The scientific impact of nations on scientific and technological development

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Determining how scientific achievements influence the subsequent process of knowledge creation is a fundamental step in order to build a unified ecosystem for studying the dynamics of innovation and competitiveness. Yet, relying separately on data about scientific production on one side, through bibliometric indicators, and about technological advancements on the other side, through patents statistics, gives only a limited insight on the key interplay between science and technology which, as a matter of fact, move forward together within the innovation space. In this paper, using citation data of both scientific papers and patents, we quantify the direct impact of the scientific outputs of nations on further advancements in science and on the introduction of new technologies. Our analysis highlights the presence of geo-cultural clusters of nations with similar innovation system features, and unveils the heterogeneous coupled dynamics of scientific and technological success. This study represents a first step in the buildup of a comprehensive framework for knowledge creation and innovation.

I. INTRODUCTION

Developing a comprehensive conceptual framework capturing the emergent properties of the knowledge creation process requires, as building blocks, quantitative indicators providing insights into the structure and dynamics of innovation systems. In this respect, numerous metrics for the impact of scientific research based on publication outputs exist in the literature—see Waltman [1] for a recent overview of the field. Similar (yet less refined) indicators for technological development based on patent data have been introduced as well [2, 3]. However, the majority of these metrics focus on either scientific and technological activities separately. For instance, by relying only on citations within journal papers, scientific impact metrics can assess how much a given scientific achievement is relevant for the community of researchers, but neglect its potential impact on other research and development (R&D) areas. Nevertheless, any effort for a thorough understanding of the innovation system cannot leave out of consideration the interactions between scientific and technological developments.

On this perspective, patents references to scientific papers—the so called *prior art* [4]—can be used to assess the importance of scientific research on technology outputs. The mainstream approach, originally developed in Narin *et al.* [5], Narin [6], is to compute the *science intensity* parameter, namely the average number of references to scientific literature per patent. While originally intended to identify leading-edge companies, this indicator has been subsequently used for discovering the value of scientific research and forecasting future disruptive technologies. Despite the various issues which may affect patent citation data [7] (such as the difference between patent offices practices, the extent to which references reflect sources of inspiration beyond legal purposes, and the contribution of the examiner beyond the inventor),[1] nowadays patent citations are regarded as reliable information to build meaningful indicators for the impact of science on technology [9–14]. The inverse feedback, namely the impact of technology on science, has been proxied by patents cited from scientific publications [15, 16], which have however a less clear interpretation than references in the opposite direction [17]. Notably, various studies [5, 14, 18, 19] conclude that interactions between science and technology are much more complex (and reciprocal) than a linear model of knowledge flow would suggest. Indeed, scientific and technological activities mutually benefit from such interactions: patent-cited papers perform better in terms of standard bibliometric indicators [20], and patents that reference published material receive more citations—primarily because their influence diffuses faster in time and space [21].

Besides giving insights on specific knowledge creation patterns, citation-based indicators can also offer a broader and more systematic view on science-technology relations, potentially addressing policy relevant issues on how to efficiently shape national innovation systems. Indeed, when performed at the level of nations, science intensity has been often compared to technological productivity (*i.e.*, number of patents per capita), finding a positive relation in specific technological fields (biotechnology, pharmaceuticals, organic fine chemistry and semiconductors) [22–25]. In particular, science intensity appears to be relevant for scientific sectors having a sufficient body of knowledge [26].

In this work we add to the current discussion by comparing the impact of national scientific systems on the global scientific knowledge and technological development. To task, we use refined bibliometric indicators based on citation scientific documents accrued either from other papers or from patents. Consequently, we introduce a

[1] Different issues affect citations within scientific papers as well, like the improper citation practices (boosting self or friend's citations, or satisfying referees) that are not related at all to the acknowledgment of a paper's importance [8].

technology intensity parameter, focused on the knowledge outflow from science to technology and thus representing the natural counterpart of science intensity (which reflects the inflow in the opposite direction). We then relate the proposed metrics to national expenditures in R&D. In line with previous studies [27], our analysis highlights the presence of geo-cultural clusters with similar innovation system features, and represents a step forward towards a quantitative characterization of the complex interconnection between science and technology in the knowledge creation and innovation process.

