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Patents as indicators of the technological position of countries on a global level?

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Abstract

The technological capabilities of a country play a key role in identifying paths to economic growth and development. Policymakers have a special interest in understanding the advantages and opportunities that arise in a location, with the purpose to make good public policy recommendations. One widely used measure in the literature of economic complexity is the revealed comparative advantage (RCA) index. In this paper, we propose the concept of revealed comparative advantages weighted (RCA_w) as a measure of technological capability, using metrics of concentration (number of patents) and impact (patents citations) at the same time. Here, we analyze near two million patents granted by the United States Patent and Trademark Office (USPTO) associated with 44 countries in the period 2006–2015. We show that the GDP per capita of a country is positively correlated ($R^2=30\%$) with the number of citations that its patents receive. We also find evidence indicating that more complex countries lose a lower rate of their capabilities. Finally, we built a network to represent the connections of technologies based on this RCA_w matrix called Citation Space. We found that the proximity of two technologies and the technological diversity of a country varies significantly if we use RCA or RCA_w. We hope that these findings contribute to enriching the discussion about citation matters at the time of describing capabilities of a territory.

Article highlights

- We observe that the more developed countries receive on average more citations for their patents than non-developed countries.
- Complex countries tend to lose a smaller rate of technologies if we measure their capabilities using the technological diversity weighted.
- Revealed comparative advantage weighted (RCA_w) is a good indicator to reflect the capabilities of a territory–since in the case of technology, it is a measure that considers number of patents and citations.

Keywords Patents · Citations · Economic complexity · ECI · Impact · Technological diversity

Extended author information available on the last page of the article

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Introduction

There have been many ways to theorize about factors that determinates long-run sustainable economic growth. In the early 1950s, neoclassical growth theory (Schumpeter, 1942; Solow, 1956) attempts to explain long-run economic growth by looking at exogenous factors, such as capital accumulation, labor, and technological changes. Later, in the mid-1980s, endogenous growth theory (Lucas, 1988; Nelson, 1985; Romer, 1986) holds that economic growth is explained by endogenous forces, that are significant contributors to economic growth, such as investment in human capital, innovation, and knowledge. Indeed, this theory also focuses on positive externalities and spillover effects of a knowledge-based economy which lead to economic development.

Hidalgo et al. (2007) proposed a breakthrough approach to study economic development. They do a network (called *The Product Space*) to represent the relatedness of export of products. Their work allowed to identify patterns of diversification, and to measure the likelihood that countries diversified as function of common or similar products already present in the territory. Hidalgo and Hausmann (2009) introduce the concept of Economic Complexity to explain economic growth from a perspective of capabilities of countries. They define capabilities as modularized chunks of embedded knowledge required to produce products. The economic complexity reflects the structures that emerges to hold and combine those knowledges in a location.

Since then, economic complexity has been used to explain industrial evolution (Neffke et al., 2011), entry of new industries (Boschma et al., 2013), concentration of complex activities in large cities (Balland et al., 2020), patterns of technological diversification and specialization (Petralia et al., 2017), role of market institutions in diversification (Boschma & Capone, 2015), optimal economic diversification strategies in related products and research areas (Alshamsi et al., 2018). These studies contributed with evidence to the principle of relatedness (Hidalgo et al., 2018), that describes the probability that an economic activity enters (or exits) of a region or country as function of the number of related activities present in that location.

In this study, we are interested in studying the impact that patent citations can have on our understanding of the country's capabilities. For this, we consider citations as complement to calculate comparative advantages of a country in terms of their technologies. Even though patents are a good proxy to measure the technological evolution of countries, our hypothesis is that citations can reveal us more information about the real position of technological portfolios of countries at worldwide.

We introduce the concept of revealed comparative advantage weighted (RCA_w) as a way to measure the impact of citations over the current capabilities that a country hold. We conduct a comparative analysis between technological diversity (based on RCA) and weighted technological diversity (based on RCA_w) on a period of 10 years (2006–2015). To complement our analysis, we analyze the citation dynamics among countries based in different criteria, such as Gross Domestic Production (GDP) per capita, if the country is member of the Organization for Economic Cooperation and Development (OECD), and their Economic Complexity Index (ECI). Finally, we build two networks: "Technological Space" (inspired in the previous work of Boschma et al., 2015) and "Citation Space", and we compare the proximity matrices associated with each one.

