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Publishing Patterns in BRIC Countries: A Network Analysis

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Abstract: How similar are the publishing patterns of among Brazil, Russia, India and China (BRIC countries) in comparison with other countries? This is a question that we addressed by using networks as a tool to analyze the structure of similarities and disparities between countries. We analyzed the number of publications from 2006 to 2015 that are reported by SCImago Journal and Country Rank. With this information, we created a network in order to find the closest countries to BRIC ones, and also to find communities of similar countries favoring data analysis. We found that Brazil, China and Russia are not that close to the core cluster of countries that are more diversified. In opposition, India is closer to a community of countries that are more diverse in terms of publishing patterns. Furthermore, we found that, for different network topologies, Brazil acts as a bridge to connect developing countries and that Russia practices patterns that tend to isolate it from most of the countries.

Keywords: BRIC; publishing patters; networks

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1. Introduction

Brazil, Russia, India and China, the BRIC countries, represent growing economies in different regions of the planet [1]. These countries tend to lead their regions because of their characteristics of high levels of population density and growing-emerging economies. BRIC countries have improved their higher educational systems (see for example [2]) and are improving national policies to compete in the research arena.

It is possible to analyze how good countries are in creating new knowledge by analyzing their research output [3–6]. Usually these studies cover the impact of countries in terms of numbers and indicators of publications and citations. Our approach was quite different. We placed at the center of our analysis the *patterns* of publishing and used them to create a network of similarities between countries.

We also made the distinction between production (number of papers published) and performance or success (i.e., number of citations acquired). Although, both aspects are related to research activity, they are expressions of different capacities and can be analyzed separately. In this article, we are interested in *patterns of production* and not in *patterns of performance*, mainly because production shows how capable countries are (including the institutions and the people working there) to create new knowledge in different areas of science. On the other hand, success or performance is aimed at studying how that knowledge is used in the scientific community (see for example [6]).

In this article, we characterize the publishing patterns of countries to create a network of similarities that allows us to visualize and understand how similar/dissimilar the countries are.

In particular, we analyze where the BRIC countries are located in this landscape, and we also find the closest countries to each BRIC country.

Network visualizations have been demonstrated as powerful tools to analyze complex phenomena [7], and their application to the analysis of research in general has been increasing during the last decade even though it has been used for almost half a century (see for example a pioneer co-citation network analysis by Henry Small [8]). Related to the development of research activity, networks have been applied to analyze: citation patterns [9–11], co-authorship/collaboration [12,13], and research policy [14]. Within these types of network-based analyses, those oriented toward understanding countries have focused on the analysis of patterns of collaboration, mainly as projection of co-authorship networks, as for example [15–17].

Regarding the specific analysis of research production in BRIC countries, a few studies have been proposed. Kumar and Asheulova analyzed the research output of BRIC countries by applying statistical methods to the data in Scopus [18]. Yang et al. [19] analyzed the structure of disciplines in BRIC countries, comparing them to the ones included in the G7. The latter study used information from the database of the Science Citation Index of Web of Science (WoS). The authors assigned each paper to the country of the correspondence author; in other words, one paper to one country. The disciplines were the ones defined by the Journal Citation Reports (JCR) from Thomson Reuters. The authors concluded that BRIC countries are mainly focused on physics, chemistry, mathematics and some areas of engineering. Our study differentiates from the previous one, first in the data (we used SCImago), and also in the classification and the method used to find similarities between countries.

The rest of this article is organized as follows: in Section 2, we detail the data and methods used; in Section 3, we present our core results; finally, in Section 4 we discuss and conclude our findings.

2. Data and Methods

To analyze the publishing patterns of countries, we gathered information from SCImago [20]. This site is based on the Scopus database and presents information of the number of citable documents per country in each category. Categories are defined according to the Scopus classification of science. This classification includes 27 main areas divided into 308 subcategories. We chose SCImago for three main reasons: first, it includes all the spectrum of research (Sciences, Social Sciences and Arts-Humanities) in contrast with other dedicated databases such as PubMed or DBLP; second, SCImago is public, that is to say, users do not need to pay for a subscription to access the site—and the data, which is a particularly interesting situation for institutions and people (certainly in BRIC countries) that would like to replicate, validate, or contrast our results; finally, SCImago includes a wide number of journals, in contrast with Web of Science®, which is limited in quantity of journals but also biased in language, since most of the journals indexed are written in English (see for example [21] for a discussion on this bias). We claim that a better signal of the production in science of BRIC countries (most of them non-Anglophone) is represented by the information published on SCImago rather than, for instance, Web of Science®.

In SCImago, each journal may be assigned to one or more categories of science. In addition, each paper is assigned—completely—to the countries that correspond to the affiliations of the authors. This assignation increases the number of authorships for each country. We will refer to this number as value of authorships. We queried information for all available countries from 2006 to 2015. Accordingly, our resulting dataset comprises 224 countries, 10 years, and 308 categories. Even though SCImago incudes information since 1996, we chose this time interval because China, one of the BRIC countries, experienced a surge in research activity starting 2006 [22,23]. Furthermore, as we wanted the freshest information available, we carried out research up until the year 2015. The information was analyzed during the first week of June 2016.

To handle the data, we created a matrix A of countries and categories. We aggregated the data in the whole interval using the average over the ten years. Then, each entry A_{ij} of the matrix A contains the average of values of authorships of a given country *i* in the category of science *j* in the interval 2006–2015.

Figure 1a presents a visualization of this matrix and Figure 1b shows the share or relative production of each category inside the country. For visualization purposes, matrices in Figure 1a,b are transposed and they show only the top 30 countries ranked (from left to right) by the values of authorships and the top 50 categories. It must be noted that both China and India are ranked in the top 10 countries, while Brazil and Russia are ranked in the top 15; this fact shows that all the BRIC countries are important contributors in the global scene of science.

