark Office (USPTO), which will hereafter be called USPTO.

Regarding the group of documents (articles or patents) that fill these databases, each one can be split into two parts according to the date of the document and the reason to obtain its metadata: the ISI database contains all articles published in 2017 and the article cited by the patents granted by the USPTO in 2017; the USPTO database contains all patents granted by USPTO in 2017 and the USPTO patents cited by them.

From these starting points – data for 2017 – we extended our databases to include patents and articles cited in the 2017 USPTO patents; therefore, we considered citations of patents or articles by other patents to arrange our local databases. Retrieving the metadata of the cited patents is a more straightforward procedure because we just need to loop up the cited patent number on the USPTO search. However, for article citations in patents, the procedure is far more complicated because the reference to the article appears as nonstructured text in the patent. To handle that, we developed an algorithm to split the reference parts (author, title, journal, and year) and loop up these terms on the Web of Science - similarly to Ribeiro et al. (2014). When the search finds an article, its metadata are downloaded and added to the ISI database; this procedure allows the analysis to proceed to a second part of our database, comprising data about scientific papers.

One key and strategic stage of constructing our databases is the standardization of the names of the institutions that host the authors of the articles and that are patent assignees. This is not a simple process because the same institution may have different names in these different sources.

This automated removal of some of the institution names minimizes these differences. For example, names such as Google Corporation and Google Corp., when processed, become just Google, increasing the possibilities of a correct matching between our two databases.[2]

From these databases, we identify each of the different types of knowledge flows as follows:

a) Coauthorship in Science: For each 2017 ISI article, all possible combination pairs among their authors are calculated, and the country of their institution is compared - see Ribeiro et al. (2018). An international flow is obtained when these countries are different. In 2017, there were 2,774,251 articles and 576,081 with international collaboration.

b) Patent Citation: The citations of other patents of each 2017-granted USPTO patent are identified and then compared to the country of the assignee of the cited patent and the original patent – see Britto, Ribeiro and Albuquerque (2021a). An international flow is obtained when these countries are different. In 2017, there were 352,566 patents and 188,980 international citations.

c) Article Citation in Patent: The citations to ISI index articles of each 2017-granted USPTO patent are identified as presented above and compared the institution country of the first author of the article and the country of the patent assignee – see RIBEIRO et al. (2014). An international flow is obtained when these countries are different. In 2017, there were 22,571 patents that cited scientific papers and 15,437 with international citations.

4. A network representation of IKFs

Once we have identified all those international knowledge flows, we can create a network where the nodes represent the institutions

[2] These matching problems are not trivial. Those comments have an important implication for next sections: our results tend to underestimate the real size of the overlapping networks.

that participated in the knowledge flow, and those nodes' connections (links between them) represent the flow. Therefore, the network links represent the IKF. Hereafter, we will refer to them as international knowledge links (IKLs).

As we identified three types of IKFs from the patents and articles, we can organize the network representation into three layers, each containing just one type of IKF. However, each layer is not disconnected from the others due to institutions that participate in more than one type of flow. Those multiflow-type institutions appear in our network representation connecting different layers. Therefore, they perform a critical role in creating a multilayered network.

The investigation of these three layers of IKLs' networks and how they overlap is the focus of the rest of this paper. We will proceed in two steps, each dealing with a different level of aggregation and interaction among these networks. The first step will investigate each layer, describing them and defining their basic properties. In the second step, we investigate the entanglement among these layers by analyzing the nodes that appear simultaneously in two or three layers. These multilayered nodes are essential in our analyses because they connect the different layers, turning them into a network of networks.

4.1 First step: identification and analysis of three layers

In our network representation, an IKL connects two institutions – two nodes located in different countries. Institutions are composed of individuals – science and technology personnel, scientists and researchers – that populate firms and universities/research institutions. We stress the participation of individuals within these institutions because they are the authors and inventors of the articles and patents. As individuals, they may have significant interaction through different channels – formally and informally, within their institutions, in conferences, meetings and in collaborative research.[3] These personal, work, and academic-related interactions seem to go beyond the interactions that leave traces in patent citations and scientific coauthorships – captured in IKLs of this investigation.

As mentioned above, this paper investigates three different types of IKLs. The first type of IKL connects coauthors of scientific papers located in institutions in different countries (see Table 1, second line). Since these coauthors and their institutions interact – an active process of collaborative writing of a scientific paper – this link is bidirectional. This IKL traces collaboration in the generation of new knowledge. From data of scientific papers (Web of Science, for 2017)—comprising an original base of 2,774,251 articles, of which 576,081 are articles with international collaboration—we identified 15,920,875 cross-border links, corresponding to 36.7% of the knowledge links present in the base (see Table 2).[4] These links connect 62,186 nodes – institutions that host the authors of these scientific articles. The predominant institutions in these IKLs are university/research institutions. There are 51,194 universities/research institutes represented in these 62,186 nodes.

On the one hand, these data define this set of IKLs as university-led – the five leading institutions are the Chinese Academy of Sciences, the University of Oxford, the University of Cambridge, Zhezhiang University and UCL. On the other hand, these data show how firms are involved in the process of scientific collaboration, as there are more than 10,000 firms as nodes of these IKLs. The first firm in this ranking is IBM, in the 478th position.

