ST. 4: Inovação em setores intensivos em recursos naturais: agricultura, energia e mineração

Redes de cooperação internacional em energias verdes e tecnologias de mitigação de mudanças climáticas

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RESUMO – *No presente artigo, analisa-se a rede de cooperação internacional em patentes verdes, mais especificamente em energias verdes, a partir de dados da OCDE agregados no período 1990 à 2015 para países membros da OCDE e do G20. Para tanto, utilizou-se uma aplicação da Teoria dos Grafos aplicada à uma rede composta pelos dados de patentes e copatenteamento entre países, em termos do total de patentes e de patentes verdes. Para analisar a especialização de países e colaborações em energias verdes utilizou-se a medida de 'vantagem tecnológica relevada'. A partir da análise da rede chegamos à três conclusões principais: a rede é bastante densa, especialização de países em energias verdes é muito mais comum que a especialização de cooperações, e existem duas estratégias diferentes de colaboração na rede. Em relação a essas duas estratégias elas são: um foco em um grande número de colaborações relativamente pouco especializadas; ou foco em um número menor de colaborações relativamente mais especializadas. A primeira estratégia é muito utilizada por países mais centrais à rede (EUA, China, Alemanha) ao passo que a segunda é utilizada por países menores (quais?) porém mais especializados.*

Palavras-Chave – Energias Verdes; Análise de Redes; Copatenteamento; Vantagem tecnólogica reveleada

ABSTRACT – The study aims to *analyse the international cooperation network in green patentes, more specifically in relation green energies, based on OECD data from 1990 to 2015 for G20 and OCDE countries. The analysis is based on graph theory applied to patents and copatenting data and of patents per country, both for*

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general purposes patents and for green energy patents. In order to analyse the specialisation of countries in this technology domain, has beenused the revealed technology advantage indicator. From the network analysis Three main conclusions were achieved: the analysed network is well connected, specialisation at the country level is more common than specialisation in terms of collaborations, and two main strategies for countries in the network were identified. In relation to the two aforementioned strategies, large countries tend to focus on a high number of collaborations that are not specialised in green energy, whereas smaller countries tend to focus on fewer connections that are more specialised and connect them to specialised countries.

Key-Words – Green Energy; Network Analysis; Copatenting; Revealed Technology Advantge

1. INTRODUCTION

The development of climate change mitigation technologies, including their innovations and diffusion, is crucial for the sustainable growth of our planet. The need for radical change in relation to the global industrial system, in order to make that system more environmentally (and possibly socio-environmentally) sustainable is deeply connected with the ‘green revolution’, specially in relation to the needed transition from a carbon-based system to clean, sustainable and non-depletable sources (MAZZUCATO; PEREZ, 2014; MAZZUCATO, 2015). Green technologies have the unique ability of reducing the impacts of economic activities on the environment by providing solutions to issues related to: producing and distributing energy, transportation, buildings, waste management, and greenhouse gas (GHG) emissions (HASCIC; MIGOTTO, 2015; FABRIZI; GUARINI; MELICIANI,2018).

Government intervention is key for promoting private investments in R&D in green technologies (OLMOS; RUESTER; LIONG, 2012; VEUGELERS, 2012). The role of the State in the Green Revolution centres around transforming the national energy infrastructure. The high sunk costs of existing technologies induce such State support for supply and demand. In that sense, some countries are using State supported green investments as a driver of sustainable growth, minimising environmental impacts while aiming at higher technology development (MAZZUCATO, 2015). Figure 1 shows that China, United States and European Countries (especially Germany and the United Kingdom) were the main global investors in renewable energy between 2010 and 2019.

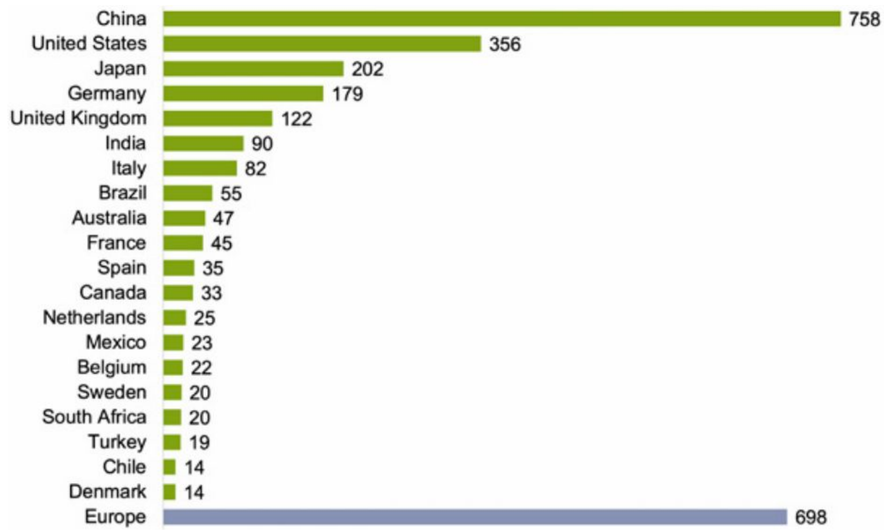

Image 1: Global green investment - 2010 to 2019 Q2 - Billions of USD
Source: Frankfurt school of finance & management; Unep (2019, p. 14)

National private and public organisations do not need to act alone: international cooperation is a relevant source of innovation in the field. To support green technology development is pivotal due to their positive spillovers in the introduction and diffusion stages, thus providing less incentive to firms developing green technologies when in comparison to non-green technologies (RENNINGS, 2000; CECERE et al., 2014; WALZ et al., 2017). Henceforth, regulation and policy become relevant for promoting green technologies, especially because green technologies also combine high technological intensity, regulatory and market uncertainties, irreversibility and long payback periods for green assets (CORTAZAR; SCHWARTZ; SALINAS, 1998; GHISETTI; QUATRARO, 2017; GAWEL et al., 2017). In that sense, there exists potential benefits for collaboration between countries in relation to green technologies.

In activities that the scientific and technology progresses tend to be faster and knowledge is more dispersed, individual hardly possess all required skills for leap-frogging to the technological frontier in multiple integrated areas in order to innovate. Beyond the high level of multidisciplinary and mutability of the knowledge basis, the required complementary and financial assets for developing highly uncertain R&D processes also prompt cumulative and collective learning processes by several (POWELL; GRODAL, 2005).

Through preferential attachment, establishing contracts with heterogeneous actors provide advantages for such firms: knowledge diffusion, status, resource sharing, access to highly specialised assets and cross-organisation knowledge processes. Organisations with broad networks

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of collaborations are exposed to more experience, more diversified abilities and, thus to a higher number of economic opportunities. Portfolio heterogeneity thus guarantees access to broader knowledge bases. The intensity of internal R&D and the technological sophistication are also positively correlated to both the number and the quality of strategic collaborations established. The more a firm uses external knowledge, the more likely that firm is to collaboration with more firms in the future (POWELL; GRODAL, 2005).

Hascic and Migotto (2015) and Walz et al. (2017) provide descriptive evidences of copatenting in green technologies as a measure of international collaboration between countries. Moreover, data on diffusion, international fluxes of knowledge and spillovers advanced with the use of network analysis by allowing the descriptive study of collaboration structures between countries[4] (BRESCHI; LISSONI, 2005). Those analyses proved relevant for identifying hierarchies and other configurations of such intricate network of collaborations, contributing to the study of network formation on the field (COWAN; JONARD, 2004; MAGGIONI; UBERTI, 2009) and indicating that each country's position impacts upon its emphasis on collaborating with other countries (DE PRATO; NEPELSKI, 2012).