In order to identify the publishing patterns of countries, we needed to find the relative importance (abundance) of each category of science within each country. We characterized the pattern of a country as a vector V in which its features correspond to the "share" of each category in that country. These values are comprised in a "share" matrix denoted by S (see Figure 1b) where each entry S_{ij} of S is computed using the following Equation:

$$\boldsymbol{S_{ij}} = \frac{\boldsymbol{A_{ij}}}{\sum_j \boldsymbol{A_{ij}}} \tag{1}$$

Each vector $\acute{V}_i$ that characterizes the publishing patterns of country i, corresponds to a row in S. Then, we used these vectors to find similarities among countries and centrality measures for each BRIC country. Figure 1b presents a visualization of these vectors for the top 30 countries and for the top 50 categories. We can also note the differences between matrices in Figure 1a,b, where the latter shows fewer differences among countries, and the former shows publishing patterns (behavior in publishing) for each country.

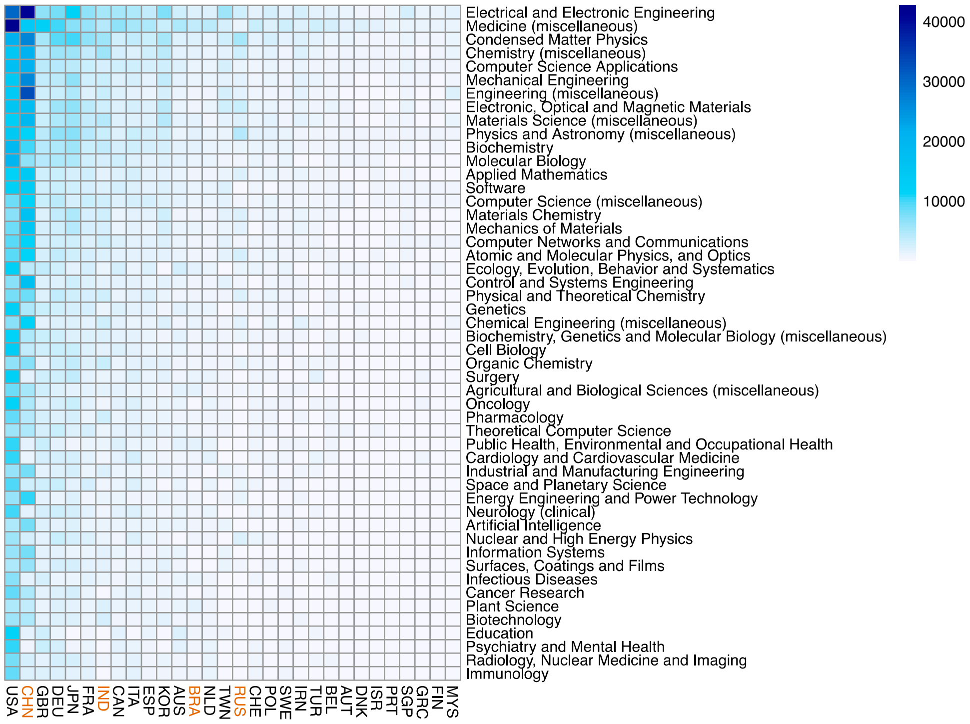
We computed the similarity using the cosine similarity function. Cosine similarity $\varnothing_{cc\prime}$ between countries c and c' is calculated as follows:

$$\varnothing_{\boldsymbol{cc\prime}} = \frac{\boldsymbol{V_c} \cdot \boldsymbol{V_{c\prime}}}{|\boldsymbol{V_c}|\,|\boldsymbol{V_{c\prime}}|} \tag{2}$$

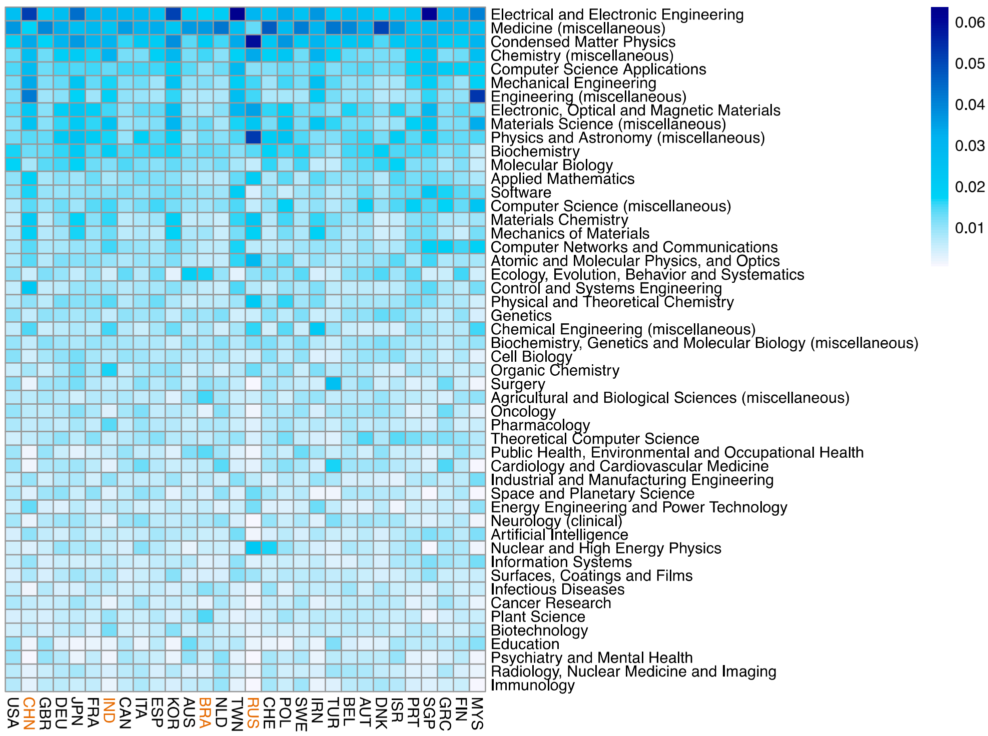
where the numerator computes the dot product or scalar product between vectors of countries and the denominator computes the product of norms. The resulting similarity matrix $\varnothing$ is symmetric.

To visualize the similarities between countries, we also created a network (see Figure 2) that allows us to have the "big picture" about the landscape of countries if clustered by similarities in publishing patterns. To detect communities we applied the algorithm Infomap [24], which is an algorithm that uses random walks to generate sequences of jumps from one node to another, and then it applies Huffman codes to detect patterns of jumps that are repeated most frequently, which are finally defined as communities. The algorithm of Huffman, also known as Huffman Coding, optimizes the number of digits needed to code (name) each node by assigning more digits to less frequent nodes. Even though other algorithms that can detect communities in a network were available, we preferred the Infomap algorithm because it is considered one of the most powerful methods, and it is not limited to particular networks as in the case of the Generalized Louvine method [25], another widely used algorithm, but oriented toward large networks.