Theoretical framework

Measurement of technological capabilities of countries is a key topic nowadays. Patents are known as a good technological indicator, since their classification system is technology-based (Jaffe, 1986) that provides a unique source of information on industrial innovation (Archibugi & Planta, 1996). Since then, patents have been widely used to create maps of innovation systems at regional and national levels. Also, data from co-classification among patent classes can indicate what distinguishes an innovation system (Dolfsma & Leydesdorff, 2011).

Jaffe (1986) used the distribution of the firms' patents over patent classes to characterize the technological position of them. Shelton and Leydesdorff (2012) used patent data to measure performance of national research agencies. In this context, one method used to calculate the impact of patents is through of their citations (Archibugi & Planta, 1996). Narin and Olivastro (1988) and Trajtenberg (1990) suggest that patent citation is an indicator of technological impact of an invention, and Lee et al. (2016) affirms that patent citation is more commonly used to measure the validity of a technology.

In order to understand the uneven development of countries, Hidalgo et al. (2007) proposes a novel approach to understand economic development, using a network to visualize the co-occurrence of exports. They found that most high-technology products are densely connected to each other, while low-technology products are weakly connected to each other, and countries tends to evolve towards products related to their current productive matrix. Hidalgo and Hausmann (2009) propose to study of economic growth and development from the perspective of the complexity of activities that are present in a territory, and they suggest that development is associated with an increase in activities, and the complexity that emerges from the interaction of them. This idea is the basis behind of the field of economic complexity.

In an effort to explore the long-term evolution of patent portfolios, Boschma et al. (2015) found evidence in the US cities that existing technological capabilities conditions the entry and exit of a technology in a city. Neffke et al. (2011) found that industries or product portfolios, respectively, are more likely to enter a region if they are technologically related to the preexistent regional industries or portfolio. That is, relatedness of a technology to the city's capabilities is a crucial driving force behind technological changes, and long-term evolution of technological diversification.

Boschma et al. (2014) determinates the scientific impact of diversification in relation to the dynamics of the city's scientific knowledge in biotechnology. Guevara et al. (2016) use a data set of scientific publications to analyze the structure of research production, allowing predict changes in the level of development of individuals, organizations, and countries, for research fields, and Janavi et al. (2020) analyze countries' scientific diversification strategies and its impact on scientific progress of countries by identifying the strengths and weaknesses of the scientific system by emphasizing scientific productivity border, which can identify proximal domains to the country's scientific capabilities and lead countries toward greater scientific diversity.

These studies show that existing technological capabilities of a territory conditions success or failure in the incorporation of new technologies in their current set. This evidence about the spatial concentration of technology, skills and knowledge is the foundation behind the principle of relatedness (Hidalgo et al., 2018), empirical principle that describes the probability that a region enters (or exits) an economic activity as a function of the number of related activities present in that location, it has leading to large volume of technological-relatedness studies at multiple spatial scales.

Hidalgo (2021) review the literature in economic complexity to summarize its theory and applications, showing evidence that economic complexity has been validated by studies at multiple geographic scales, and in a variety of economic activities (including technology patents).

We contribute to the literature with a quantitative measure of the effects of countries' patent citations on their technological diversity, its impact on their current portfolios, and their technological relevance relevance at worldwide.

Methodology

We analyze how differ the comparative advantages of a country when we use a measure of impact (e.g. number of citations), instead of the number of patents granted. For this purpose, we propose a weighting of revealed comparative advantage (RCA) proposed by Balassa almost 50 years ago, using the number of citations of a patent as proxy of technological impact.

Data

We use the patents granted by the United States Patent and Trademark Office (USPTO) between 2006 and 2015, as a proxy of technological capabilities at worldwide. This patent office is a valuable source to describe the state of the art of global technological innovation, since the USPTO data base is appropriate to study global innovation (Kim & Lee, 2015). We download the data set using a public API supported by this office called *PatentsView*. We associated the country of a patent based on their assignee, and to classify technologies, we used the Cooperative Patent Classification (CPC) standard at 3-digit level.

We consider in this study countries with more than 500,000 inhabitants in 2015. Then, we filter countries and technologies with less than 100 patents granted.