The second type of IKL connects patent assignees between a citing patent and a cited patent (see Table 1, fourth and fifth lines). Since the patent inventors cite existing patents – reflecting a process of knowledge absorption and diffusion – an active process occurs only on one side of the knowledge flow; therefore, this link is unidirectional. This IKL

3 See Cohen, Nelson and Walsh (2002, p. 15) for the importance of these formal and informal channels of interaction.

4 These data confirm the exponential growth of the IKLs, that in 2000 were 545,372 and in 2012 were 7,312,107 (see RIBEIRO et al., 2018, p. 167).

TABLE 2
Data on basic networks – different layers institutions connected by ikls (2017)

Layer	Document type	Documents	Type of international flow	Documents with inter. flow	%	Knowledge Links (National and Inter.)	International Knowledge Links	%	Countries
#1	Articles	2,774,251	Articles with international collaboration	576,081	20.8%	43,383,852	15,920,875	36.7%	173
#2	Patents	319,983	Patents with international patent citation	188,980	59.1%	11,107,692	1,249,320	11.2%	119
#3	Patents	319,983	Patents with international article citation	15,799	4.9%	150,352	70,667	47.0%	73

SOURCE: WebOfScienc and Patstat - authors' elaboration.

traces two processes, depending on the analyst's point of view: a cited patent shows how knowledge is spread (knowledge diffusion), while a citing patent gives an indication of how knowledge is used as an input for new knowledge. From our data on patent citations (PatStat, data for 2017) – comprising an original base of 319,983 patents, of which 188,980 are patents with an international patent citation - we identified 1,249,320 cross-border links, corresponding to 11.2% of the knowledge links present in the base (see Table 2).[5] These links connect 34,207 citing nodes and 197,299 cited nodes – institutions that are patent assignees, employing inventors who are authors of these patents. The predominant institutions, both among citing and cited nodes, are firms. According to our data, among these 34,207 citing nodes, there are 32,519 firms, and among these 197,299 cited nodes, there are 185,374 firms. Therefore, these data define this set of IKLs as firm-led – the five leading firms are IBM, Samsung, Qualcom, Apple and Microsoft. Although firm-led, our data show that universities are important here – the first university as a citing node in this ranking is MIT, in the 131st position.

The third type of IKL connects patent assignees that cite scientific articles (see Table 1, sixth line). Since the patent inventors cite existing scientific papers – a process of knowledge absorption and diffusion – an active process also occurs only on one side of the knowledge flow; therefore, this link is unidirectional. This IKL traces one institution (the patent assignee) using knowledge created in another institution – the host of the author(s) of the scientific paper, a clue of how one institution uses knowledge created in another to generate new technology. From our data on patent citations of scientific articles (PatStat and Web of Science, data for 2017) – comprising an original base of 319,983 patents, of which 15,799 are patents with international article citations – we identified 70,639 cross-border links, corresponding to

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[5] These data confirm the growth of these IKLs over time, as Britto, Ribeiro and Albuquerque (2021a, p. 718) found 210,271 IKLs in 1991 and 995,296 in 2009.

47.0% of the knowledge links present in the base (see Table 2).[6] These links connect 4,721 citing nodes (patent assignees) with 8,938 cited nodes (institutions with scientific articles) – patent inventors that cite scientific authors in their process of new technology creation. In this type of IKL, there are different predominant institutions, depending on the point of view of the investigation: among the citing nodes, firms predominate – 4,193 firms among 4,721 nodes (patent assignees) - and among the cited nodes universities predominate – 4,578 universities among 8,938 nodes. It is important to stress the high share of firms among the cited scientific articles.

These three different types of IKLs form different network layers. Table 2 summarizes the main features of each layer, with their predominant institution, including the basic data presented in this subsection.

The international dimension of each network is shown in the last column of Table 2 – number of countries that host the institutions (nodes) in each layer. There are 173 countries with institutions in the network of scientific collaboration (a university-led network), 119 countries in the network of patents citations of patents (a firm-led network) and 73 countries in the network of patents citations of scientific papers (a firm-led network).

Table 3 organizes the data by the network layers, presenting these data for layer #1—the network of scientific collaboration displayed by the 15,920,875 IKLs—layer #2—the network of patent citations with its 1,249,320 IKLs—and layer #3—the network of patent citations of scientific papers with its 70,639 IKLs.

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6 We cannot make a direct comparison with our previous investigation on this type of IKF (RIBEIRO et al., 2014). However, an indirect hint about the growth of this dimension may be grasped from a comparison between the total of patents which we analyzed with data for 2009 – 10,985 USPTO patents with citations to ISI-indexed papers (including all patents, domestic citations of scientific papers and patents with cross-border citation of scientific papers) – and our data for 2017 – there are 15,437 USPTO patents with only cross-border citation of scientific papers. Even if all patents in 2009 had only cross-border citations of scientific papers, the growth would have been quite significant.