For visualization purposes, we filtered links of the network below a threshold (0.895) to maintain only the strongest links. It must be noted that the community structure (and the visualization) are highly dependent on this parameter. A low value (more links) will produce a tiny structure of communities (1 or 2), while a high value (fewer links) will produce more clear communities but a lot of connected components and isolated nodes. As a consequence, we looked for this threshold with the criteria of searching a value—with three decimal digits—small enough to get each BRIC country in a different community, since we want to highlight the similarities and differences among these four countries.



(**a**)



(**b**)

Figure 1. Matrix heat map visualization for top 30 countries (from left to right). Countries are ranked—from left to right—by the average values of authorships in the time interval between 2006 and 2015. Rows represent categories of science and columns represent countries. (**a**) Matrix where each entry represents the average values of authorships; (**b**) Matrix where each entry represents the "share" of each category in each country.

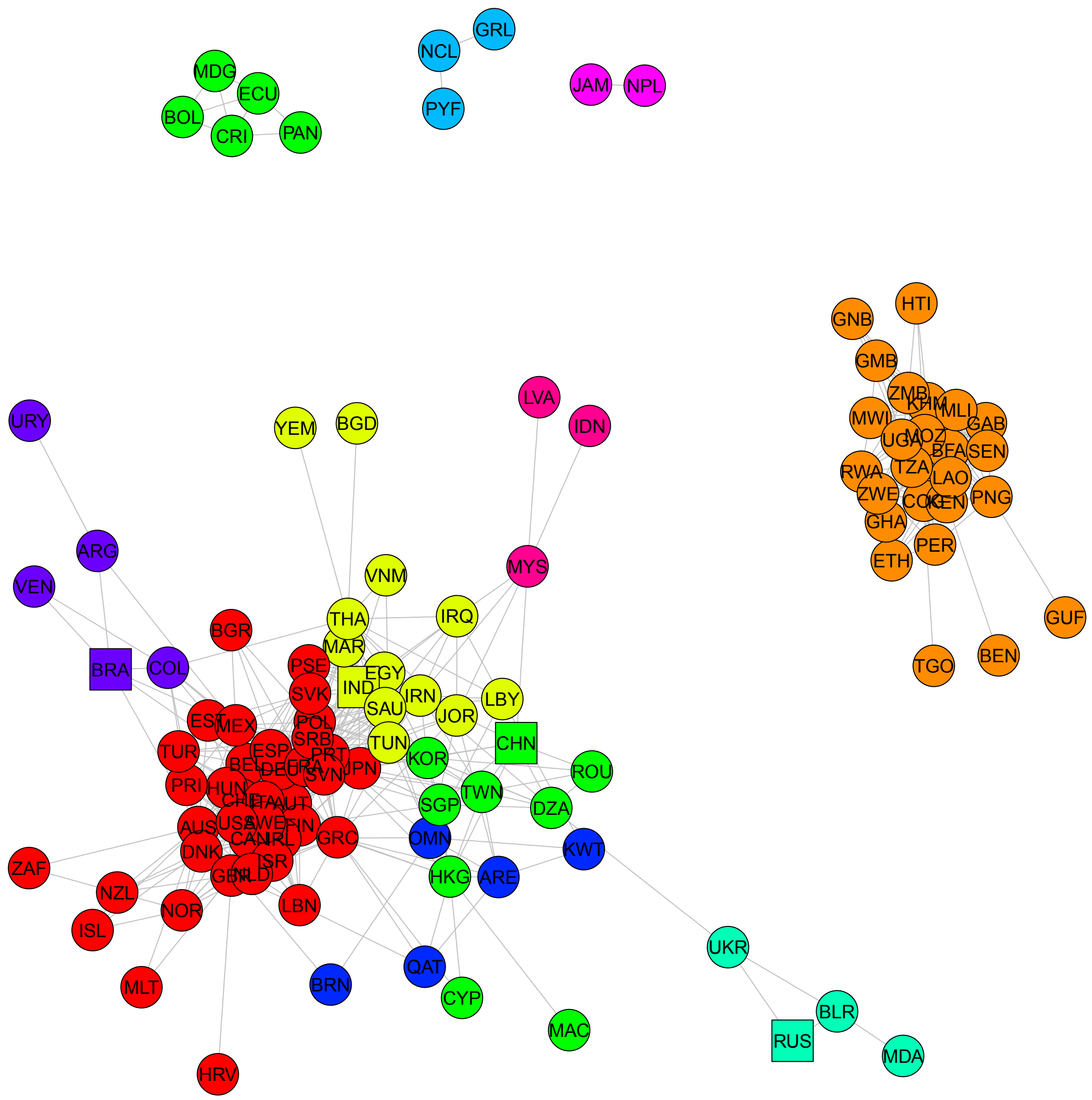


Figure 2. Network visualization of similarities between 111 countries according to publishing patterns. Similarity was computed using cosine similarity function. Links below 0.895 were eliminated just like isolated countries. Colors were assigned according to communities automatically detected by the algorithm *Infomap* [24]. Nodes corresponding to BRIC countries are highlighted with squares. Country codes are defined according to the standard ISO 3166-1 alpha-3 codes. A list of communities and their corresponding countries has been included in Appendix A.

3. Results

3.1. Communities in the Network of Countries are Close to Represent Regions

By analyzing Figure 2 and the table in Appendix A, we observe that communities detected by the algorithm *Infomap* [24] correlate with regions and/or level of development. For example, the central and highly connected cluster (red community) is composed mainly of developed countries such as United States, Germany, France, or Japan. On the contrary, we find isolated clusters of developing countries like the African countries (orange community) or some Latin American countries such as Ecuador and Bolivia (light green community).

The biggest connected component of the network includes six additional communities beside the red one. We note that in the biggest connected component the red community plays a central role, while, for instance, communities colored aqua, violet, and tomato are in the periphery.