To compare the differences in the citations of patents granted from developed or developing countries, we use Gross Domestic Product (GDP) per capita, Economic Complexity Index—a measure of economy's capability, published on the Observatory of Economic Complexity (OEC) (Simoes & Hidalgo, 2011), and we also classify countries as members or not from Organization for Economic Cooperation and Development (OECD).

Revealed comparative advantage weighted

The revealed comparative advantage (RCA) is an index defined by Balassa (1965) to measure the export potential of a country. Let us suppose that the country C exports a higher fraction of a product P, in relation to the fraction of the P exported at global trade. In this scenario, we affirm that C has comparative advantages in P. This intuitive idea to measure the country's export capabilities has been used in economic geography to measure technological capabilities using patents (Boschma et al., 2015). Nevertheless, as we describe before, there are studies that suggest all patents do not have the same impact. This last point of view makes us think that the number of patents may not be the optimal path to describe technological capabilities. How about if we weight the number of patents granted by country, with respect to the number of citations that these patents have, to measure technological capabilities?

We propose a homologous index, which we call revealed comparative advantage weighted (RCA_w), to represent relative advantages of a country using citations as factor. First, we define $\mathrm{RCA}_{c,t}(i)$ to represent the share of technology i of a country c in the period t, in comparison with the share of i at worldwide in the same period (1).

$$\mathrm{RCA}_{c,t}(i) = \frac{\mathrm{patent}_{c,t}(i)/\sum_i \mathrm{patent}_{c,t}(i)}{\sum_c \mathrm{patent}_{c,t}(i)/\sum_c \sum_i \mathrm{patent}_{c,t}(i)}, \tag{1}$$

where $\mathrm{patent}_{c,t}(i)$: Total patents granted in technology i of country c in period t; $\sum_i \mathrm{patent}_{c,t}(i)$: Total patents granted from country c in period t; $\sum_c \mathrm{patent}_{c,t}(i)$: Total patents granted in technology i at worldwide in period t; $\sum_c \sum_i \mathrm{patent}_{c,t}(i)$: Total patents granted worldwide in period t.

Then, we define $\mathrm{Citations}_{c,t}(i)$ as the fraction of citations that represent a technology i in a country c in time t, in comparison to the fraction of citations of i at worldwide on the same period (2).

$$\mathrm{Citations}_{c,t}(i) = \frac{\mathrm{citations}_{c,t}(i)/\sum_i \mathrm{citations}_{c,t}(i)}{\sum_c \mathrm{citations}_{c,t}(i)/\sum_c \sum_i \mathrm{citations}_{c,t}(i)}, \tag{2}$$

We use $\mathrm{Citations}_{c,t}(i)$ as a multiplicative factor of $\mathrm{RCA}_{c,t}(i)$ to adjust the comparatives advantages of a technology i beyond just to use patenting levels. We call this measure *revealed comparative advantage weight* (RCA_w) (3).

$$\mathrm{RCA}_{w_{c,t}}(i) = \mathrm{Citations}_{c,t}(i) \cdot \mathrm{RCA}p_{c,t}(i) \tag{3}$$

Values higher than one indicates that a country has comparative advantages in the technology i when considering number of patents and citations. We are interested into study in which technological classes a country win, lose, and keep comparative advantages according to the weighing by citations. For instance, if country P has in technology Q a RCA > 1, and $\mathrm{RCA}_w < 1$, this means that P has capabilities in Q in number of patents, but not in impact of its patents.

Technological diversity and technological diversity weighted

The $M_{w_{c,t}}(i)$ matrix is calculated based on $\mathrm{RCA}w_{c,t}(i)$ (4)

$$M_{w_{c,t}}(i) = \begin{cases} 1, & \mathrm{RCA}w_{c,t}(i) > 1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

In this study, technological diversity weighted (TD_w) measures the number of technologies in which a country has comparative advantages using RCA_w (5). Analogous to TD_w, we calculate a technological diversity (TD) using RCA.

$$\mathrm{TD}w_{c,t}(i) = \sum_c M_{w_{c,t}}(i) \tag{5}$$

$$\mathrm{TD}_{c,t}(i) = \sum_{c} M_{c,t}(i) \tag{6}$$

The comparison between TD and TD_W allows us to explore if there are variations in the capabilities from each country when we include the impact of patents as variable. For instance, if $\mathrm{TD}_w > \mathrm{TD}$, we can say that the country increases its diversity with the adjust by citations.