II. MATERIALS AND METHODS

Data and basic statistics

Basic statistics on scientific productivity and impact are collected from the SciVal platform (`www.scival.com`), a new API aggregating data from Scopus (`www.scopus.com`). The collected data cover years from 1996 to 2015, and refer to $N_c = 45$ nations and to $N_d = 27$ scientific macro sectors (according to the Scopus classification). The scientific production of a nation indicates the scholarly output authored by all the researchers affiliated with an institution of that nation. Note that Scopus statistics are built using a full counting method[2] favoring small nations with high level of internationalization to the detriment of large standalone nations [28, 29]. Note also that Scopus (as other bibliometric databases) basically has a full coverage of English-written documents published in international peer-reviewed journals. Documents written in other languages and published in national journals are however important especially in Social Science and Humanities [30, 31], which were thus excluded from our analysis (also as they are not particularly relevant for technological output), resulting in $N_d = 22$ scientific sectors considered. Concerning patent data, SciVal covers five patent offices: the World Intellectual Property Organization (WIPO), the Intellectual Property Owners association (IPO), the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO). Note that the database lacks relevant offices such as the China Trademark and Patent Office (CTPO), which can lead to bias as patent applicants usually apply first at the home country office (and successively to other offices when deemed necessary) [32]. Moreover, there are strong differences from office to office on regulation and practices of patent handling. For instance, JPO usually splits applications in several narrower patents [33], while USPTO does not publish all the applications but enforces by law a patent applicant to refer to any prior documents known to him (the so called "duty of disclosure") [11]. This results in different citation frequencies among USPTO, EPO and JPO patents, yet the multitude of patent references and the aggregation of various offices can mitigate the problem. Keeping all the described issues of the dataset in mind, we collect from SciVal the aggregate statistics on citations that scientific documents receive from other papers as well as from patents. Thus, for each nation i, scientific sector α and year t we consider the whole set of the scientific documents produced $[DOC]_{i\alpha}(t)$, and we record the following basic metrics:

- $[CIT]_{i\alpha}(t)$, the number of citations from scientific documents,
- $[PCC]_{i\alpha}(t)$, the number of citations from patents (*patent-citation count*),
- $[PCD]_{i\alpha}(t)$, the number of these documents that are cited by patents (*patent-cited documents*).

We complement this information with measurements of national expenditures in research and development (R&D), collected from the Organization for Economic Cooperation and Development (OECD, `www.oecd.org`). Data refer to GERD (Gross Expenditures on R&D) values for $N_f = 44$ nations from 1981 to 2015,[3] divided into three sub-components depending on the funded sector: BERD (Business Expenditure on R&D) for the business sector, HERD (Higher Education Expenditure on R&D) for basic research performed in the higher education sector, and GOVERD (Government Intramural Expenditure on R&D) for the government sector (we remand to OECD [34] for the official definition of these quantities). Note that data coverage is not uniform, with several missing values before 1995. Additionally, HERD is available only for 37 nations while BERD only for 34 nations. We therefore restrict the analysis to years $1996 - 2015$ (compatibly with the SciVal database), and to the $N_f = 34$ nations whose data is available [4].

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[2] In principle, papers can be assigned to nations using either a full counting or a fractional counting method [1]. In the former, a publication co-authored by various nations is fully assigned to each of them, whereas, in the latter the assignment is weighted, *e.g.*, by the fraction of authors or affiliations belonging to that nation.

[3] All expenditures are expressed in terms of current purchasing power parity (in millions of US dollars).

[4] To compensate for the few missing values in the restricted database, we use linear interpolation on the available data.

Impact metrics

To measure the impact of the scientific production of a nation on the subsequent global scientific activity, we use standard scientometrics tools based on shares of scientific citations received [1]. In particular here we use the *citation share over document share* [27]:

$$Sci\ [Csh/Dsh]_i(t) = \left(\frac{\sum_\alpha [CIT]_{i\alpha}(t)}{\sum_{j\alpha}[CIT]_{j\alpha}(t)}\right) \Bigg/ \left(\frac{\sum_\alpha [DOC]_{i\alpha}(t)}{\sum_{j\alpha}[DOC]_{j\alpha}(t)}\right) = \frac{1}{A_{sci}(t)} \frac{\sum_\alpha [CIT]_{i\alpha}(t)}{\sum_\alpha [DOC]_{i\alpha}(t)}, \tag{1}$$

where the average paper citations per document $A_{sci}(t) = (\sum_{j\alpha}[CIT]_{j\alpha}(t)/(\sum_{j\alpha}[DOC]_{j\alpha}(t))$ allows for proper time normalization. Note that in the above formula all papers are given the same weight, whereas, other metrics use a field normalization approach by giving different weight to papers belonging to different scientific sectors [35]. Remarkably, the different approaches found in literature lead to practically the same results when applied to nations [27].