BRIC countries—all of them—belong to different communities (as anticipated) and they are part of the biggest connected component.

3.2. India Is the Most Connected Country of BRIC Countries

While India belongs to a community with a high level of connection to the central community, Brazil and China, on the other hand, are located in communities with few strong links with other communities. Furthermore, Russia is not well linked in a community, having poor levels of connection and being far from the central community.

We can argue these statements by looking at the centrality measures (Table 1) for each BRIC country in the network. Here, India (rank 36) is the most connected country if measured by the weighted degree as proxy of connectivity. Also in this rank, China, Brazil, and Russia are in positions 59, 73, and 90 respectively. Countries of the red community (the most connected) are in the top of this list.

Table 1. Ranking of centrality values for countries. Measures of centrality: Weighted degree (Deg.), betweenness centrality (Bet) and closeness centrality. After position 46 some countries are omitted in order to present all the values for BRIC countries. Total countries in the database: 111.

R	Cnt.	Deg.	Cnt.	Bet.	Cnt.	Closeness	R	Cnt.	Deg.	Cnt.	Bet.	Cnt.	Closeness
1	FRA	35.3831	TUN	309	PRT	0.000247732	**28**	TZA	17.8817	OMN	42	**IND**	**0.00024582**
2	PRT	34.0925	DZA	289	FRA	0.000247601	**29**	ISR	17.8782	CAN	39	ISR	0.000245793
3	ESP	32.7788	AUS	284	ESP	0.000247344	**30**	MOZ	17.794	EGY	34	NLD	0.000245752
4	BEL	29.2233	GRC	255	GRC	0.000247037	**31**	UGA	17.7334	COL	33	TWN	0.000245707
5	DEU	29.1146	THA	244	DEU	0.000247007	**32**	COG	17.7022	KOR	31	EGY	0.000245692
6	FIN	27.9019	MEX	233	SVN	0.000246942	**33**	KEN	17.6852	KEN	27	JOR	0.000245677
7	AUS	27.7945	PRT	221	TUN	0.000246895	**34**	KHM	16.8457	PNG	27	SVK	0.000245662
8	GRC	26.687	UKR	219	FIN	0.000246881	**35**	KOR	16.652	COG	25	DNK	0.000245624
9	SVN	25.6122	FRA	196	BEL	0.000246843	**36**	**IND**	15.6788	**CHN**	**25**	SGP	0.000245547
10	AUT	25.4961	IRN	183	AUT	0.000246635	**37**	ZMB	14.9879	SAU	22	HKG	0.000245535
11	CAN	25.4855	MYS	151	POL	0.000246623	**38**	THA	14.5088	UGA	22	PRI	0.000245517
12	SWE	25.4594	GBR	136	AUS	0.00024659	**39**	BFA	14.0277	POL	19	PSE	0.000245457
13	USA	24.514	SVN	128	JPN	0.000246559	**40**	LAO	13.773	SVK	18	MAR	0.000245145
14	ITA	24.4791	JOR	112	MEX	0.000246551	**41**	PRI	13.6925	KHM	17	EST	0.00024514
15	GBR	24.4533	JPN	107	IRN	0.00024653	**42**	MLI	12.9829	PRI	17	COL	0.000245035
16	POL	24.0606	HKG	104	CAN	0.000246418	**43**	EGY	12.8684	DEU	16	OMN	0.000244908
17	MEX	23.8172	FIN	95	SRB	0.000246386	**44**	PNG	11.9105	USA	16	LBN	0.000244744
18	JPN	22.0594	SRB	86	SWE	0.00024637	**45**	SVK	11.8762	AUT	15	ARE	0.000244704
19	IRL	21.6832	**BRA**	84	USA	0.000246314	**46**	SEN	11.1559	LBY	15	**CHN**	0.000244541
20	CHE	21.6348	ARG	75	ITA	0.000246303	...	...	...	...	...	...	...
21	HUN	21.2888	BLR	75	GBR	0.000246166	**50**	LBN	10.9595	NLD	9	**BRA**	**0.000244176**
22	TUN	20.9383	TWN	64	SAU	0.000246139	**59**	**CHN**	8.3141	SWE	6	NZL	0.000243198
23	IRN	20.2583	ARE	62	CHE	0.00024613	**67**	COL	7.2478	**IND**	3	YEM	0.000241946
24	DNK	19.6071	DNK	60	IRL	0.000246092	**73**	**BRA**	5.4234	MWI	2	LVA	0.000239513
25	NLD	18.8552	SGP	57	KOR	0.000246026	**76**	CRI	3.6705	NCL	1	**RUS**	0.000236782
26	SAU	18.4491	ESP	54	HUN	0.000245978	**90**	**RUS**	1.858	HRV	0	SEN	0.00010228
27	SRB	18.1784	BEL	53	THA	0.000245965	**105**	BEN	0.9042	**RUS**	0	MDG	8.34×10^{-5}

3.3. Brazil Connects Communities

If we analyze the network of the strongest similarities in Figure 2, we can find that Brazil connects its community to other communities. Brazil connects its community (violet) mainly with the red community. The case of China and India is quite different, since the countries of the latter (yellow community, which is composed mainly of Middle Eastern countries such as Saudi Arabia or Iran) do not depend on India to connect with other communities. This is verified by the ranking and values of betweenness centrality in Table 1. While Brazil has a high value (rank 19), China and India occupy positions 36 and 67, respectively. Finally, in this topology, Russia is not needed for any country to connect with others.

It must be noted that the previous analysis was performed on the visualization and network topology presented in Figure 2. Observations can be different if the threshold to delete weak links changes. For this reason, in further sections we also present a quantitative analysis on the fully connected matrix and other threshold values, and we will show how these measures can be different (see Sections 3.5 and 3.6).

3.4. Dominant Areas Per Community

We also analyzed the other way around, that is, what the production is like in particular fields of science inside each community. We do this by averaging the countries' production in each field, for all the countries inside each community. Table 2 resumes the dominant scientific fields for the communities that host a BRIC country. By doing this, we can analyze which are the areas that generate these (dis)similarities. A detailed version of this table is available in Appendix B, which includes the mean values and all the results for each community.