TABLE 3
Basic data on each layer: Layer, number of links, number of institutions (nodes), links per node, power-law exponent and predominant institution (2017)

LAYER	LINKS	NODES	LINKS PER NODE	PL EXP	PREDOMINANT INSTITUTION
#1: ART-COL-ART	15,920,875	62,186	256	1.72	University (*)
#2: PAT-CITE-PAT	1,249,320	34,207 citing	37	2.18	Firm - citing nodes (**)
		197,299 cited			Firm - cited nodes
#3: PAT-CITE-ART	70,639	4,721 citing	15	1.99	Firm - citing nodes (***)
		8,938 cited			Universities - cited nodes

SOURCE: WebOfScience, Patstat - authors' elaboration.
(*) There are 51,194 universities between 62,186 nodes; (**) Citing nodes: 32,519 firms between the 34,207 nodes. Cited nodes: 185,374 firms between the 197,299 nodes. (***) Citing nodes: 4,193 firms between 4,721 nodes. Cited nodes: 4,578 universities between the 8,938 nodes.

Table 3 introduces an analysis of the structural properties of those networks, since we analyzed the connection distribution of each layer and obtained a power law. This relation is a univocal characteristic of scale-free networks that, as discussed before, are conceived as self-organized systems (BARABÁSI, 2016).

The power-law exponents of these three networks are 1.72, 2.18 and 1.99. This feature of the data for 2017 is compatible with our findings in previous investigations for layer #1 (RIBEIRO et al., 2018) and layer #2 (BRITTO; RIBEIRO; ALBUQUERQUE, 2021a), which showed that these power-law properties persisted over time.

These properties of our three networks indicate an important methodological issue: we are not dealing with simple connections between national innovation systems but with complex networks that are developing new layers in innovation systems. The processes that form, shape and strengthen these layers do not eliminate the national boundaries of innovation system but have the potential to generate different dynamics - with possible implications for changing the levels of complexity of the whole system.

Once we have described each of these three network layers, the second step of our analysis is to investigate how they overlap and entangle. Therefore, we are dealing with multilayer networks. The investigation of these three layers of IKLs and how they overlap constitutes the focus of the rest of this paper. The next step starts from the nodes of each of these three layers, searching for the nodes that are found in more than one layer – defining multilayer nodes.

4.2 Second step: entanglement among the layers

In the previous section, we described each network layer, each one involving just one kind of IKF. However, we also have institutions that participate in documents with more than one kind of knowledge flow. In these cases, we identify the node representing the institution located in a specific layer, and as they have different flows, they will be connected to different layers (Figure 1). Therefore, those nodes will connect two or three layers. The second step of our analysis is to investigate how the layers overlap and entangle through those multilayered nodes

In this sense, another aspect related to entanglement of these networks is shown in Table 4, which summarizes the number of nodes that are in the overlapping of two different networks (two-layered nodes). The total number of links, comprising international articles, patents with international citations and patents with international cited articles, reached 301,361 links in 2017. Those two-layer networks comprise a number of nodes representing institutions that are well positioned in the global process of knowledge generation, diffusion and absorption, comprising 5,347 institutions in 2017 (see Table 4)

The institutions that are both in the first and second layers are institutions that are involved in the process of scientific collaboration to generate new knowledge – cross-border coauthorships – and are learning with knowledge generated abroad – cross-border patent citation. According to Table 4, institutions in both layers comprised 844 institutions in 2017.

The institutions that are in the second and third layers have a strong learning side, aiming both at the technological side – cross-

TABLE 4
Data on documents and nodes - overlapping multiple layers (2017) data on documents and nodes - overlapping multiple layers (2017)

LAYER	NODES	Layer #1- Articles w/ international coauthorship	Layer #2 - Patents w/ international patent citations	Layer #3 - Patents w/ international citations of scientific papers	Sum of Documents
Basic Layers	307,351	576,081	188,980	15,437	780,498
Multilayer #1-#2	844	67,790	57,544	-	125,334
Multilayer #2-#3	4,203	-	112,539	14,867	127,406
Multilayer #1-#3	401	44,414	-	4,207	48,621
Total Two-Layered Nodes	5,347	112,204	170,083	19,074	301,361
Three-Layered Nodes	365	41,313	50,089	3,976	95,378

SOURCE: WebOfScience, Patstat - authors' elaboration.

border patent citations – and at the scientific side – cross-border patent citation of scientific papers. According to Table 4, institutions in both of those two layers reached 4,203 institutions in 2017. The institutions that are in the first and third layers combine (a) direct involvement in the generation of knowledge through cross-border coauthorships and (b) patenting practices that include cross-border citations of scientific papers. According to Table 4, institutions in both of those two layers reached 401 institutions in 2017. Table 4 also shows how hierarchical the entanglement of those three networks is: in 2017, there were 301,361 articles or patents in that layer, with 5,347 two-layer nodes.

Table 4 also illustrates a new level of overlapping – three-layer nodes. In 2017, we identified 365 three-layer nodes among 5,347 two-layer nodes. Furthermore, the participation of those three-layer nodes in articles with international collaboration, patents with international citations and patents with international cited articles reached 95,378 links in 2017.

These three-layer nodes form a special network - a network of networks. In 2017, 365 three-layer nodes connect all three basic networks and the networks formed by 5,347 two-layer nodes. In fact, considering the broad number of links analyzed—comprising international articles, patents with international citations and patents with international cited articles—and the number of links connected through the three layers of those networks, we can observe a process of entanglement. In fact, the total number of IKLs connected by three-layer nodes reached 1,154,558 links, comprising 6.7% of the IKLs in 2017 (see Table 5). As a network of networks, this set of three-layer nodes has a very special position that defines the hierarchical nature of the international layers of IKLs and that suggests a role for the organization of innovation systems as a whole.