Diversity Change

To formalize the rate of net gained diversity, we call Diversity Change to the measure about how patent citations impact in the known capabilities of countries (based on RCA) as the difference between TD_w and TD, divided by the TD (7).

$$\text{Diversity Change}_{c,t} = \frac{\mathrm{TD}_{w_{c,t}} - \mathrm{TD}_{c,t}}{\mathrm{TD}_{c,t}} \tag{7}$$

Values higher than zero indicates that a country c increases its diversity when we use citations. For example, if $\text{Diversity Change}_{c,t} = -0.35$, this value means that c lost 35% of its comparative advantages. We can interpret this value as an over-estimation of the technologies that are present in a territory.

Citation Space

Based on the methodology proposed by Hidalgo et al. (2007), we build a network to represent links between technologies using $\mathrm{RCA}w_{c,t}(i)$ called Citation Space. We calculate how close are two technologies i,j using the proximity ($\phi_{w_{i,j}}$). Values close to unity indicates that two technologies are correlated, as we present in (8):

$$\phi_{w_{i,j}} = \min\left\{P\left(\mathrm{RCA}w_{j,t} > 1\right), P\left(\mathrm{RCA}w_{i,t} > 1\right)\right\}, \tag{8}$$

Then, we compute the maximum spanning tree, and we overlap in the network the pairs of technologies with proximity higher than 0.6. Finally, we compare our Citation Space with a network built based on RCA matrix, in a similar way to that proposed by Boschma et al. (2014), in the "Technological Space".

Results

We analyze 1,979,038 patents granted by the USPTO in the period 2006–2015 for 44 countries in 126 CPC classes. The countries with higher citation rate are Australia (6.3, $N=11{,}238$), United States (5.4, $N=1{,}014{,}847$), Israel (5.1, $N=11{,}874$), Finland (4.5, $N=11{,}815$), and Cyprus (4.4, $N=273$). The countries with lower citation rate are Turkey (0.8, $N=208$), United Arab Emirates (0.9, $N=101$), Slovenia (1, $N=194$), Czechia (1, $N=299$), and Saudi Arabia (1, $N=1413$). On one hand, we found positive correlation ($R^2=30\%$) between citations by country and its GDP per capita (Fig. 1a). On another hand, we compare the average citations by CPC section and by OECD members/no-members, we observe that OECD countries have 2.6 citations per patent, compared to 2.1 citations per

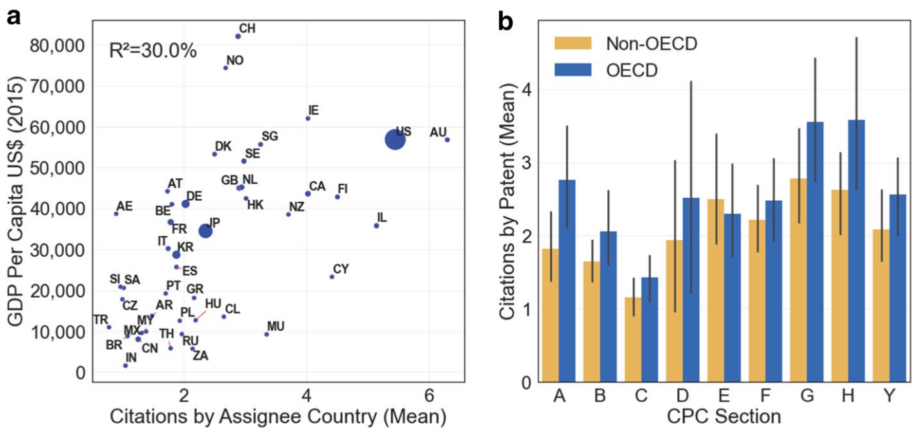

Fig. 1 **a** Bivariate plot of Citations by Assignee Country (x-axis) and GDP Per Capita in 2015 (y-axis), **b** bar plot of citations by patent in each CPC section, comparison in each section by OECD members/Non-members

patent for non-OECD countries. When analyzing the citations by CPC section, we can see that the higher differences in citations between OECD members and non-members are presented in sections Electricity (H, $\Delta = 0.96$), Human necessities (A, $\Delta = 0.94$), and Physics (G, $\Delta = 0.77$) (Fig. 1b). Although there are no statistically significant differences, there is a trend of higher citations of patents granted by OECD members in 8 of 9 CPC sections.