This working paper examines the intensity of international cooperation of green technologies for OECD[5] and G20[6] countries using copatenting networks. Our analysis uses patent data for the period between 1990 and 2015, according to (OECD, 2018) database. After this brief introduction, we now describe the database used, then we portray the indicators used, with this section being followed by the network analysis. Afterwards we provide some brief concluding remarks, followed by the bibliography.

2. DATABASE

The analysis is based on an index of international collaboration in technology development provided by OECD that considers as co-inventions all patent fillings that have at least two

[4] Including, but not restricted to density, centrality, clustering, etc.
[5] Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States of America
[6] Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Africa, South Korea, Turkey, the United Kingom and the United States of America

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inventors that reside in different countries. The value for each pair of countries is the total number of patents jointly developed.

Studies about the determinants of international collaboration on technology research commonly use co-patenting data as an index (GUELLEC; VAN POTTELSBERGHE DE LA POTTERIE, 2001; PICCI, 2010). Although largely used, such index has some limitations: for example, R&D cooperation based on the residence of the inventor would be distorted by subsidiaries of multinational and transnational companies (BERGEK; BRUZELIUS, 2010).

Were selected data from all 36 OECD countries as well as from the non-OECD G20 countries, thus including the BRICS countries. We analysed data from 1990 to 2015[7]. The co-invention data used refers to the total patents of each country and to the disaggregated green technologies (ENVTECH[8]). Amongst all green technologies we selected only the climate change mitigation technologies related to energy (generation, transmission, distribution) containing: renewable energy generation, energy generation from non-fossil sources, nuclear energy, combustion technologies with mitigation potential, technologies related to energy efficiency and enabling technologies related to the energy sector.

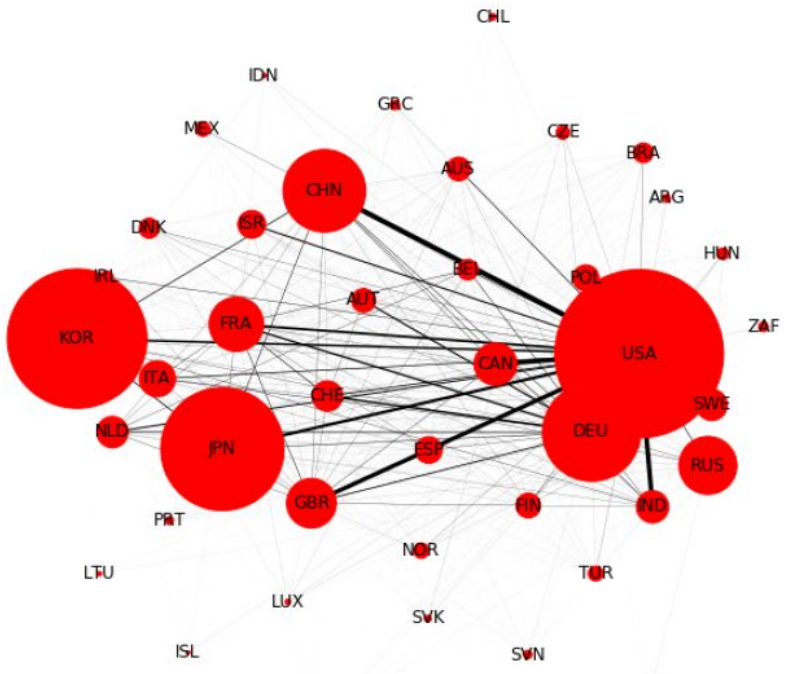

Image 2: Total patents developed internally (node weight) and co-patents (edge weight) - G20 and OECD - 1990-2015.

[7] Priority Date, i.e., the first date of presentation of said invention in the world, considered the closest to the actual invention date, according to the Paris Convention.
[8]http://www.oecd.org/environment/consumption-innovation/ENV-tech\%20search\%20strategies,\%%20version\%20for\%20OECDstat\%20(2016).pdf

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Source: Own elaboration based on OECD (2018).

3. NETWORKS AND INDICATORS

The analysis held is based on Graph theory. A graph is an abstract diagrammatic representation of an interconnected structure composed by elements named 'nodes' (vertices) that are linked in pairs by one or more types of connections (edges, links or connections). Social contexts may be represented in terms of patterns identified in relations (be it economic, political, interactive or even sentimental relations) between the nodes that composed any given system. The study of a network structure requires a number of methods and analytical concepts that differ from traditional statistical analysis by adopting concepts and relational processes that assume the relevance of established connections and inter-dependencies between autonomous units. Such connections and inter-dependencies can be understood as 'channels' to transfer material or immaterial resources. Network structures are composed by the stable patterns of relationship between the agents that compose such network, i.e., the patterns of a network configure its structure. We may understand the variables that measure such patterns as 'structural variables' (WASSERMAN; FAUST, 1999).

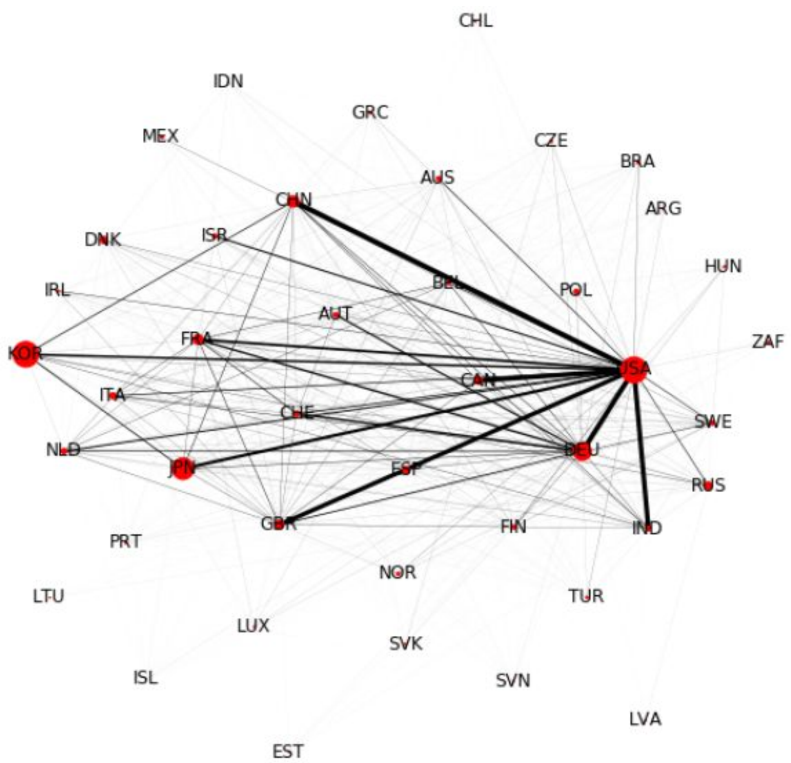

Image 3: Climate change mitigation technologies patents developed internally (node weight) and co-patents (edge weight) - G20 and OECD - 1990-2015.

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Fonte: Own elaboration based on OECD (2018).

Figures 2 and 3[9] show respectively the networks for total patents and for climate change mitigation technology patents. We weight the edges in those figures by the number of patents co-patented by countries in the European Patent Office (EPO), and we weight the nodes in those figures by the number of patents that each country filled in the EPO. The total quantity of patents[10] indicates the technological development of each country and it is used as the node weight in the network[11]. Were measured the collaboration between countries by the number of patents that has at least two inventors from two different countries, thus weighting the edges of our network by that measure. If a patent has three or more co-inventors, then that patent is credited as one unit more for each country in relation to their collaborations, i.e., double counting.