Table 2. Ranking of top 10 ranked areas for each community. We considered the average value of production inside the community for each area. Details of values and data on the other communities are presented in Appendix B.

R	Community 3: Yellow (Including India)	Community 4: Light Green (Including China)
1	Electrical and Electronic Engineering	Electrical and Electronic Engineering
2	Chemistry (miscellaneous)	Engineering (miscellaneous)
3	Condensed Matter Physics	Condensed Matter Physics
4	Medicine (miscellaneous)	Mechanical Engineering
5	Materials Science (miscellaneous)	Chemistry (miscellaneous)
6	Engineering (miscellaneous)	Computer Science Applications
7	Mechanical Engineering	Materials Science (miscellaneous)
8	Biochemistry	Electronic, Optical and Magnetic Materials
9	Chemical Engineering (miscellaneous)	Materials Chemistry
10	Materials Chemistry	Medicine (miscellaneous)
R	**Community 6: Aqua (Including Russia)**	**Community 9: Violet (Including Brazil)**
1	Condensed Matter Physics	Medicine (miscellaneous)
2	Physics and Astronomy (miscellaneous)	Animal Science and Zoology
3	Electronic, Optical and Magnetic Materials	Condensed Matter Physics
4	Electrical and Electronic Engineering	Ecology, Evolution, Behavior and Systematics
5	Chemistry (miscellaneous)	Agronomy and Crop Science
6	Atomic and Molecular Physics, and Optics	Electrical and Electronic Engineering
7	Materials Science (miscellaneous)	Chemistry (miscellaneous)
8	Materials Chemistry	Plant Science
9	Nuclear and High Energy Physics	Agricultural and Biological Sciences (miscellaneous)
10	Mechanics of Materials	Biochemistry

We can observe how India and China's communities are more oriented toward technological areas, such as electronic and mechanical engineering, while Russia's community is mainly focused on physics-oriented fields. On the other hand, in Brazil's community, countries participate mainly (at least five of ten categories) in agricultural or animal sciences.

By looking deeply, we can also observe that the resulting patterns are not only due to the areas in which countries publish, but also to the number of papers produced in each field. This can be noted by analyzing the detailed information included in Appendix B, where we might see, for instance, that the community of leading countries has values above 1200 papers on average in each top-ranked area while developing communities publish below 100 papers on average in top-ranked areas.

3.5. Analysis of Similar Countries to BRIC Countries

By looking at the (fully connected) similarity matrix $\varnothing$, we can find which countries are more similar to BRIC countries. In Table 3 we show the top 10 similar countries for each BRIC country. If we only analyze links greater than 0.9, we might note that China maintains strong similarities mainly with Asian countries. In the case of Russia, it only has strong similarities with two former countries of the Soviet Union. The case of Brazil is quite similar to the case of Russia, since Brazil only has strong similarities with four Latin American countries.

On the other hand, India is quite different. India has strong similarities with the countries in the top 10 ranking. Those countries are mainly European and three of them are part of the G7. When we extend this analysis to the full top 10 list, we note that again China has similarities mainly with Asian countries like South Korea, Singapore, or Japan. Something similar occurs in the case of Brazil, where we may note that 5 of the 10 most similar countries are Latin American countries. In the case of Russia, 9 of the 10 countries are from Europe and at least three of them are former Soviet Union countries. Russia is a special case in which the similarities with other countries tend to be low. Finally, we can also observe that among BRIC countries, only India is in the top 10 list of China and there are no other strong similarities between BRIC countries.

3.6. Centrality Measures for BRIC Countries

As we mentioned previously, the selection of a threshold to delete weak links produces different results in the topology of the network. In our previous analysis we chose this value with the intention of producing a meaningful community structure to analyze BRIC countries based on strong links. However, it is necessary to provide more information about the variations of the network for different threshold values. In the current section, the threshold will not be oriented toward the community structure but toward the distribution of similarities. We also wanted to analyze how the characteristics of BRIC countries (as nodes of the network) change with these variations.

In order to define different values for the threshold, we looked at the distribution of similarities of the fully connected network (see Figure 3) and then we computed the deciles of the distribution. We used these 9 values (excluding the minimum and the maximum) to create 9 different networks and to analyze the values of: degree centrality (weighted degree), betweenness centrality, and closeness centrality for each node, in particular for each BRIC country.

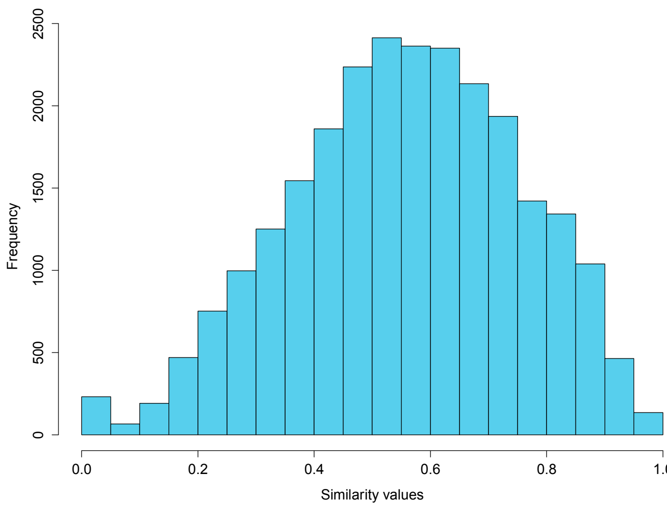


Figure 3. Histogram of values of similarities for the fully connected network.

Table 4 resumes the rank occupied for each BRIC country (see a detailed table in Appendix C) for 10 different variations in the threshold, 9 values from the deciles of the distribution of similarities, and 1 additional value corresponding to the filter used to create the community structure in Figure 2.

Regarding centrality proxied by degree, the low level of centrality (position in ranking, see first block in Table 4) is constant for Russia, which occupies the last position of the four BRIC countries along the 10 variations of the threshold. The case of Brazil is interesting, as it is a central country until the eighth value (D8) after which its ranking starts decreasing. This can be explained in the sense that strong connectivity of Brazil is certainly produced with countries that have weak connections, and these countries tend to disappear from the network once the threshold is high as in the ninth and tenth values. In these two final networks, India and China increase their position.