Are the differences between developed and undeveloped countries make more noticeable when measuring technological capabilities using this new approach proposed in this study?

We found that 88.6% of the countries analyzed decreased their diversity when we adjust RCA by citations. On average, the countries decreased their diversity in 21.5%. The countries that increased or maintained their diversity were Japan (13.2%), China (9.7%), South Korea (0%), United States (0%), and Sweden (0%). The countries with higher decrease of their diversity were Cyprus (56.4%), Thailand (51.4%), Slovenia (48.3%), Poland (46.9%), and Greece (45.4%) (Fig. 2a). The data show us that diversity weighted has unequal effects on the capacities of the countries. The top 10-countries with highest GDP decreased their diversity by 3.4%, compared to the rest of the countries, which decreased by 26.1%. Also, the diversity of OECD members decreased by 20.8%, as opposed to non-OECD members, which decreased by 22.2%. We observe that high-income countries tend to have more citations in their patents compare with low-income countries.

Then, we do an analyzes of diversity. Figure 2a compares the variations of comparative advantages in the countries analyzed in this study. We consider as a new capability the technologies with RCA < 1 and $RCA_w > 1$; and as capability lost the technologies with RCA > 1 and $RCA_w < 1$. Chile reports five new capabilities; nevertheless, this country loses twenty capabilities; unlike Japan which wins six technologies, and just loses one technology with the adjust by citations.

We learn from Fig. 2a that there is not a pattern between the gains and losses of technologies, nevertheless we observe that countries that are known worldwide as creators of technology have better weighted diversity values. In this vein, we explore changes in the set of technologies available in a country in function of its economic complexity. We observe a positive correlation ($R^2 = 23\%$) between values of Diversity Change and ECI, which gives