TABLE 5
Participation of three-layer nodes in IKLs (2017)

LAYER	LINKS	LINKS CONNECTED TO THREE-LAYER NODES	%
#1: ART-COL-ART	15,920,875	841,886	5.3%
#2: PAT-CITE-PAT	1,249,320	297,338	23.8%
#3: PAT-CITE-ART	70,639	15,334	21.7%
Total	17,240,834	1,154,558	6.7%

SOURCE: Web of Science, Patstat - authors' elaboration.

4.3 Multilayered institutions

Institutions are the nodes of our analysis, the starting and ending points of each IKL. The characteristics of the participating institutions in the layers are also another indication of how this international dimension is strengthening.

Therefore, for 2017 (see RIBEIRO; BRITTO; ALBUQUERQUE, 2022), we made a preliminary disaggregation of those data by the nature of institutions, and we found that those layers had different features. The first layer – scientific coauthorship – is a university-led layer (there are 51,194 universities among 62,186 of those nodes. The second layer – patent citing patents – is a firm-led network (there are 32,519 firms among those

34,207 nodes). The third layer – patent citing scientific papers – is another firm-led network (there are 4,193 firms among those 4,721 nodes).

Table 6 has been organized to examine the position of each three-layer node in the three different basic networks, signaling the differentiated predominant roles of institutions in innovation systems. Table 6 is organized in three parts, each dealing with rankings from different layers.

Table 6A shows the ten leading institutions in a ranking organized by their participation in layer #1. As layer #1 is a university-led network, all ten leading institutions are universities. Cross-checking these institutions with a ranking prepared by Nature Index (NATURE, 2021) for Academic Institutions, all ten leading institutions in Table 5A are on the list for 2018, although in different positions – Peking University is in the 8th position, the University of California, Berkeley, is in the 6th position and Xian Jiaotong University is in the 130th position. The first firm in this ranking is IBM, in the 42nd position.

Table 6B shows the ten leading institutions in a ranking organized by their participation in layer #2. As layer #2 is a firm-led network, as expected, all ten leading institutions are firms. According to the Nature Index (Nature, 2021) ranking for corporate institutions, five of these firms in Table 5B are on the list for 2018 (IBM, Samsung, Intel, Google and Sony). If we look for the ten leading firms in the Nature Index for 2018, nine of them are in this network of networks (GNS Science is the only firm that is not in our network of networks, but it is in layer #1). The first university in our network of networks, in this ranking according to layer #2, is TSINGHUA UNIVERSITY, in the 69th position.

Table 6C shows the ten leading institutions in a ranking organized by their participation in layer #3. As layer #3 is a firm-led network, once again, all ten leading institutions are firms. There are 6 firms both in Table 6B and 6C: an indication of similarities between these two networks. The first university in our network of networks, in this ranking according to layer #3, is NORTHWESTERN UNIVERSITY, in the 19th position. It is interesting to note that the leading institutions in each of the three layers also operate as connection nodes between those layers, integrating the set of 365 institutions that operate as three layers' nodes.

TABLE 6
Ranking of institutions in the network of networks, according to different layers (2017)

INSTITUTION	ARTICLES W/ INTER. COAUTHORSHIP	PATENTS W/ INTER. CITATION	PATENTS W/ INTER. ARTICLE
TABLE 6A: TEN LEADING INSTITUTIONS ACCORDING TO LAYER #1			
TSINGHUA UNIVERSITY	1,783	103	5
PEKING UNIVERSITY	1,432	9	3
MCGILL UNIVERSITY	1,366	3	1
MONASH UNIVERSITY	1,189	4	2
XIAN JIAOTONG UNIVERSITY	1,148	3	1
FUDAN UNIVERSITY	1,037	5	1
KING SAUD UNIVERSITY	1,033	57	4
JOHNS HOPKINS UNIVERSITY	995	2	1
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA - BERKELEY	981	47	5
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA - SAN DIEGO	971	47	18
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA - LOS ANGELES	964	47	23
TABLE 6B: TEN LEADING INSTITUTIONS ACCORDING TO LAYER #2			
INSTITUTION	**ARTICLES W/ INTER. COAUTHORSHIP**	**PATENTS W/ INTER. CITATION**	**PATENTS W/ INTER. ARTICLE**
INTERNATIONAL BUSINESS MACHINES; INTERNATIONAL BUSINESS MACHINES CORPORATION; INTERNATIONAL BUSINESS MACHINES CORPROATION; INTERNATIONAL BUSINESS MACHINES CORPORATION	249	5,179	366
SAMSUNG ELECTRONICS CO., LTD.; SAMSUNG ELECTRONICS; SAMSUNG ELECTRONICS CO., LTD.; SAMSUNG ELECTRONICS CO. LTD.; SAMSUNG ELECTRONICS CO., LTD; SAMSUNG ELECTRONICS CO., LTD.; SAMSUNG ELECTRONICS, CO., LTD.; SAMSUNG ELECTRONICS., LTD.; SAMSUNG-ELECTRONICS CO., LTD	31	4,613	110
QUALCOMM INC.; QUALCOMM INCORPORATED; QUALCOMM, INCORPORATED	5	1,898	252
APPLE INC.; APPLE, INC.	2	1,682	65
INTEL CORPORATION	50	1,484	62
LG ELECTRONICS; LG ELECTRONICS INC; LG ELECTRONICS INC.; LG ELECTRONICS, INC.	3	1,451	33
GOOGLE INC; GOOGLE INC.; GOOGLE, INC.	42	1,276	119
SONY CORPORATION	3	1,166	35