Table 3. Top 10 similar countries for each BRIC country. Regions (Reg): North America (NA), Latin America (LA), Africa (AF), Asia (AS), Oceania (OC) and Europe (EU).

	Brazil			Russia			India			China		
R	**Country**	**Sim**	**Reg**	**Country**	**Sim**	**Reg**	**Country**	**Sim**	**Reg**	**Country**	**Sim**	**Reg**
1	Colombia	0.912	LA	Ukraine	0.933	EU	Egypt	0.966	AF	Taiwan	0.946	AS
2	Venezuela	0.909	LA	Belarus	0.925	EU	Iran	0.953	AS	Algeria	0.936	AF
3	Mexico	0.906	LA	Bulgaria	0.891	EU	Saudi Arabia	0.951	AS	Iran	0.935	AS
4	Argentina	0.904	LA	Poland	0.878	EU	South Korea	0.931	AS	Rep. of Korea	0.935	AS
5	Australia	0.897	OC	Moldova	0.866	EU	Palestine	0.930	AS	Singapore	0.924	AS
6	Belgium	0.896	EU	France	0.854	EU	Poland	0.926	EU	Hong Kong	0.915	AS
7	Spain	0.895	EU	Romania	0.853	EU	Portugal	0.923	EU	Malaysia	0.911	AS
8	Puerto Rico	0.891	LA	Japan	0.849	AS	Japan	0.923	AS	Japan	0.910	AS
9	Denmark	0.890	EU	Germany	0.845	EU	Iraq	0.920	AS	Romania	0.903	EU
10	Hungary	0.890	EU	Slovakia	0.844	EU	Slovenia	0.919	EU	**India**	**0.893**	**AS**

Table 4. Ranking of BRIC countries for centrality measures for ten different thresholds used to filter weak links. Nine filters correspond to deciles of the distribution of similarities. The last column (Fi) includes the filter used to create the network in Figure 2. See Appendix C for detailed values.

D1 = 0.292		D2 = 0.386		D3 = 0.454		D4 = 0.511		D5 = 0.562		D6 = 0.616		D7 = 0.672		D8 = 0.732		D9 = 0.817		Fi = 0.895	
Weighted Degree or Degree Centrality																			
9	BR	**7**	BR	**7**	BR	**6**	BR	**4**	BR	**7**	BR	**5**	BR	**19**	BR	**30**	IN	**36**	IN
104	IN	**111**	IN	**113**	IN	**110**	IN	**103**	IN	**82**	IN	**59**	IN	**42**	IN	**34**	BR	**59**	CH
170	CH	**172**	CH	**166**	CH	**161**	CH	**139**	CH	**129**	CH	**96**	CH	**72**	CH	**60**	CH	**73**	BR
189	RU	**184**	RU	**178**	RU	**172**	RU	**161**	RU	**144**	RU	**135**	RU	**111**	RU	**103**	RU	**90**	RU
Betweenness Centrality																			
33	RU	**122**	CH	**118**	IN	**145**	BR	**66**	BR	**78**	BR	**25**	BR	**31**	BR	**5**	BR	**19**	BR
56	CH	**143**	IN	**155**	BR	**185**	CH	**140**	CH	**147**	CH	**128**	CH	**79**	RU	**9**	RU	**36**	CH
140	IN	**163**	RU	**199**	RU	**188**	IN	**189**	RU	**159**	RU	**139**	RU	**86**	IN	**40**	CH	**67**	IN
173	BR	**202**	BR	**208**	CH	**197**	RU	**200**	IN	**191**	IN	**147**	IN	**117**	CH	**106**	IN	**105**	RU
Closeness Centrality																			
85	IN	**171**	IN	**126**	BR	**61**	BR	**20**	BR	**18**	BR	**5**	BR	**9**	BR	**2**	BR	**28**	IN
114	CH	**197**	BR	**181**	IN	**166**	IN	**142**	IN	**126**	IN	**76**	IN	**66**	IN	**50**	IN	**46**	CH
129	RU	**209**	CH	**200**	CH	**193**	RU	**170**	CH	**162**	RU	**137**	CH	**122**	CH	**72**	CH	**50**	BR
209	BR	**210**	RU	**201**	RU	**203**	CH	**177**	RU	**165**	CH	**153**	RU	**142**	RU	**112**	RU	**76**	RU

Subsequently, we analyzed intermediation by looking at betweenness centrality (see second block in Table 4); that is, the number of shortest paths—between all countries—that pass for a chosen country. In the case of Brazil, it is clear that its role as an intermediate country is greater than other BRIC countries, since it leads the ranking starting at the fourth threshold. Furthermore, starting at the seventh value, Brazil occupies high positions in the global ranking, such as 31, 25, 19, or 5. We cannot extend this observation to other BRIC countries since their values of betweenness centrality are highly sensitive to the variations of the filter.

Finally, if we measure how close each BRIC country is from all the other countries in the network (closeness centrality. See third block in Table 4), we find in the case of Russia that except for 2 of the 10 filters, it is always in last position of the ranking of BRIC countries. Furthermore, Russia is far from the global network of countries since it usually (except for 1 filter) occupies positions below the 110th position.

4. Discussion

In a first observation, we have found that Brazil, Russia, and China tend to be similar to those countries that share the same language or belong to the same region. This is not the case with India, which is a country with closer similarities to countries that are more diverse in their publishing patterns; most of these countries are developed countries.

We claim that our findings can be explained by international collaboration and/or particular interests/capacities of each country. In the first case, international collaboration is usually a consequence (a measure) of co-authorship between authors from different countries, for example in the SCImago database. For instance, it is more likely that Brazilian scientists collaborate with Argentinian or Mexican scholars, and they certainly share similar research interests and, consequentially, publishing patterns. On the other hand, if co-authorship (collaboration) is not the cause that produces similarities between countries, those similarities could be due to interests or capacities of countries in publishing in the same areas of science with similar levels of production, as we presented in Section 3.4. This analysis (the *causes* of similarities between countries), however, would demand further discussion—outside the scope of this study—which should include the control of the effect of co-authorship on the analysis of the interests or publishing capacities of countries.