Nevertheless, the analysis considers not only pure patent and co-patent numbers, but also the specialisation of each country and each edge in relation to green technologies. In order to do so, the revealed technological advantage index (RTA) was calculated. It measures the relative specialisation of each node and edge, i.e., each country and each collaboration, by weighting the relevance of a certain type of patent (in this case green technologies or climate change mitigation technologies) within the country by the relevance of said country in relation to the global number of patents (in this case capturing all patents).

$$RTA_a = \frac{\left(\frac{x_a^i}{x_{world}^i}\right)}{\left(\frac{X_a}{X_{world}}\right)} \tag{1}$$

Equation 1 defines the RTA. In it 'x_a^i' represents the number of patents of an 'a' country in a specific 'i' technology domain, 'x_{world}^i' represents the global number of patents in that specific 'i' technology field, 'X_a' represents the total number of patents of that specific 'a' country, and 'X_{world}' the global number of patents. That index weights the

[9] Both figures as well as any graph shown in this article uses the Kamada-Kawai layout.
[10] The number of inventions (simple patent families) developed by national inventors independently of the intellectual property jurisdictions, i.e., we consider all worldwide known patent families.
[11] We stress that use of patent data as innovation or innovative performance indicators has its controversies in the evolutionary and innovation economics. Patents represent an input indicator for innovative processes, not the innovative process itself, because patents are related to the novelty and to the inventions themselves. The availability of patent data makes that indicator of the most used indexes for technological advances, despite its well-known limitations. Moreover, patents are extremely heterogeneous, especially in relation to their (future) economic impacts. Thus, said heterogeneity prompts the need for ponderation in relation to citation data or other qualitative methods of adjustment.

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relevance of a country's green patents in relation to the number of green patents in the world by the relevance of that country in terms of the global patents in all sectors. If the RTA is zero, than that country has no green patents or no patents at all, and if the RTA is equal to one, than its share of green technology is equal to its total share of patents in relation to the world, i.e., the ratio of green patents over total for the country is the same as the global ratio. If the RTA is above one the country's ratio of green over total is higher than the global average, which indicates a specialisation of that country in green technology when compared to the rest of the world. "Specialisation" is conceived as a consequence of a country's actions, regarding the ability of each country to be relatively more or less specialised in green technologies or other types of technology. This relative advantage thus is in no way related to Adam Smith or David Ricardo's interpretation of "advantages": the index not only changes with technology types, but changes with deliberate policy decisions, i.e., is completely open to change.

The RTA was used to weight both the nodes (countries) and the edges (collaborations), given the specialisation of each country and the specialisation of each collaboration. Apart from the RTA, were also use widely used indicators, such as the degree of each node, cliques, K components, pagerank, clustering, eigenvector centrality, betweenness centrality and edge betweenness centrality.

There is a number of indicators and indexes often used to analyse the relevance of nodes in network structures. The prominence or relevance of a given node may be understood as a result of the node location in a strategic position within such network (WASSERMAN; FAUST, 1999). We define degree[12] as the number of connections that a certain '*i*' node has to other '*j*' node, given the fact that they are different nodes of the same network. Node centrality is defined as the ability of a node to establish links with the other Nodes in a network. '$C_D(n_i)$' (according to equation 2) is defined as an index of '$d(n_i)$' the individual centrality in terms of the degree of connection of the node 'n_i'. An agent with an elevated degree is in direct contact with many adjacent nodes, and thus, tends to recognised by the other agents as a focal point of relational information, thus occupying a central position in the network (WASSERMAN; FAUST, 1999).

[12] Our network is undirected, as such we do not differentiate between 'in' and 'out' measures, e.g. in-degree and out-degree.

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$$C_D(n_i) = d(n_i) = \sum_j x_{ij} = \sum_i x_{ji} \quad (2)$$

A limitation of the degree as a measure is that it depends on the number of actors (*g*), in which the higher number of counterparties is '*g-1*'. As such, we propose the standardisation of the index by the proportion of nodes adjacent to 'n_i'; as such, '$C_D(n_i)$'is now independent of the size of '*g*' as can be compared to the same measure in other networks (equation 3).

$$C'_D(n_i) = \frac{d(n_i)}{g-1} \quad (3)$$

Furthermore, interaction between two adjacent nodes may depend on the remaining nodes of the network, especially on nodes located along the path between that first pair of nodes. Geodesic distance is defined as the smallest distance between two nodes in the network. Nodes located along the geodesic distance path may then exert some type of control or relational influence in relation to the pair of nodes in the ends of such distance. As such, interjacent nodes are capable of exerting a higher degree of control or influence on the network. Centrality in this case is measured in terms of the control or influence, such that central nodes are in the middle of the geodesic distances of multiple pairs of nodes that compose the network (WASSERMAN; FAUST, 1999).

Suppose that the edges have equal weight and that information goes along the smallest geodesic distances, then the betweeness centrality index for a '*i*' node is the sum of the probabilities that such node is interjacent to geodesic distances for all pairs of nodes adjacent to '*i*', according to equation 4 in which is the number of geodesic distances that contain the '*i*' node, 'g_{jk}' is the total number of geodesic distances between *'j'* and *'k'* nodes. As such, '$g_{ik}(n_i)/g_{jk}$' is the probability that *'i'* is an interjacent node to the nodes *'j'* and *'k'* (WASSERMAN; FAUST, 1999).

$$C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}} \quad (4)$$

The betweeness index assumes null value when the node is not interjacent to any two nodes, and assumes the value '((g-1)*(g-2)/2)' if the node is interjacent to all pairs of nodes in the network. As such, we can standardise the index by dividing it by the maximum value, according to equation 5 (WASSERMAN; FAUST, 1999).

$$C'_B(n_i) = \frac{C_B(n_i)}{\frac{((g-1)*(g-2))}{2}} \quad (5)$$

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The edge betweeness centrality was also considered, which has a similar concept as to betweeness centrality, the difference being that one is analysing the centrality of a certain edge, not of a single node. As such, it analyses the degree of control or influence of such edge, i.e., the influence that a certain path has in relation to all other paths.

Eigenvector centrality index may be described as the degree variation considering the number of adjacent nodes weighted by the relative centrality of each adjacent node. Being '*e*' the centrality measure and 'λ' a eigenvector proportionality, then the centrality index of each node is proportional to the sum of the adjacent nodes' centrality index. One can understand the eigenvector centrality index as a 'popularity' index, given the fact that the central node is connected to nodes that are also well connected (BORGATTI; EVERETT; JOHNSON, 2013). Equation 6 depicts the mathematical analysis of the eigenvector centrality.

$$e_i = \lambda \sum_j x_{ij} e_j \tag{6}$$

Cliques are undirected graphs that are a subset of a larger network. For every two vertices in a clique there is an edge connecting them, i.e., the subgraph is complete. The maximum clique is the clique of the largest possible size given the original network (BOPPANA; HALLDÓRSSON, 1992).

In relation to k-components, they are the maximal subgraph of a certain network that has connectivity equal to '*k*', i.e., one must remove at least '*k*' nodes in order to break the subgraph into more components. K-components are inherently hierarchical: there may be a list of several 2-components, as well as a number of 3-components, and so on (MOODY; WHITE, 2003; KANEVSKY, 1993).

In relation to link analysis, the use of pagerank is proposed. Pagerank is a measure that ranks each node in the graph in relation to the structure of the incoming links. Although originally developed as an algorithm to rank web pages, it can be used to analyse the 'prestige' of nodes in a network. Moreover, it is aimed at directed networks, although undirected networks are 'converted' into directed ones by converting each edge into two edges (PAGE et al., 1999).