SOURCE: WebOfScience, Patstat - authors' elaboration

TABLE 6C: TEN LEADING INSTITUTIONS ACCORDING TO LAYER #3			
INSTITUTION	**ARTICLES W/ INTER. COAUTHORSHIP**	**PATENTS W/ INTER. CITATION**	**PATENTS W/ INTER. ARTICLE**
INTERNATIONAL BUSINESS MACHINES; INTERNATIONAL BUSINESS MACHINES CORPORATION; INTERNATIONAL BUSINESS MACHINES CORPROATION; INTERNATIONAL BUSINESSMACHINES CORPORATION	**249**	**5,179**	**366**
QUALCOMM INC.; QUALCOMM INCORPORATED; QUALCOMM, INCORPORATED	**5**	**1,898**	**252**
HUAWEI TECHNOLOGIES CO. LTD.; HUAWEI TECHNOLOGIES CO., LTD; HUAWEI TECHNOLOGIES CO., LTD.; HUAWEI TECHNOLOGIES, CO., LTD.; HUAWEI TECHNOLOGIES., LTD.	**39**	**1,086**	**123**
GOOGLE INC; GOOGLE INC.; GOOGLE, INC.	**42**	**1,276**	**119**
SAMSUNG ELECTRONICS CO., LTD.; SAMSUNG ELECTRONICS; SAMSUNG ELECTRONICS CO., LTD.; SAMSUNG ELECTRONICS CO. LTD.; SAMSUNG ELECTRONICS CO., LTD; SAMSUNG ELECTRONICS CO., LTD.; SAMSUNG ELECTRONICS, CO., LTD.; SAMSUNG ELECTRONICS., LTD.; SAMSUNG-ELECTRONICS CO., LTD	**31**	**4,613**	**110**
AT & T INTELLECTUAL PROPERTY, I, L.P.; AT&T INTELLECTUAL PROPERTY I, L.P.; AT&T INTELLECTUAL PROPERTY I. L.P.; AT&T INTELLECTUAL PROPERTY I., L.P.; AT&T INTELLECTUAL PROPERTY, I, L.P.	**10**	**661**	**105**
SEMICONDUCTOR ENERGY LABORATORY CO., LTD.; SEMICONDUCTOR ENERGY LABORATORY CO., LTD; SEMICONDUCTOR ENERGY LABORATORY CO., LTD.	**2**	**935**	**99**
TELEFONAKTIEBOLAGET L M ERICSSON (PUBL); TELEFONA KTIEBOLAGET LM ERICSSON (PUBL); TELEFONA KTIEBOLAGET LM ERICSSON(PUBL)	**7**	**1,043**	**71**

SOURCE: WebOfScience, Patstat - authors' elaboration

These data suggest that different institutions may have different positions of proximity to the three different basic networks. These different proximities may be another indication of the asymmetric nature of the networks: IBM has inherently greater approximation to layers #2 and #3 than the University of California, which is nearer layer #1.

Since we are investigating a firm-led network (of networks), there are at least two different types of firms populating this network. On the one hand, there are large and established firms, exemplified by IBM, Hoffman-La Roche, GE Electric, and Robert Bosch, that built their innovative and learning capabilities in long-term processes. On the other hand, there are very young firms, exemplified by BioNtech (founded in 2008), Moderna (founded in 2010), Carcassia Ltd. (founded in 2006) and Otosense (founded in 2013) – firms that were already created as well-connected institutions, with links to universities and other firms that generated their own IKLs in 2017. These young firms might suggest a way – a route, if you will - to take advantage of these international layers to grow and innovate.

The set of firms in this network of networks may also suggest that some sectoral systems of innovation may have strong international linkages, shown by their presence in this network of networks. A preliminary search to match the 268 three-layer nodes that are firms with their NACE classification identified 193 firms in our ORBIS database. This preliminary identification shows the leading NACE sectors: 1) NACE 26 "Manufacture of computer, electronic and optical products" – 46 firms matched – 2) NACE 21 – "Manufacture of basic pharmaceutical products and pharmaceutical preparations" – 30 firms matched – 3) NACE 72 – "Scientific research and development" – 19 firms matched (within this sector, there is a subsector NACE 7211 – "Research and experimental development on biotechnology" – 12 firms matched); 4) NACE 20 – "Manufacture of chemicals and chemical products" – 17 firms matched; 5) NACE 28 – "Manufacture of machinery and equipment n.e.c." – 9 firms matched; 6) NACE 58 – "Publishing activities" – 9 firms matched; and 7) NACE 62 – "Computer programming, consultancy and related activities" – 9 firms matched. At least in sectors such as these, the long-term survival and initial and/or persistent growth of firms seems to depend upon a heavy and simultaneous insertion in those three international layers.