Our results also show that even when China and Russia are top-ranked contributors of scientific literature, those countries (and their communities) are still not able to maintain high similarities with countries in the central cluster. Conversely, India is well connected to this central cluster just like other countries of the same community from the Eastern world. This could be explained by the diversification across science of countries in the central cluster. These countries tend to diversify to most of the areas of science, while China and especially Russia seem to be more specialized in categories related to physics and astronomy (see Figure 1 and Appendix B). See [26] for an analysis of how countries diversify over a network of categories of science.

In the same line, we have shown that Russia is the most isolated country of the four BRIC countries, this claim is persistent not only for the network that we created with the aim of detecting communities, but for different topologies of the network (see degree and closeness centrality in Table 4).

Finally, we have also shown that Brazil is an important bridge between the world and countries in Brazil's community, which are mainly developing countries. This condition is also stable for different topologies of the network. However, this is not the case for China, which is an important bridge but only when high values of the threshold are selected to create the network of similarities.

Supplementary Materials: The following resources are available online at http://www.mdpi.com/2304-6775/4/3/20/s1, Figure S1: Network of Countries in High Resolution.

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Appendix A. Assignment of Countries to Communities

Community 1: Red
Austria, Australia, Belgium, Bulgaria, Canada, Switzerland, Germany, Denmark, Estonia, Spain, Finland, France, United Kingdom, Greece, Croatia, Hungary, Ireland, Israel, Iceland, Italy, Japan, Lebanon, Malta, Mexico, Netherlands, Norway, New Zealand, Poland, Puerto Rico, State of Palestine, Portugal, Serbia, Sweden, Slovenia, Slovakia, Turkey, USA, South Africa
Community 2: Orange
Burkina Faso, Benin, Congo, Fmr Ethiopia | Ethiopia, Gabon, French Guiana, Ghana, Gambia, Guinea-Bissau, Haiti, Kenya, Cambodia, Lao People's Dem. Rep. Mali, Malawi, Mozambique, Peru, Papua New Guinea, Rwanda, Senegal, Togo, United Rep. of Tanzania, Uganda, Zambia, Zimbabwe
Community 3: Yellow
Bangladesh, Egypt, **India**, Iraq, Iran, Jordan, Libya, Morocco, Saudi Arabia, Thailand, Tunisia, Viet Nam, Yemen
Community 4: Green light
China, Cyprus, Algeria, **China**, Hong Kong SAR, Rep. of Korea, China, Macao SAR, Romania, Singapore, Taiwan
Community 5: Green
Bolivia, Costa Rica, Ecuador, Madagascar, Panama
Community 6: Aqua
Belarus, Rep. of Moldova, **Russia**, Ukraine
Community 7: Sky blue
Greenland, New Caledonia, French Polynesia
Community 8: Blue
United Arab Emirates, Brunei Darussalam, Kuwait, Oman, Qatar
Community 9: Violet
Argentina, **Brazil**, Colombia, Uruguay, Venezuela
Community 10: Fuchsia
Jamaica, Nepal
Community 11: Tomato
Indonesia, Latvia, Malaysia

Appendix B. Top 10 Scientific Areas per Community (Average Over Countries)

R	Community 1: Red		Community 7: Sky blue	
1	Medicine (miscellaneous)	3510	Aquatic Science	26
2	Electrical and Electronic Engineering	2673	Ecology, Evolution, Behavior and Systematics	25
3	Condensed Matter Physics	2193	Ecology	12
4	Biochemistry	1549	Oceanography	11
5	Physics and Astronomy (miscellaneous)	1540	Medicine (miscellaneous)	8
6	Chemistry (miscellaneous)	1470	Pediatrics	7
7	Molecular Biology	1456	Agricultural and Biological Sciences (miscellaneous)	7
8	Computer Science Applications	1452	Plant Science	6
9	Electronic, Optical and Magnetic Materials	1439	Biochemistry, Genetics and Molecular Biology (miscellaneous)	5
10	Mechanical Engineering	1288	Infectious Diseases	5
R	**Community 2: Orange**		**Community 8: Blue**	
1	Infectious Diseases	69	Medicine (miscellaneous)	97
2	Medicine (miscellaneous)	58	Electrical and Electronic Engineering	96
3	Public Health, Environmental and Occupational Health	40	Computer Science Applications	61
4	Parasitology	29	Computer Networks and Communications	55
5	Ecology, Evolution, Behavior and Systematics	24	Engineering (miscellaneous)	49
6	Agronomy and Crop Science	24	Mechanical Engineering	48
7	Agricultural and Biological Sciences (miscellaneous)	21	Energy Engineering and Power Technology	43
8	Biochemistry, Genetics and Molecular Biology (miscellaneous)	21	Chemical Engineering (miscellaneous)	41
9	Animal Science and Zoology	20	Condensed Matter Physics	41
10	Ecology	14	Software	41
R	**Community 3: Yellow (included India)**		**Community 9: Violet (included Brazil)**	
1	Electrical and Electronic Engineering	857	Medicine (miscellaneous)	1020
2	Chemistry (miscellaneous)	799	Animal Science and Zoology	669
3	Condensed Matter Physics	794	Condensed Matter Physics	579
4	Medicine (miscellaneous)	743	Ecology, Evolution, Behavior and Systematics	576
5	Materials Science (miscellaneous)	616	Agronomy and Crop Science	554
6	Engineering (miscellaneous)	499	Electrical and Electronic Engineering	464
7	Mechanical Engineering	488	Chemistry (miscellaneous)	438
8	Biochemistry	439	Plant Science	421
9	Chemical Engineering (miscellaneous)	422	Agricultural and Biological Sciences (miscellaneous)	409
10	Materials Chemistry	411	Biochemistry	393
R	**Community 4: Green light (included China)**		**Community 10: Fuchsia**	
1	Electrical and Electronic Engineering	6647	Medicine (miscellaneous)	119
2	Engineering (miscellaneous)	4393	Public Health, Environmental and Occupational Health	35
3	Condensed Matter Physics	4274	Infectious Diseases	25
4	Mechanical Engineering	3729	Pediatrics, Perinatology and Child Health	18
5	Chemistry (miscellaneous)	3294	Ecology, Evolution, Behavior and Systematics	15
6	Computer Science Applications	3229	Plant Science	15
7	Materials Science (miscellaneous)	3035	Agronomy and Crop Science	13
8	Electronic, Optical and Magnetic Materials	2979	Biochemistry, Genetics and Molecular Biology (miscellaneous)	13
9	Materials Chemistry	2462	Geography, Planning and Development	13
10	Medicine (miscellaneous)	2404	Water Science and Technology	12
R	**Community 5: Green**		**Community 11: Tomato**	
1	Ecology, Evolution, Behavior and Systematics	79	Engineering (miscellaneous)	755
2	Animal Science and Zoology	35	Electrical and Electronic Engineering	560
3	Medicine (miscellaneous)	32	Materials Science (miscellaneous)	443
4	Ecology	28	Condensed Matter Physics	409
5	Plant Science	27	Medicine (miscellaneous)	351
6	Infectious Diseases	24	Chemistry (miscellaneous)	345
7	Agricultural and Biological Sciences (miscellaneous)	23	Computer Science (miscellaneous)	345
8	Genetics	17	Computer Networks and Communications	273
9	Public Health, Environmental and Occupational Health	15	Computer Science Applications	273
10	Biochemistry, Genetics and Molecular Biology (miscellaneous)	15	Multidisciplinary	265
R	**Community 6: Aqua (included Russia)**			
1	Condensed Matter Physics	1757		
2	Physics and Astronomy (miscellaneous)	1421		
3	Electronic, Optical and Magnetic Materials	1001		
4	Electrical and Electronic Engineering	997		
5	Chemistry (miscellaneous)	896		
6	Atomic and Molecular Physics, and Optics	771		
7	Materials Science (miscellaneous)	715		
8	Materials Chemistry	626		
9	Nuclear and High Energy Physics	611		
10	Mechanics of Materials	561		