Were also used the clustering indexes regarding each node. For weighted graphs, the clustering index is defined as the geometric average of the subgraph edge weights, with the index being normalised by the maximum weight in the network, following the equation 7. For

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nodes connected only to one node the clustering index is equal to zero, as there are no fraction of possible triangles that pass through that node. The latter is the definition for clustering indexes in undirected networks, nevertheless the concept still stands: the index analysis how many (and the relevance in case of weights) triads can be done using that specific node.

$$C_u = \left(\frac{1}{deg(u)*deg(u-1)}\right) * \sum_{uv} \sqrt[3]{\hat{w}_{uv} * \hat{w}_{uw} * \hat{w}_{vw}} \quad (6)$$

In the equation 7, '*deg(u)*' is the degree of the node '*u*', '*v*' and '*w*' are other two nodes (v, w ≠ u), and $\hat{w}_{uv}$ is the weight of the edge between nodes '*u*' and '*v*' (SARAMÄKI et al., 2007).

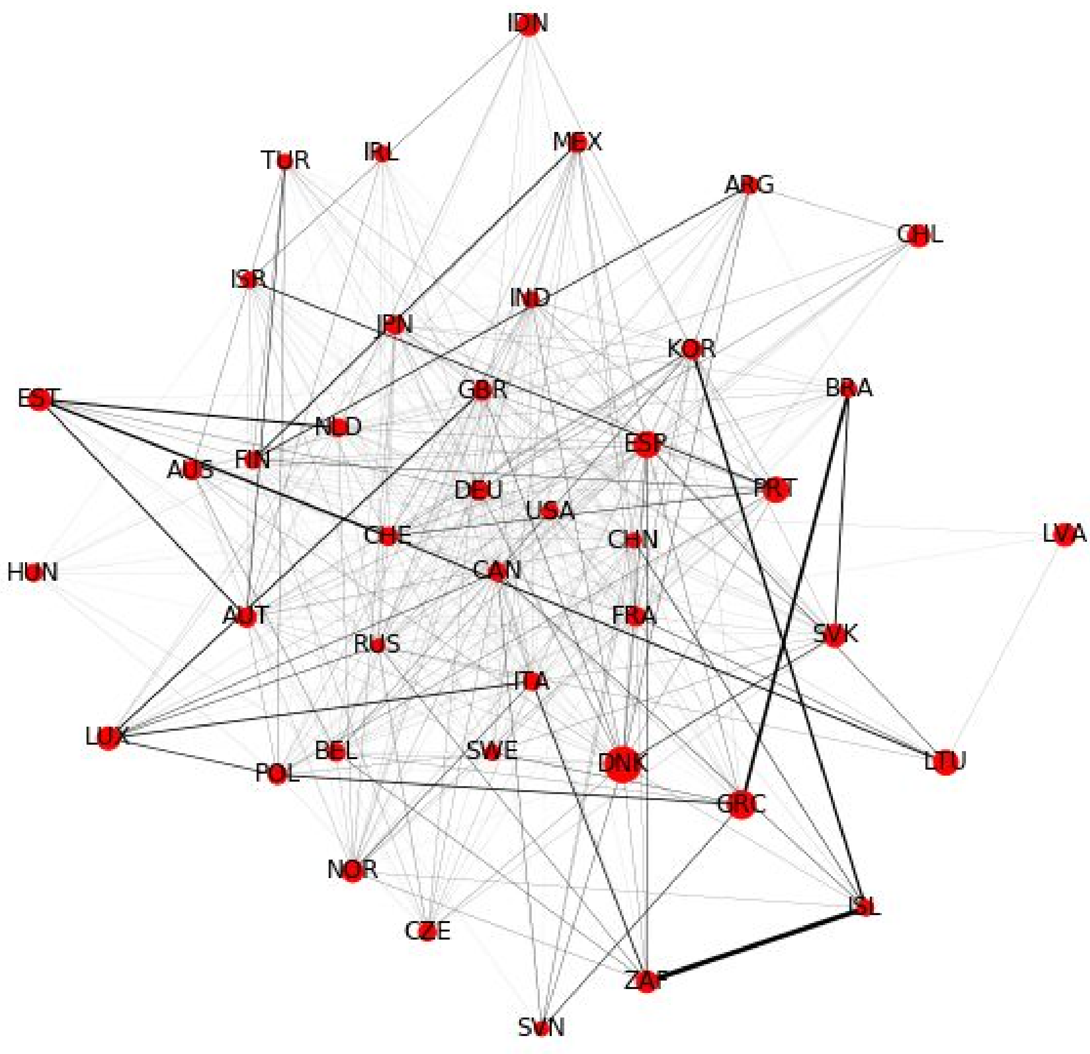

Image 4: RTA for countries (node weight) and RTA for connections (edge weight) - G20 and OECD - 1990-2015.

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Source: Own elaboration based on OECD (2018).

4. NETWORK ANALYSIS

Having described the indicators used to analyse our network, now is displayed and analyseed our main network (figure 4). From a structure analysis, the relevance of Germany (DEU), United States of America (USA) and Canada (CAN) is perceived, as they are located near the origin of the Graph.

Analysing the histogram of distribution of degree per country (figure 5), it is posible to conclude that the network is well connected: its mean is 21.24, i.e. in average each country is connected to more than half the countries in the network; and its median is 20.5, i.e., half of the countries are connected to almost half of the entire graph. Moreover, the mode of the degree, with four countries, is also high: 33. The highest degree, 40, belongs to the United States of America. BRICS countries have significant degrees: Brazil, Russia (RUS), India, China and South Africa (ZAF) have respectively degree 15, 30, 30, 33, 12.

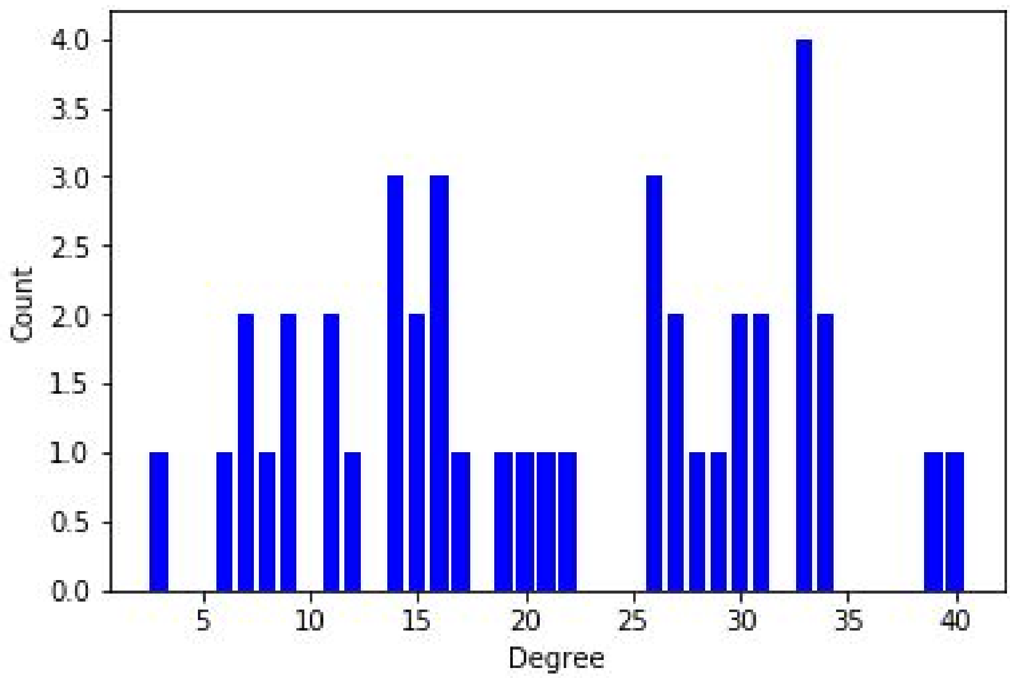

Image 5: Histogram of the degree of nodes (countries) in the main network.