4.4 What multiplex network is this?

After describing the key features of these three basic networks (section 3), how they overlap and how they form a network of networks (subsection 5.2), we may evaluate what type of network this is. Specifically, we may try to describe some of its basic properties based on the referenced concept of multiplex networks as presented in the literature reviewed (section 2): multilayered networks that have layers with different sizes and with not all nodes participating in all layers. As we presented in Table 4, there is a small subset of three-layer nodes that overlap and intersect with all networks, an asymmetrical structure that shapes these networks as self-organized systems (see Table 2).

With this structure of three basic layers with multilayer hubs and nodes as presented in Figure 1, we may return to Kivelä et al. (2014, p. 206-207) and check our previous identification of this network as a multiplex network. Kivelä et al. (2014, p. 206) propose a typology of networks that involve different properties: 1) "Is the network node-aligned?", 2) "Is the network layer-disjoint?", 3) "Do all layers have the same number of nodes?", 4) "Are the couplings diagonal?", 5) "Do interlayer couplings consist of layer couplings?", and 6) "Are the interlayer couplings categorical?".[7] A preliminary analysis of this multilayer network shows that 1) it is not node-aligned, 2) it is not layer-disjoint, 3) each layer has a different number of nodes, 4) the couplings are diagonal, 5) the interlayer couplings consist of layer couplings, and 6) the interlayer couplings are not categorical.

Furthermore, in relation to one feature of multiplex networks, "correlated multiplexity", we did not find in our networks the pattern of correlated multiplexity that is "most frequent" (LEE et al., 2014, p. 55): positively correlated multiplexity. As the data presented in Table 5 show, the "node with a large degree in one layer" does not necessarily have "more links in other layers". The different rankings

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[7] Kivelä et al. (2014, p. 271) explains each property.

in Tables 6A and both Tables 6B and 6C show that a large degree in layer #1 does not replicate in layers #2 and #3.

This very tentative and preliminary analysis of the properties of our network shows how peculiar it is – a complicated network, showing a nonsymmetric hierarchical structure.[8] Since each of its component layers shows power-law properties and self-organization properties, we may conclude that their overlapping preserves their self-organized properties.

5. Concluding remarks

The contribution of this paper starts with the choice of the unit of analysis: an international knowledge link (IKL), a knowledge flow that leaves a trace and connects two nodes in different countries. The second contribution is the choice of the nodes for this analysis: institutions – firms, universities or research institutes that host paper authors or patent inventors. These IKLs form layers, depending on the nature of their type: layer #1, a university-led network formed by international collaboration in science; layer #2, a firm-led network formed by international citations of patents; and layer #3, a firm-led network formed by international citations of scientific papers by patents. Our database, prepared with data from 2017, identified 17,240,834 IKLs distributed in these three layers' networks.

The nodes connected by these IKLs are institutions: a definition that enables our analysis to integrate these three different layers, forming three self-organized networks. Following a conjecture that we are investigating multilayered networks, the first step of our investigation is the identification of 307,351 nodes in the three basic layers, the second step the identification of 5,347 two-layer nodes and the third step the mapping of 348 three-layer nodes – thus, a network of networks.

8 As we discussed in a previous paper (RIBEIRO et al., 2017) on how capitalism is a complex system with very peculiar properties, which distinguish it from other complex systems of the physical and biological worlds, consistent with Goldenfeld and Kadanoff (1999). In the realm of networks, it also seems that contemporary economy shows very peculiar structures of networks. A theme that deserves further discussion.

The overlapping of these three networks by these multilayered nodes shapes a very peculiar and asymmetric network.

The size of those international layers rearranges the hierarchy in relation to other levels of innovation systems. With the consolidation of these new layers, local and regional institutions can be domestically connected with institutions that are part of international networks. Small world properties may help isolated local institutions tap into international knowledge flows using only domestic connections. Opportunities such as these are very important for public policies in current times – and this may be a concrete example of how to use the new hierarchy of innovation systems.

These basic layers overlap and entangle – a process of self-organization of international knowledge links. These three basic layers are analyzed in the paper, uncovering an important structural feature of those networks – they are free-scale networks; therefore, they have properties such as hierarchy, small-worldness and self-organization. The power-law properties of the three basic networks – fingerprints of self-organization – suggest that these networks are resilient, and we surmise that the network of networks formed by their overlapping might preserve these self-organized properties. The structural properties of these networks of IKLs justify the conjecture that, in contemporary innovation systems, there are more than simple international connections between different national systems of innovation but rather layers of international knowledge links that form new levels of innovation systems.

These empirical findings help our elaboration on GISs. Their stability, robustness and structured growth indicate that these international layers are elements that show how consistent the international dimension of innovation systems is in contemporary capitalism – national borders have been systematically overcome by this evolution of innovation systems.

GISs are more than the parts analyzed in this paper, but the evidence collected here helps to understand how constitutive institutions shape the whole system. The properties of these basic and entangled networks are important for our evaluation of the current stage of formation of GISs.

The robustness of these layers, their resulting networks of networks and the free-scale properties identified in the analysis support the conjecture of consolidation of these international layers. This consolidation transforms the nature of innovation systems, as these international connections are large and strong enough to represent a structural change in the system. The empirical evidence organized in this paper suggests that we are in the third stage of a typology of the transition towards a global system of innovation (BRITTO; RIBEIRO; ALBUQUERQUE, 2021b, p. 272): the stage that corresponds to the "consolidation of an international layer and a new hierarchy of innovation systems".