Appendix C. Centrality Values for Variations in the Threshold Applied

Nine different values (D1, . . . D9) were used as thresholds to filter links in the similarity network before computing centrality measures. These thresholds were selected according to the values of deciles of the distribution of similarities. A final threshold (0.895) is also presented, which corresponds to the one used in Figure 2 and Table 1. R = Ranking, C = Country.

Weighted Degree or degree centrality														
D1= 0.29155			D2= 0.3863			D3= 0.4542			D4= 0.5112			D5= 0.56195		
R	C	Value	R	C	Value	R	C	Value	R	C	Value	R	C	Value
9	BRA	152.64	7	BRA	150.61	7	BRA	146.23	6	BRA	140.94	4	BRA	136.13
104	IND	130.38	111	IND	122.48	113	IND	112.32	110	IND	102.20	103	IND	93.68
170	CHN	105.39	172	CHN	94.71	166	CHN	86.03	161	CHN	77.32	139	CHN	75.71
189	RUS	94.30	184	RUS	83.62	178	RUS	73.96	172	RUS	68.18	161	RUS	64.39
D6= 0.616			D7= 0.6715			D8= 0.7324			D9= 0.8168			Filter = 0.895		
R	C	Value	R	C	Value	R	C	Value	R	C	Value	R	C	Value
7	BRA	121.28	5	BRA	107.84	19	BRA	76.66	30	IND	48.24	36	IND	15.68
82	IND	85.39	59	IND	78.90	42	IND	69.19	34	BRA	47.22	59	CHN	8.31
129	CHN	69.20	96	CHN	64.77	72	CHN	57.17	60	CHN	33.87	73	BRA	5.42
144	RUS	58.51	135	RUS	48.23	111	RUS	36.37	103	RUS	16.21	90	RUS	1.86
Betweenness Centrality														
D1= 0.29155			D2= 0.3863			D3= 0.4542			D4= 0.5112			D5= 0.56195		
R	C	Value	R	C	Value	R	C	Value	R	C	Value	R	C	Value
33	RUS	75	122	CHN	8	118	IND	14	145	BRA	12	66	BRA	49
56	CHN	30	143	IND	5	155	BRA	7	185	CHN	2	140	CHN	15
140	IND	2	163	RUS	4	199	RUS	1	188	IND	2	189	RUS	1
173	BRA	0	202	BRA	0	208	CHN	0	197	RUS	1	200	IND	0
D6= 0.616			D7= 0.6715			D8= 0.7324			D9= 0.8168			Filter = 0.895		
R	C	Value	R	C	Value	R	C	Value	R	C	Value	R	C	Value
78	BRA	49	25	BRA	159	31	BRA	149	5	BRA	853	19	BRA	84
147	CHN	10	128	CHN	16	79	RUS	43	9	RUS	437	36	CHN	25
159	RUS	7	139	RUS	12	86	IND	38	40	CHN	83	67	IND	3
191	IND	0	147	IND	8	117	CHN	15	106	IND	14	105	RUS	0
Closeness Centrality														
D1= 0.29155			D2= 0.3863			D3= 0.4542			D4= 0.5112			D5= 0.56195		
R	C	Value	R	C	Value	R	C	Value	R	C	Value	R	C	Value
85	IND	0.008060	171	IND	0.006550	126	BRA	0.006118	61	BRA	0.005942	20	BRA	0.005833
114	CHN	0.007894	197	BRA	0.006385	181	IND	0.005790	166	IND	0.005261	142	IND	0.004853
129	RUS	0.007825	209	CHN	0.006224	200	CHN	0.005383	193	RUS	0.004885	170	CHN	0.004643
209	BRA	0.007309	210	RUS	0.006217	201	RUS	0.005371	203	CHN	0.004771	177	RUS	0.004582
D6= 0.616			D7= 0.6715			D8= 0.7324			D9= 0.8168			Filter = 0.895		
R	C	Value	R	C	Value	R	C	Value	R	C	Value	R	C	Value
18	BRA	0.005447	5	BRA	0.005283	9	BRA	0.004684	2	BRA	0.000691	28	IND	0.000246
126	IND	0.004546	76	IND	0.004521	66	IND	0.004178	50	IND	0.000673	46	CHN	0.000245
162	RUS	0.004308	137	CHN	0.004072	122	CHN	0.003712	72	CHN	0.000666	50	BRA	0.000244
165	CHN	0.004291	153	RUS	0.003895	142	RUS	0.003336	112	RUS	0.000646	76	RUS	0.000237

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