To measure the impact of the scientific production of a nation on the global technological development, we adopt the same reasoning used for eq. (1) and replace the citations from scientific papers with the citations from patents. We get:

$$Tech\ [Csh/Dsh]_i(t) = \left(\frac{\sum_\alpha [PCC]_{i\alpha}(t)}{\sum_{j\alpha}[PCC]_{j,\alpha}(t)}\right) \Bigg/ \left(\frac{\sum_\alpha [DOC]_{i\alpha}(t)}{\sum_{j\alpha}[DOC]_{j\alpha}(t)}\right) = \frac{1}{A_{tech}(t)} \frac{\sum_\alpha [PCC]_{i\alpha}(t)}{\sum_\alpha [DOC]_{i\alpha}(t)}, \tag{2}$$

where again time normalization is achieved trough the average patent citations per document $A_{tech}(t) = (\sum_{j\alpha}[PCC]_{j\alpha}(t))/(\sum_{j\alpha}[I$
As for the case of scientific success, using field normalization here leads to very similar results, as demonstrated by the high Pearson correlation of 0.98 between the temporal average of the indices obtained with the two different approaches (the Pearson correlation between the scientific metric variants is 0.96 [27]).

We remark that the rationale behind the proposed metrics of success is that whenever a nation receives a larger share of citations compared to the fraction of papers it publishes, it is producing science that has a greater impact than the world average. As compared to the average-based indices already proposed in the literature [1][5], the advantages of the specific formulation we adopt here are the minimization of fluctuations due to small scientific sectors, and the independence on the classification scheme used for science, which we pay by loosing a proper field normalization.

III. RESULTS AND DISCUSSION

The scientific and technological impact metrics of nations, respectively obtained with equations (1) and (2), are shown in Figure 1. Line colors correspond to different cultural, economic and geographical regions, for which we report representative countries (other nations are reported in gray): magenta identifies the United States, blue denotes Western Europe (France, Germany, United Kingdom, Italy, Spain), black are BRICS countries (Brazil, Russia, India, China, South Africa), cyan denotes Northern Europe (Belgium, Netherlands, Sweden, Switzerland), red denotes Eastern Europe (Czech Republic, Hungary, Poland) and yellow identifies Asian countries (Japan, South Korea, Singapore, Taiwan). Concerning technological success, shown in panel (*b*), a clear separation emerges between very efficient nations (*i.e.*, USA, Switzerland and Singapore in the late years), Europe and developed Asian countries, and the rest of the world. This pattern is observed also when field normalized metrics are used (Fig. S1), and when the analysis is restricted to individual patent office data (to get rid of home advantage effects, Fig. S2) as well as to specific scientific sectors (Fig. S3). The trend of the time normalization coefficient, *i.e.*, the average number of patent citations per document (shown in the inset of panel (*b*)) indicates a characteristic time scale for patents citations of about $10-15$ years, thus longer than that for scientific citations (as shown in the inset of panel (*a*)). Indeed, papers need time to attract citations from other papers [38], and even more time to get citations from patents. This happens because patent applications are not processed in real time but with a delay of $30-40$ months, depending on the patent office [39, 40][6]. Panel (*a*) shows instead the scientific success of the different nations. Although it is still possible to find a separation between geographical areas, no particular gap is observed between Europe and the most efficient nations.

To better understand the relation between scientific and technological impacts, Figure 2 shows the scatter plot of these values for the various nations. Panel (*a*) reports values averaged over years $1998-2012$. Indeed, we see that

[5] An alternative approach to average-based indicator is represented by percentile-based indicators [36], which are less sensitive to outliers given by highly cited publications [37]. Yet, when performing analyses at large scales (*e.g.*, for nations, wide scientific areas, and long time windows), the law of large numbers acts by smoothing out the distortions due to such outliers [27].

[6] This reduces the validity of the available data in the last 3 years [41]