Source: Own elaboration based on OECD (2018).

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In relation to cliques, through clique removal we found 16 independent sets. The maximum clique, is composed of sixteen countries: Australia, Canada, Switzerland, China, Germany, Spain, Finland, France, the United Kingdom, India, Italy, Japan, Netherlands, Russia, Sweden and the United States. The countries in the maximum clique are basically the largest investors in green energy (see figure 1) (FRANKFURT SCHOOL OF FINANCE & MANAGEMENT; UNEP; BNEF, 2019). Regarding the k-components, the network appears to be very densely connected: we are able to produce a 21 country k-component, with k equal to 17. As such, it is established the abundant presence of connections in the analysed network, and now analysed the relevance of each connections.

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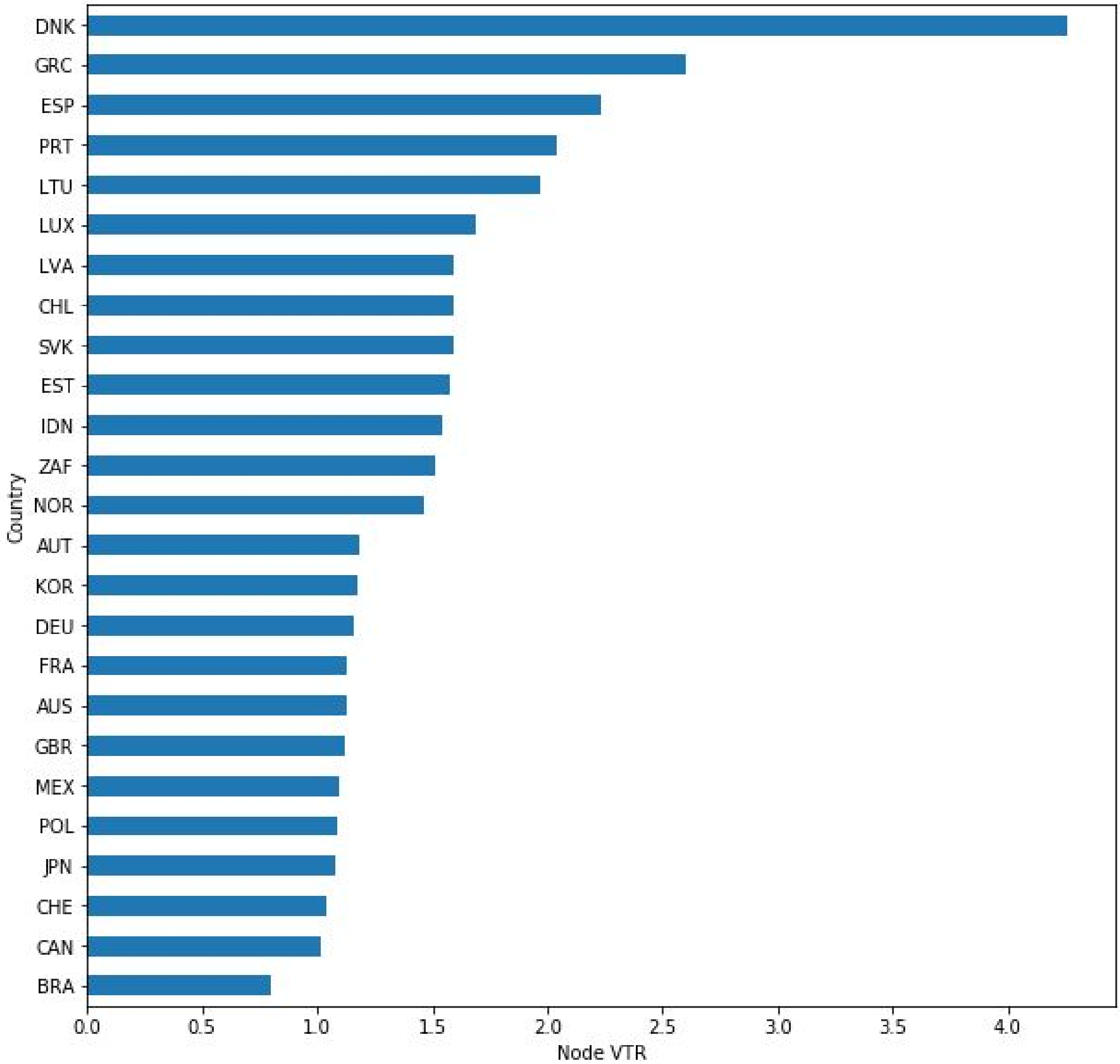

Image 6: Countries with RTA > 1 in the network[13].

Souce: Own elaboration based on OECD (2018).

As both nodes' and edges' weights are measured in RTA, i.e., each county specialisation is analysed in terms of country share and patterns of collaborations respectively. . In relation to countries' RTA, 24 countries display a clear specialisation in green technologies. In relation to BRICS countries, only South Africa figures among them. Nevertheless, Asian and European countries figure heavily among the list: Japan, United Kingdom, France, Germany, Korea, Portugal, Spain, as well as Norway and Denmark, two Nordic countries with high

[13] Although Brazil's RTA is of 0.795975, we include it in the list in order to compare Brazil to specialised countries

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RTAs. Furthermore, nine out of the countries with RTA > 1 are among the list of the top 20 investors in green technology: Japan, Germany, United Kingdom, Australia, France, Spain, Canada, South Africa and Denmark (FRANKFURT SCHOOL OF FINANCE & MANAGEMENT; UNEP; BNEF, 2019).

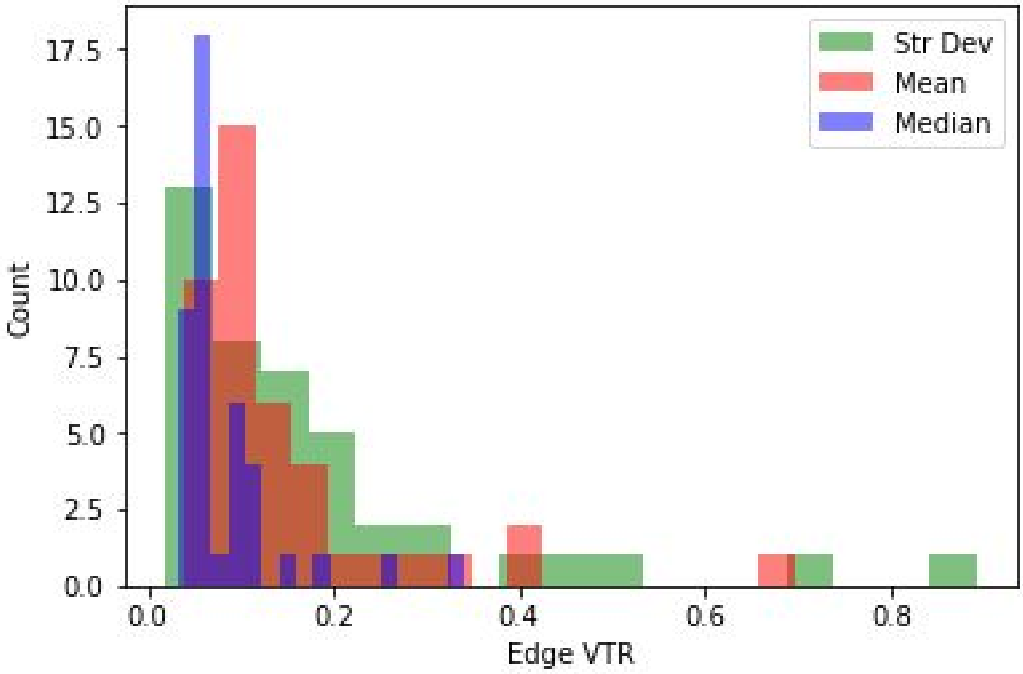

Image 7: Histogram of mean, median and standard deviation of edge RTA per country.