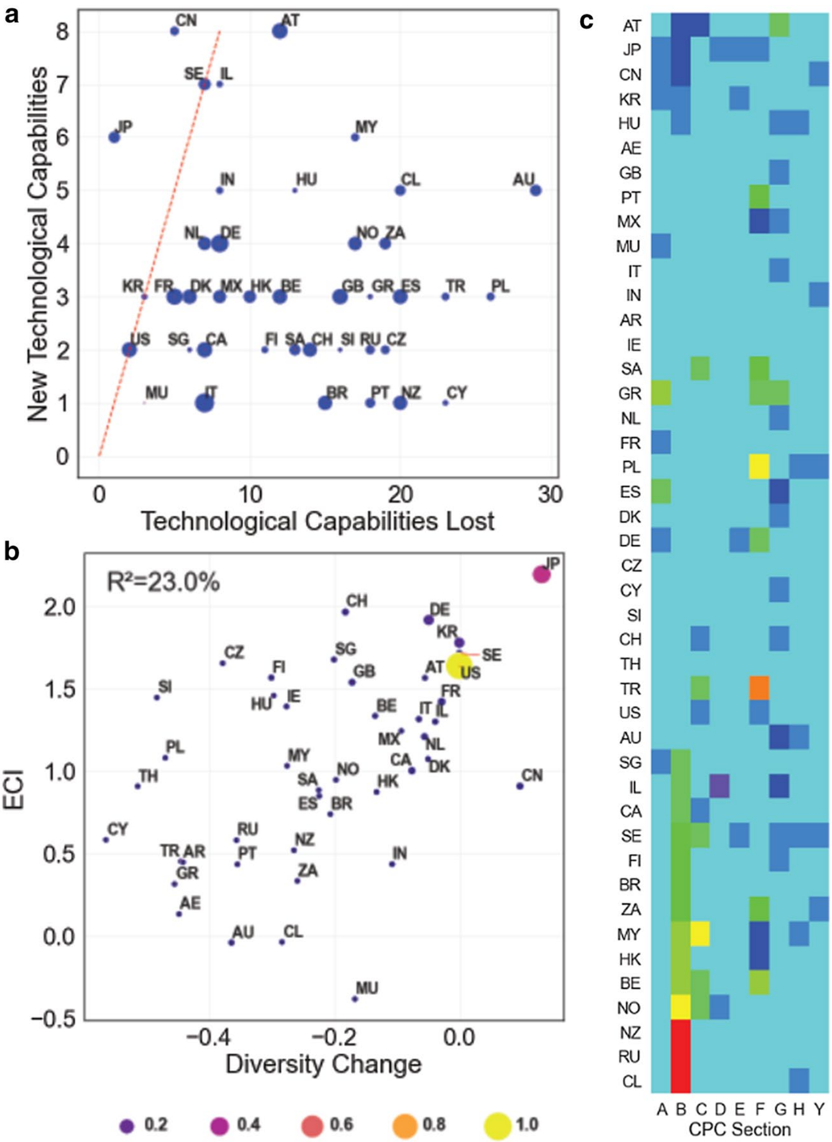

Fig. 2 **a** Bivariate plot of technological capabilities lost (*x*-axis) and new technological capabilities (*y*-axis). Values to the left of the dashed red line indicates that the country have a positive net technological gain. **b** Bivariate plot of Diversity Change (*x*-axis) and ECI (*y*-axis). **c** Heatmap of net gains diversity by CPC section and country. (Color figure online)

us evidence to suggest that the rate of net technological gain is correlated with the complexity of a country. Table 1 provides a summary of these results.

Figure 2c shows the net comparative advantages of technologies by CPC section. The "Performing Operations; Transport" (B) is the section with higher loss (in average) of comparative advantages (– 1.5). In this section, the countries with highest

Table 1 Summary of TD, TD_w, ECI, and Diversity Change

Country	ECI	Technological diversity (TD)	Technological diversity weighted (TD_w)	Diversity Change
Argentina	0.45	34	19	−0.44
Australia	−0.04	66	42	−0.36
Austria	1.57	73	69	−0.05
Belgium	1.34	67	58	−0.13
Brazil	0.74	68	54	−0.21
Canada	1	66	61	−0.08
Chile	−0.04	53	38	−0.28
China	0.91	31	34	0.1
Cyprus	0.58	39	17	−0.56
Czechia	1.66	45	28	−0.38
Denmark	1.07	60	57	−0.05
Finland	1.57	30	21	−0.3
France	1.42	71	69	−0.03
Germany	1.92	82	78	−0.05
Greece	0.31	33	18	−0.45
Hong Kong	0.87	53	46	−0.13
Hungary	1.46	27	19	−0.3
India	0.44	28	25	−0.11
Ireland	1.39	29	21	−0.28
Israel	1.3	26	25	−0.04
Italy	1.32	93	87	−0.06
Japan	2.19	38	43	0.13
Malaysia	1.03	40	29	−0.28
Mauritius	−0.38	12	10	−0.17
Mexico	1.25	54	49	−0.09
Netherlands	1.21	54	51	−0.06
New Zealand	0.52	72	53	−0.26
Norway	0.95	66	53	−0.2
Poland	1.08	49	26	−0.47
Portugal	0.44	48	31	−0.35
Russia	0.58	45	29	−0.36
Saudi Arabia	0.89	49	38	−0.22
Singapore	1.68	20	16	−0.2
Slovenia	1.45	29	15	−0.48
South Africa	0.33	58	43	−0.26
South Korea	1.78	20	20	0
Spain	0.85	76	59	−0.22
Sweden	1.72	48	48	0
Switzerland	1.97	66	54	−0.18
Thailand	0.91	37	18	−0.51
Turkey	0.45	45	25	−0.44
United Arab Emirates	0.13	38	21	−0.45
United Kingdom	1.54	76	63	−0.17

Table 1 (continued)

Country	ECI	Technological diversity (TD)	Technological diversity weighted (TD_w)	Diversity Change
United States	1.64	59	59	0

decreases in capabilities are for New Zealand (− 6), Chile (− 6), and Russia (− 6), and the countries that increased their capacities the most are Japan (+ 2), China (+ 2), and Austria (+ 2).