We found that each layer follows a free-scale network structure associated with a self-organized system and creates an intrinsic hierarchy. The subnetwork that connects the three layers is also a free-scale network. As it is composed of multiskilled institutions capable of participating in the three types of international flows we analyzed, the hierarchy imposed by this free-scale subnetwork can be understood as a hierarchy inside the hierarchy because the multiskilled institutions are already configured as special institutions. Therefore, we have a quite complex network structure that is most likely not being created by a random process.

Furthermore, we identify elements that interact with each other—institutions through international knowledge flows, hierarchy among those elements, association with self-organized systems, robustness, and specialization—when we analyze the predominant sort of institution that composes each layer and the subnetwork that connects the three layers. Consequently, we have the fundamental aspects necessary to define a system, and in the context of this analysis, that would be an important sign of the progressive consolidation of a Global Innovation System.

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References

ABRAMO, G. Who benefits from a country's scientific research? Journal of Informetrics, United States of America, 12, n. 1, p. 249-258, 2018.

AGHION, P.E; JARAVEL, X. Knowledge spillovers, innovation and growth. Economic Journal, London, v. 125, n. 583, p. 533-573, 2015.

ALBERT R.; BARABÁSI, A.L. Statistical mechanics of complex networks. Reviews of Modern Physics, New York, v. 74, p. 47, 2002. http://dx.doi.org/10.1103/RevModPhys.74.47.

ARROW, K. Economic welfare and the allocation of resources for invention. In: LAMBERTON, D. (Ed). Economics of information and knowledge. Harmondsworth: Penguin Books, 1971. p. 141-159.

BARABÁSI, A.L. Network Science. Cambridge: Cambridge University Press, 2016.

BARABÁSI, A.L.; ALBERT, R. Emergence of scaling in random networks. Science, Washington, v. 286, n. 5439, p. 509-512, 1999. http://dx.doi.org/10.1126/science.286.5439.509.

BATHELT, H.; LI, P. Processes of building cross-border knowledge pipelines. Research Policy, v. 49, n. 3, p. 103928, 2020.

BINZ, C.; TRUFFER, B. Global innovation systems - a conceptual framework for innovation dynamics in transnational contexts. Research Policy, Amsterdam, v. 46, p. 1284-1298, 2017.

BOCCALETTI, S. et al. The structure and dynamics of multilayer networks. Physics Reports, Netherlands, v. 544, n. 1, p. 1-122, 2014.

BORNMANN, L., WAGNER, C., LEYDESDORFF, L. The geography of references in elite articles: Which countries contribute to the archives of knowledge? PLoS ONE, California, v. 13, n. 3, p. e0194805, 2018. https://doi.org/10.1371/journal.pone.0194805.

BRANSTETTER, L. G. Looking for international knowledge spillovers: a review of the literature with suggestions for new approaches. Annales d'Economie et de Statistique, Paris, n. 49/50, p. 517-540, 1998.

BRESCHI, S.; LISSONI, F. (2004) In: Moed, H.; Glänzel, W.; Schmoch, U. (Eds.). Handbook of quantitative science and technology research: the use of publication and patent statistics in studies of S&T systems. Dordrecht: Kluwer Academic Publishers. pp. 613-643.

BRITTO, J. N. P.; RIBEIRO, L. C.; ALBUQUERQUE, E. M. International patent citations and its firm-led network. Estudos Econômicos, São Paulo, v. 51, n. 4, p. 699-732, 2021a.

BRITTO, J. N. P.; RIBEIRO, L. C.; ALBUQUERQUE, E. M. Global systems of innovation: introductory notes on a new layer and a new hierarchy in innovation systems. Innovation and Development, Ibarra, v. 11, n. 2-3, p. 259-279, 2021b.

COE, D.; HELPMAN, E. International R&D spillovers. Economic European Review, Amsterdam, v. 39, n. 5, p. 859-887, 1995.

COHEN, W.; LEVINTHAL, D. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly, Ithaca, v. 35, p. 128-152, 1990.

COHEN, W.; LEVINTHAL, D. Innovation and Learning: the two faces of R&D. Economic Journal, London, v. 99, n. 397, p. 569-596, 1989.

COHEN, W.; NELSON, R.; WALSH, J. Links and impacts: the influence of public R&D on industrial research. Management Science, Catonsville, v. 48, n. 1, p. 1-23, 2002.

DOMENICO, M., et al. Mathematical formulation of multiplex networks. Physical Review E, Maryland, v. 3, n. 4, p. 041022, 2013.

EVENSON, R. E.; KISLEV, Y. Research and productivity in wheat and maize. Journal of Political Economy, Chicago, v. 81, n. 6, p. 1309-1329, 1973.

FREEMAN, C. Technological infrastructure and international competitiveness. Industrial and Corporate Change, Routledge, v. 13, n. 3, pp. 541-569, 1982.

GLÄNZEL, W.; SCHUBERT, A. Domesticity and internationality in co-authorship, references and citations. Scientometrics, Budapest, v. 65, n. 3, p. 323-342, 2005.