Source: Own elaboration based on OECD (2018).

On the other hand, the countries closer to the centre of the graph have lower RTA when compared to other countries (figure 6). Furthermore, from the weight of the edges is perceived that the most central countries have edges with less weight, thus more connected countries have more diversified connections, whereas countries with lower degrees, as well as their connections, are more specialised in green technologies. The latter would be case of Estonia (EST), South Africa and Iceland (ISL)

When analysing if the country's ratio of green patents over the total is above the global ratio, i.e., if RTA > 1, interesting results emerge. Only eight countries have collaborations with RTA above one, thus indicating that their collaborations are specialised when compared to the rest of the world: Estonia, Netherlands, Switzerland, Iceland, South Korea, Brazil, Greece and South Africa. Moreover, only five collaborations have RTA above one:

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Estonia-Netherlands, Switzerland-Estonia, Iceland-Korea, Brazil-Greece and Iceland-South Africa. Those results indicate that most connections are below the global ratio of green over total patents. To illustrate this argument, only 0.5% of all collaborations have RTA above one, thus indicating relative specialisation of said cooperation patterns in relation to green technologies. This indicates that most collaborations are not dedicated to green technologies. Moreover, there is clear discrepancy between relative specialisation of countries and the relative specialisation of countries' collaborations in terms of RTA: 57.14% of all countries have a share of green over total patents above the global average, thus indicating specialisation. That fact becomes evident by analysing the distribution of medians and means of edge RTA per country in figure 7. The distribution of edge's RTA per country is rather well spaced, with some countries possessing high standard deviations[14].

A synthesis table (table 1) consolidates of the seven indexes for all 42 countries: Node RTA, Mean Edge RTA, Pagerank, Clustering index, Centrality, Betweeness as well as the Mean edge betweeness. Table 1 displays the ranking of each country in relation to each index [15]. Each index is divided in two groups: the upper and the lower halves. As such, green cells represent indexes that are on the upper half. Furthermore, underlined countries have at least four indexes on the upper half. Among those: Australia, Austria, Belgium, Canada, Switzerland, Germany, Spain, Estonia, Finland, the United Kingdom, Greece, Indonesia, Iceland, Luxembourg, Poland, Portugal, Russia, Sweden and South Africa. Were not considered degree among the indexes, as degree has a significant number of countries that would tie in certain positions (figure 5), nevertheless in this case, South Korea, Denmark, India, Italy, Netherlands, China and France would be added to that list of countries.

The main list of countries are mainly composed of OECD countries: only South Africa, Russia and Indonesia are non-OECD G20 countries among those countries. Although Germany, Australia and the United Kingdom are all G20 OECD countries, the majority (twelve countries) are only OECD members. In relation to BRICS countries, only Brazil is left out, with only the pagerank, clustering and centrality indexes on the upper half. Moreover,

[14] Greece, Brazil, Estonia, South Africa and Iceland all have standard deviations of their edge RTAs above 0.4, indicating a high disparity in terms of specialisation of their collaborations in terms of green technologies
[15] We refrain from displaying the values of each index in favour of ease of comparability. All indexes are thoroughly displayed on the appendix.

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Germany is the country with the highest number of indexes in the upper half: six, only its clustering index is low.

Pagerank and eigenvector work similarly as to the degree, as they are weighted, regarding the relevance of countries in relation to their weighted nodes and weighted edges. Moreover, the clustering indexes are high, indicating the network cohesion.

Country Node	Node RTA	Mean Edge RTA	Pagerank	Clustering Index	Eigenvector Centrality	Betweeness	Mean Edge Betweeness
ARG	31º	16º	32º	17º	28º	*	28º
AUS	18º	38º	35º	13º	34º	21º	33º
AUT	14º	23º	13º	24º	20º	13º	21º
BEL	27º	32º	27º	23º	16º	11º	17º
BRA	35º	7º	11º	11º	15º	*	31º
CAN	24º	27º	12º	40º	6º	20º	39º
CHE	23º	15º	3º	35º	9º	7º	19º
CHL	8º	17º	38º	1º	39º	*	10º
CHN	40º	30º	21º	37º	8º	22º	42º
CZE	26º	31º	37º	10º	36º	23º	26º
DEU	16º	33º	15º	41º	19º	5º	16º
DNK	1º	13º	6º	30º	7º	28º	41º
ESP	3º	18º	7º	39º	5º	17º	35º
EST	10º	2º	8º	3º	13º	*	14º
FIN	31º	22º	17º	26º	29º	3º	4º
FRA	17º	34º	23º	38º	22º	18º	38º
GBR	19º	29º	14º	34º	18º	6º	18º
GRC	2º	6º	4º	16º	11º	24º	30º
HUN	29º	42º	41º	14º	41º	16º	6º
IDN	11º	25º	39º	6º	38º	*	15º
IND	37º	35º	25º	27º	25º	4º	5º
IRL	32º	41º	40º	2º	40º	2º	1º
ISL	35º	1º	1º	18º	1º	*	9º
ISR	36º	24º	26º	20º	35º	8º	8º
ITA	28º	19º	9º	31º	4º	14º	24º
JPN	22º	36º	30º	29º	30º	19º	37º
KOR	15º	11º	5º	28º	3º	*	40º
LTU	5º	4º	29º	25º	26º	*	7º
LUX	6º	5º	10º	5º	10º	25º	20º
LVA	7º	37º	42º	33º	42º	*	2º
MEX	20º	12º	24º	4º	31º	*	27º
NLD	25º	28º	18º	32º	24º	12º	22º
NOR	13º	21º	28º	19º	14º	*	36º

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POL	21º	14º	20º	22º	23º	10º	11º
PRT	4º	9º	16º	7º	21º	*	34º
RUS	42º	26º	19º	36º	12º	15º	25º
SVK	9º	10º	22º	9º	17º	*	32º

Table 1: Countries' node and median edge RTAs, Pageranks, clustering indexes, centrality indexes, betweenes indexes, and mean Edge Betweeness indexes - G20 and OECD - 1990-2015

Source: Own elaboration based on OECD (2018).

Country Node	Node RTA	Mean Edge RTA	Pagerank	Clustering Index	Eigenvector Centrality	Betweeness	Mean Edge Betweeness
SVN	41º	8º	36º	12º	32º	*	12º
SWE	38º	39º	33º	21º	33º	9º	13º
TUR	39º	20º	34º	8º	37º	*	29º
USA	33º	40º	31º	42º	27º	1º	3º
ZAF	12º	3º	2º	15º	2º	*	23º

Table1 : Countries' node and median edge RTAs, Pageranks, clustering indexes, centrality indexes, betweenes indexes, and mean Edge Betweeness indexes - G20 and OECD - 1990-2015

Source: Own elaboration based on OECD (2018).