If we explore more deeply the technological classes where there is more gains and losses of capabilities, we can see that the technologies that losses more countries with capabilities are *Disposal of Solid Waste* (B09, $N=12$), *Treatment of Water* (C02, $N=12$), *Medical or Veterinary Science* (A61, 11), *Life-Saving; Fire-Fighting* (A62, $N=10$), *Casting; Powder Metallurgy* (B22, $N=9$). On another hand, technologies with gains of countries are *Information or communication technologies having an impact on other technology areas* (Y04, $N=4$), *Heat exchange in general* (F28, $N=4$), *Indexing schemes relating to engines or pumps in various subclasses of classes F01–F04* (F05, $N=3$), *Horology* (G04, $N=3$), and *Controlling, Regulating* (G05, $N=3$). At the country/technology level, we can observe some noticeable differences. In the case of Chile, *Preparatory treatment of grain for milling* (B02) have RCA = 4.1 and $RCA_w = 0$; *Cutting, meat treatment, poultry or fish processing* (A22) have RCA = 1.2 and $RCA_w = 0.9$, and in *manual cutting tools* (B26) RCA = 0.8 to $RCA_w = 1.8$. These cases are relevant, given that 8.5% of Chile's exports correspond to animal products, and 10.2% to vegetable products ("Chile (CHL) Exports, Imports, and Trade Partners" 2021). For South Korea, *Presses* (B30) RCA = 0.5, $RCA_w = 1.7$. *Crystal growth* (C30) RCA = 1, $RCA_w = 0.9$. *Technologies or applications for mitigation or adaptation to climate change* (Y02) RCA = 1.02, $RCA_w = 0.99$.

Finally, we build two networks: "Technological Space", (Fig. 3a), and "Citation Space" (Fig. 3b), using RCA and RCA_w respectively.

We compare proximities between technologies using the matrix of RCA (φ) and RCA_W (φ_w). The proximities in φ (Mean = 0.36, Median = 0.36) are higher than those observed in φ_w (Mean = 0.30, Median = 0.30) (Fig. 3c).

We observe that proximity in pairs of technologies decrease in 66.7% of the cases when we use φ_w instead of φ (Fig. 3d), and the delta of proximity ($\varphi_w - \varphi$) do not follow a pattern across pairs of technologies. On one hand, the pairs of technologies with higher increases of proximity are *Photography; Cinematography* (G03) with *Education; Cryptography; Advertising; Seals* (G09) in 0.33 from 0.33 to 0.66, *Butchering, Meat treatment, Processing poultry or fish* (A22) with *Education, Cryptography, Advertising, Seals* (G09) in 0.32 from 0.06 to 0.38, and *Vehicles* (B60) with *Hydraulic Engineering, Foundations, Soil Shifting* (E02) in 0.29 from 0.24 to 0.53. On another hand, the pairs of technologies with higher decreases of proximity are *Baking, edible doughs* (A21) with *Information or communication technologies having an impact on other technology areas* (Y04) in 0.45 from 0.53 to 0.08; *Spraying or atomizing in general* (B05) with *Disposal of solid waste, reclamation of contaminated soil* (B09) in 0.44 from 0.67 to 0.22, and *Natural or mand-made threads or fibers; spinning* (D01) with *Treatment of textiles* (D06) in 0.41 from 0.61 to 0.20.