GOLDENFELD, N.; KADANOFF, L. P. Simple lessons from complexity. Science, Washington, v. 284, p. 87-89, 1999. http://dx.doi.org/10.1126/science.284.5411.87.

GRILICHES, Z. V. I. Issues assessing the contribution of research and development to productivity growth. The Bell Journal of Economics, Santa Monica, v. 10, n. 1, p. 92-116, 1979.

GRILICHES, Z. V. I. The search for R&D spillovers. The Scandinavian Journal of Economics, Oxford, v. 94, p. S29-S47, 1992.

GROSSMAN, G.; HELPMAN, E. Innovation and growth in the global economy. Cambridge, Mass: The MIT Press, 1991.

HALL, B.; JACQUES, M.; PIERRE, M. Measuring returns to R&D. In: HALL, B.; ROSENBERG, N. (Eds.), Handbook of the economics of innovation. Amsterdam: North Holland, 2010. p. 1033-1082.

HAMMOUD, Z.; KRAMER, F. Multilayer networks: aspects, implementation, and application in biomedicine. Big Data Analytics, London, v. 5, n. 2, p. 1-18, 2020.

JAFFE, A. Demand and supply influences in R&D intensity and productivity growth. The Review of Economics and Statistics, Cambridge, Massachusetts, v. LXX, n. 3, p. 431-437, 1988.

JAFFE, A. Technological opportunity and spillovers of R&D: evidence from firm's patents, profits, and market value. The American Economic Review, Nashville, v. 76, n. 5, p. 984-1001, 1986.

JAFFE, A.; TRAJTENBERG, M. International knowledge flows: evidence from patent citations. Economics of Innovation and New Technology, Oxfordshire, v. 8, p. 105-136, 1999.

JAFFE, A.; TRAJTENBERG, M. Patents, citations, and innovations: a window on the knowledge economy. Cambridge, MA/London: MIT Press, 2002.

JAFFE, A.; TRAJTENBERG, M.; FOGARTY, M. Knowledge spillovers and patent citations: evidence from a survey of inventors. The American Economic Review, Nashville, v. 90, n. 2, p. 215-218, 2000.

JAFFE, A.; TRAJTENBERG, M.; HENDERSON, R. Geographic localization of knowledge spillovers as evidenced by patent citations. The Quarterly Journal of Economics, Cambridge, Massachusetts, v. 108, p. 577-598, 1993.

KIVELÄ, M., et al. Multilayer networks. Journal of Complex Networks, Oxford, v. 2, n. 3, p. 203-271, 2014. http://dx.doi.org/10.1093/comnet/cnu016.

LEE, K.M. et al. Networks of Networks: the last frontier of complexity. Berlin: Springer, 2014.

NARIN, F.; HAMILTON, K. S.; OLIVASTRO, D. The increasing linkage between U.S. technology and public science. Research Policy, Amsterdam, v. 26, n. 3, p. 317-330, 1997.

NATURE. Nature Index. Available from: <http://www.natureindex.com/>. Access in: 2 Dec. 2021).

NELSON, R. R. (Ed.). National innovation systems: a comparative analysis. New York: Oxford University, 1993.

NELSON, R. R. The simple economics of basic research. Journal of Political Economy, Chicago, v. 67, n. 3, p. 297-306, 1959.

NEWMAN, M. J. Networks: an introduction. Oxford: Oxford University Press, 2010.

RIBEIRO, L. C. et al. A methodology for unveiling global innovation networks: patent citations as clues to cross border knowledge flows. Scientometrics, Cham, v. 101, p. 61-83, 2014.

RIBEIRO, L. C. et al. A network model for the complex behavior of the rate of profit: exploring a simulation model with overlapping technological revolutions. Structural Change and Economic Dynamics, Netherlands, v. 43. pp. 51-61, 2017.

RIBEIRO, L. C. et al. Growth patterns of the network of international collaboration in science. Scientometrics, Cham, v. 114, p. 159-179, 2018.

RIBEIRO, L. C.; BRITTO, J. N. P.; ALBUQUERQUE, E. M. Networks of international knowledge links: new layers in innovation systems. Available from: <https://econpapers.repec.org/paper/cdptexdis/td640.htm>. Access in: 22 Jan. 2022.

SOETE, L.; VERSPAGEN, B.; WEEL, B. Systems of innovation. In: HALL, B.; ROSENBERG, N. (Eds.). Handbook of the economics of innovation. Amsterdam: North Holland, 2010. p. 1159-1180.

STRANDBURG, K. et al. Patent citation networks revisited: signs of a twenty-first century change? North Carolina Law Review, Chapel Hill, v. 87, p. 1657-1698, 2009.

TEECE, D. Technology transfer by multinational firms: the resource cost of transferring technological know-how. Economic Journal, London, v. 8, n. 346, p. 242-261, 1977.

WAGNER, C. S.; LEYDESDORFF, L. Network structure, self-organization, and the growth of international collaboration in science. Research Policy, Amsterdam, v. 34, n. 10, p. 1608-1618, 2005. http://dx.doi.org/10.1016/j.respol.2005.08.002.

WASSERMAN, S.; FAUST, K. Social network analysis: methods and applications. Cambridge: Cambridge University Press, 1994.

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