To conclude the analysis were examined a group of six countries: Denmark, Greece, Spain, Russia, Slovenia and China. In relation to the first three, they have the highest RTAs of our network, although they do not have specialised collaborations in green technologies, as shown by their lack of relevance in terms of mean edge RTA. On the other hand, their eigenvector centralities are significant, meaning that establishing collaborations are important for those three countries, i.e., they establish connections with significant RTAs. Their pageranks are higher than their degrees, meaning that they cooperate with countries that also have high centrality indexes. Their betweeness centrality are not high, indicating that they are not as relevant for maintaining the network structure, i.e., they connect countries that are already connected. Between those three countries, only Greece possessed a significant clustering index. As the network has a high average degree and eigenvector centrality, and there are no isolated groups (as shown by the analysis of k-components and cliques), such conclusion would be expected. Thus, Greece tends to establish collaborations more restricted

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to a certain group, although the country still connects to a significant number of countries given its high degree. Therefore, in this specific group of countries specialised in green technologies, it is observed a tendency to cooperate with a significant number of countries, thus guaranteeing a pride of place for them instead of a specialisation in their collaborations that would end up isolating them.

In relation to the last three countries, Russia and China present a higher specialisation of their collaborations towards green technologies given their mean edge RTAs. China possess a high eigenvector centrality, thus indicating that it collaborates with various countries in signi_cant terms, nevertheless, its low pagerank indicates that the countries that cooperate with China are not central to the network. Moreover, its low betweeness and clustering indexes indicate that China is not relevant for intermediating connections between countries. Russia also is less relevant in terms of its pagerank than in relation to its degree, indicating that it cooperates with a signi_cant number of countries even though such connections are not specially relevant. Nevertheless, the Russian mean edge betwenness centrality indicates that Russia may exert a relevant role for the countries that it cooperates with, i.e., even though its partners are specialised in relation to green technologies they may be in a fairly peripheral position in the network (e.g. Luxembourg). Slovenia di_ers from the two previous countries by not possessing relevant degree or pagerank, thus being the most isolated country in the network. Furthermore, the Slovenian clustering and mean edge betweenness indexes indicate that it establishes fewer connections than its partners, therefore, its connections are relevant for keeping the network intact, in a similar fashion as to Greece.

5. CONCLUSION

The analysis held in this working paper aimed to analys networks emerging from countries collaboration in green technologies, considering how green their patent developments and collaborations are in terms of their RTAs.

From the data analysis, a clear specialisation of most OECD countries on green technologies is noticed, especially Nordic countries. Furthermore, the analysis highlights the fact that countries with less resources tend to collaborate more than countries with more

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resources. For example, United States and Germany do cooperate more than Spain, but for the latter cooperation appear to be more relevant, given its node and mean edge RTAs.

As future research, it is suggested to break down the analysis in terms of years, analysing the evolution of the network that here was analysed in its aggregated form. Moreover, also to intersect data from countries' energy mixes, green investment volume, etc.

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7. APPENDIX

In the following appendix we present some supplementary tables of certain indexes, with their respective means and standard deviations. Moreover, we also present a figure comparing countries' standard deviation of their edge RTAs.

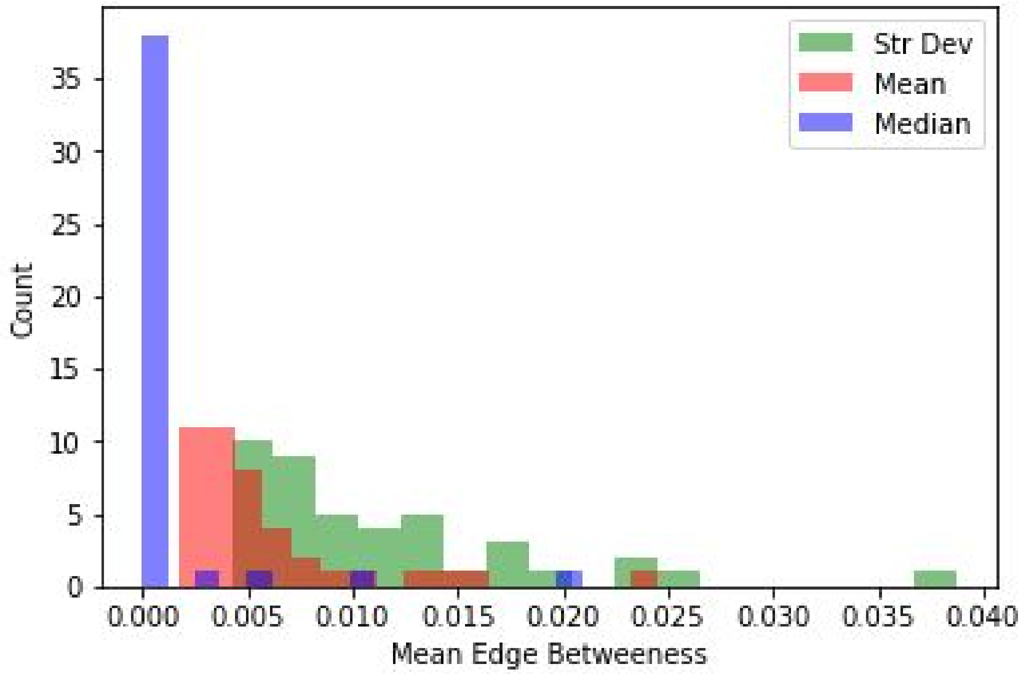

Figura 8: Histogram of means, medians and standard deviations of betweenness centrality per country.

Fonte: Own elaboration based on OECD (2018).

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Country	Pagerank	Country	Pagerank	Country	Pagerank	Country	Pagerank
LVA	0.004192	USA	0.018515	POL	0.026193	ITA	0.031767
HUN	0.006048	JPN	0.019173	RUS	0.026347	EST	0.032835
IRL	0.007598	LTU	0.019239	NLD	0.026485	ESP	0.035008
IDN	0.009605	NOR	0.019811	FIN	0.026966	DNK	0.036429
CHL	0.009692	BEL	0.019984	PRT	0.027772	KOR	0.036434
CZE	0.013548	ISR	0.020279	DEU	0.027857	GRC	0.037094
SVN	0.014409	IND	0.020359	GBR	0.027893	CHE	0.040263
AUS	0.014943	MEX	0.020651	AUT	0.028268	ZAF	0.040380
TUR	0.015705	FRA	0.023920	CAN	0.028903	ISL	0.041163
SWE	0.016704	SVK	0.024241	BRA	0.028973	Mean	0.02381
ARG	0.018200	CHN	0.025478	LUX	0.030677	Std Dev	0.00954

Tabela 2: Countries' pageranks, mean and standard deviation

Fonte: Own elaboration based on OECD (2018).