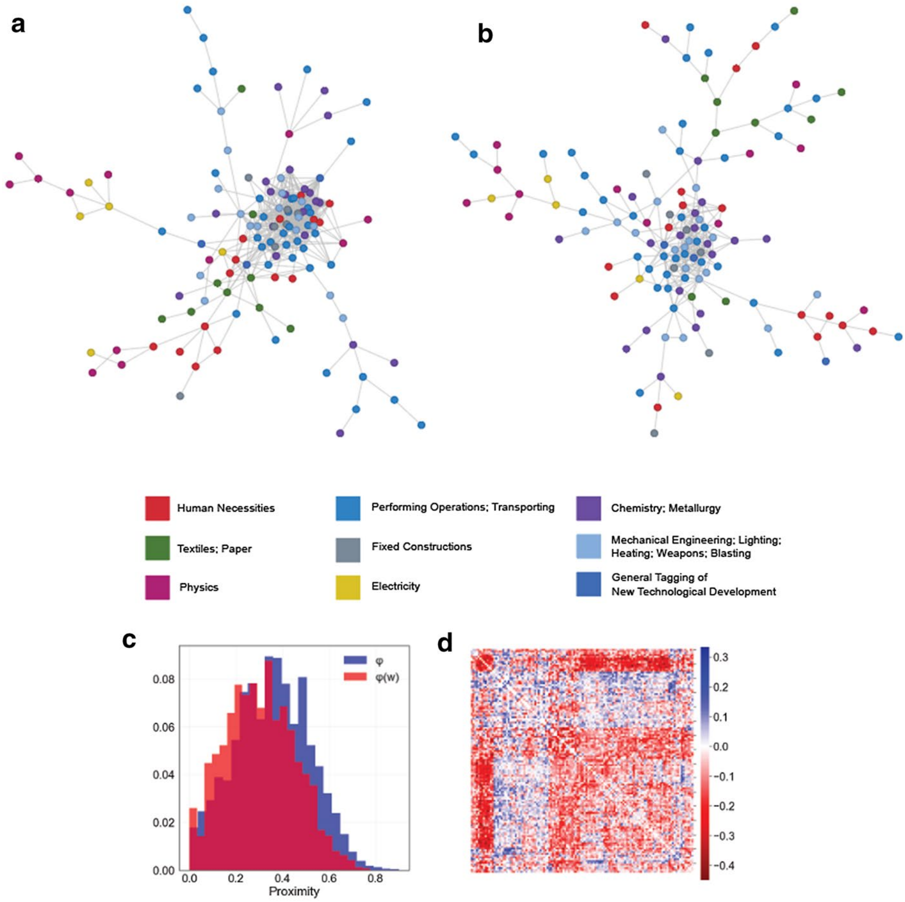

Fig. 3 **a** Citation Space, **b** Technological Space, **c** histogram of proximities using RCA (blue) and RCA_w (red). **d** Heatmap clustered (using method complete and Euclidean distance) of delta proximity ($\varphi_w - \varphi$). (Color figure online)

Discussion and conclusions

We propose in this paper a method to quantify the technological capabilities of territories using the number of patents and citations (as a measure of impact). Our study suggests that an adjust by citations, allows a good estimation of the set of technologies present in a country. Undoubtedly, the capabilities that a country holds to achieve technological growth, makes the difference to determinate if it can decrease or not their diversity.

In the descriptive analysis, we observe that the more developed countries receive on average more citations for their patents than non-developed countries. This evidence is the first indicator that allows us to correlate the impact of a technology with its country of origin.

We found that complex countries tend to lose a smaller rate of technologies if we adjust their capabilities by technological diversity weighted instead of technological diversity. In this sense, the countries that increased or maintained their diversity values were Japan

(13.2%, ECI = 2.19), China (9.7%, ECI = 0.91), South Korea (0%, ECI = 1.78), United States (0%, ECI = 1.64), and Sweden (0%, ECI = 1.71).

The difference of the proximity matrices ($\varphi_w - \varphi$) shows us that co-occurrence patterns of technologies are not the same. Beyond determining which of the two matrices have a better fit to estimate proximity between technologies, this result opens the discussion around how measures of impact (e.g., patent citations) reshape how we understand technological capabilities of countries. Our contribution to the literature is to enrich the discussion about how measures of impact can be a feasible proxy to calculate comparative advantages.

To conclude, we consider that the revealed comparative advantage weighted (RCA_w) allows to reflect the capabilities present in a territory, since in the case of technology, it is a measure that considers both the number of patents and citations. Beyond just using RCA or RCA_w, the comparison of these indicators can expand the discussion around the strategies that countries should follow in the search for technological capabilities. Policymakers have a special interest in understanding the advantages and opportunities that arise in a location, with the purpose to make good public policy recommendations. In this context, possible differences in Relatedness should be explored using both measures, to analyze if there are significant changes in the probability of entry or exit of technologies with one or another method.

Limitations

There are some limitations in our study that undoubtedly lead to future research. First, we only use patents granted provided by the United States Patent and Trademark Office (USPTO) without exploration of other patent datasets, such as European Patent Office (EPO), Japan Patent Office (JPO), and Korean Intellectual Property Office (KIPO). Also, our study just uses patent citations among US patents as well. This approach is important, due to the fact that not all the countries patent their technologies in USPTO. Certainly, through covering more patent offices, greater representativeness is obtained. Second, in terms of measuring technological capabilities of countries by number of patents, there are possible biases related to difference in regulation in patent offices around the world that may limit presence of patents in some parts of the technological spectrum.

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