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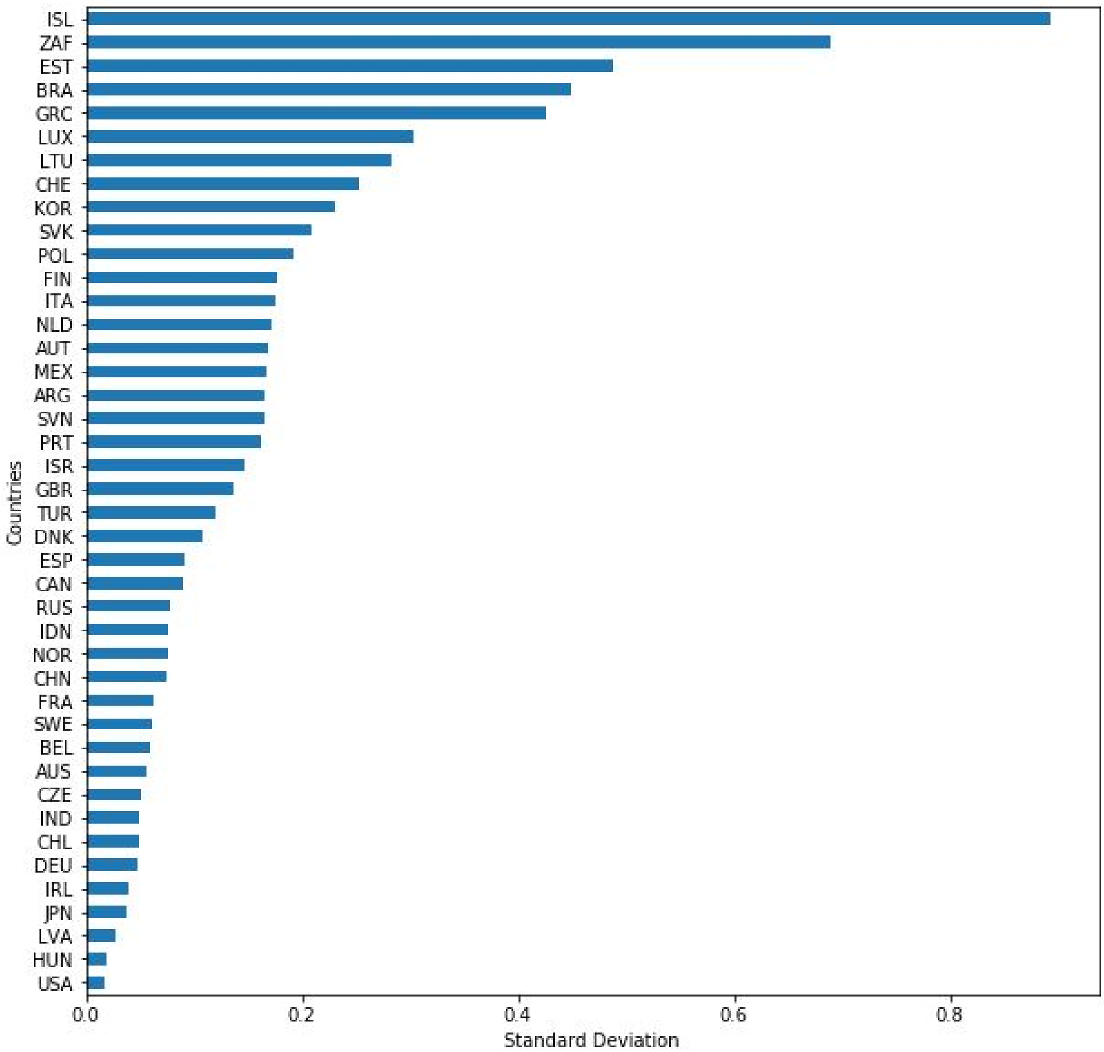

Figura 9: Histogram of mean, median and standard deviation of edge RTA per country.

Fonte: Own elaboration based on OECD (2018).

Country	Betweeness	Country	Betweeness	Country	Betweeness	Country	Betweeness
LUX	0.001220	FRA	0.014634	BEL	0.042683	IND	0.143902
GRC	0.002439	ESP	0.023171	POL	0.043902	FIN	0.153659
CZE	0.003659	HUN	0.024390	SWE	0.051220	IRL	0.168293
CHN	0.004878	RUS	0.032927	ISR	0.052439	USA	0.291463
AUS	0.008537	ITA	0.035366	CHE	0.054878	Mean	27.119048
CAN	0.008537	AUT	0.035366	GBR	0.059756	Std Dev	48.065607
JPN	0.009756	NLD	0.040244	DEU	0.081707	-	-

Tabela 3: Countries' betweenness, mean and standard deviation[16].

[16] Argentina, Mexico, Iceland, Indonesia, South Africa, Portugal, Slovenia, Slovakia, Estonia, Turkey, Norway, Lithuania, South Korea, Latvia, Denmark, Brazil and Chile were left out of the table as they all have zero betweenness

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Fonte: Own elaboration based on OECD (2018).

Country	Clustering Index	Country	Clustering Index	Country	Clustering Index	Country	Clustering Index
USA	0.512821	ITA	0.705376	ISR	0.810526	SVK	0.916667
DEU	0.535762	DNK	0.712251	NOR	0.853801	TUR	0.923077
CAN	0.566845	JPN	0.716749	ISL	0.857143	PRT	0.926471
ESP	0.623106	KOR	0.716923	ARG	0.857143	IDN	0.944444
FRA	0.625668	IND	0.719540	GRC	0.858333	LUX	0.945455
CHN	0.634470	FIN	0.729231	ZAF	0.863636	MEX	0.989011
RUS	0.643678	LTU	0.733333	HUN	0.890909	EST	1.000000
CHE	0.651515	AUT	0.743386	AUS	0.891775	IRL	1.000000
GBR	0.653409	BEL	0.756923	SVN	0.892857	CHL	1.000000
LVA	0.666667	POL	0.766667	BRA	0.895238	Mean	0.787937
NLD	0.670968	SWE	0.774929	CZE	0.916667	Std Dev	0.135495

Tabela 4: Countries' clustering index, mean and Standard Deviation.

Fonte: Own elaboration based on OECD (2018).

Country	Centrality	Country	Centrality	Country	Centrality	Country	Centrality
LVA	0.004805	MEX	0.064418	AUT	0.091095	CHE	0.136854
HUN	0.011942	JPN	0.064655	DEU	0.091559	CHN	0.151097
IRL	0.018673	FIN	0.065315	GBR	0.095610	DNK	0.155018
CHL	0.025781	ARG	0.066121	SVK	0.095861	CAN	0.155047
IDN	0.029141	USA	0.068883	BEL	0.099466	ESP	0.165057
TUR	0.045135	LTU	0.069491	BRA	0.108397	ITA	0.199430
CZE	0.047614	IND	0.073732	NOR	0.109529	KOR	0.287235
ISR	0.050339	NLD	0.086939	EST	0.113331	ZAF	0.509504
AUS	0.051628	POL	0.088279	RUS	0.122333	ISL	0.539710
SWE	0.055857	FRA	0.088308	GRC	0.126087	Mean	0.11207
SVN	0.061349	PRT	0.089925	LUX	0.126411	Std Dev	0.10735

Tabela 5: Countries' eigenvector centrality, mean and standard deviation.

Fonte: Own elaboration based on OECD (2018).

Country	Mean Edge Betweeness	Country	Mean Edge Betweeness	Country	Mean Edge Betweeness	Country	Mean Edge Betweeness
CZE	0.000581	SWE	0.002129	ARG	0.003401	CHE	0.006627
LTU	0.001161	ITA	0.002323	NLD	0.003678	CHL	0.009524
KOR	0.001597	JPN	0.002439	AUT	0.004723	IND	0.010976
ISR	0.001742	FRA	0.002462	BEL	0.005271	FIN	0.013473
CHN	0.001798	AUS	0.002851	RUS	0.005343	USA	0.020415
DNK	0.001984	ESP	0.003172	DEU	0.005807	Mean	0.003916
CAN	0.001996	BRA	0.003318	GBR	0.006514	Std Dev	0.004444

Tabela 6: Mean of Countries' edge betweenness, mean and standard deviation[17].

[17] Argentina, Mexico, Iceland, Indonesia, South Africa, Portugal, Slovenia, Slovakia, Estonia, Turkey, Norway, South Korea, Latvia, Denmark, Brazil and Chile were left out of the table as they all have zero mean edge betweenness

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Fonte: Own elaboration based on OECD (2018).

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