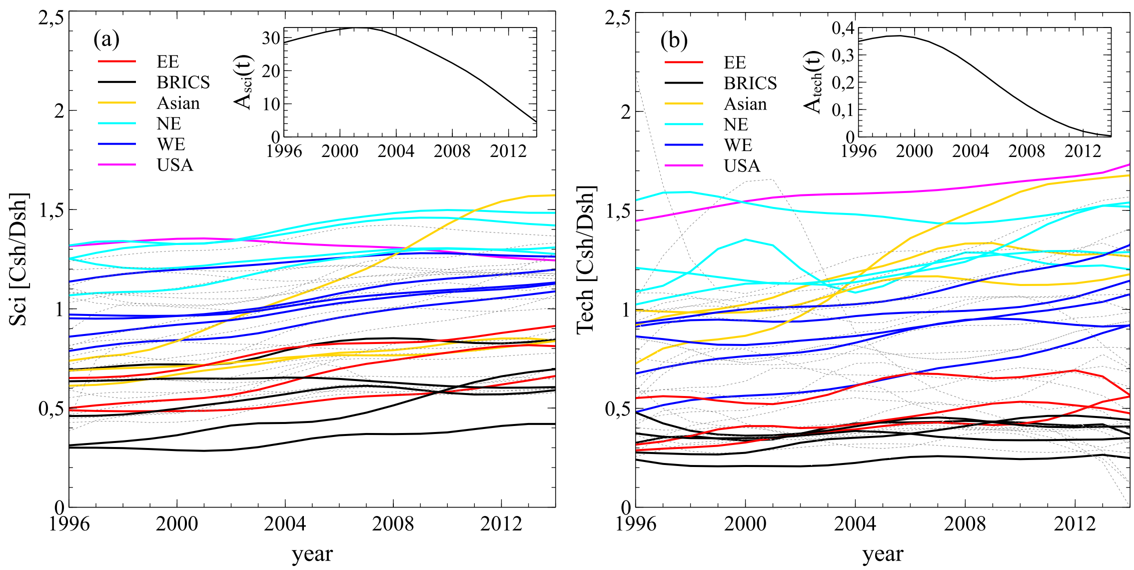

FIG. 1. Successes of different nations over years 1996 − 2014. Panel (a): scientific success defined by eq. (1). Inset: time normalization factor $A_{sci}(t)$. Panel (b): technological success defined by eq. (2). Inset: time normalization factor $A_{tech}(t)$.

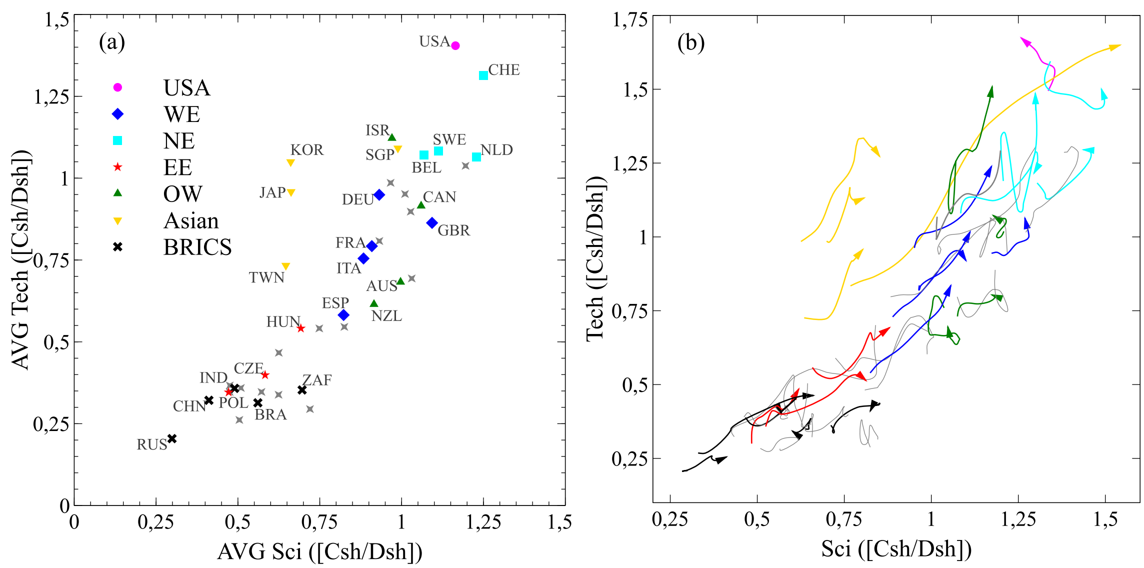

FIG. 2. Scientific versus technological impact of nations over years 1998 − 2012: average values (panel (a)) and temporal trajectories with arrows indicating the time flow (panel (b)). Besides the regions described for Fig 1, here we highlight also other western countries (Australia, Canada, Israel, New Zealand) in green.

the two impact metrics are not independent and, as expected, are highly correlated. Remarkably, the plot highlights a cultural and geographical separation. Developing nations (such as BRICS countries) are located in the bottom left section of low success both in science and technology. Then the central region is populated, in succession, by Easter European countries and Western European countries, ending with North Europe and the top performers Switzerland and USA. Asian countries lie slightly off the diagonal, featuring a higher technological impact than scientific success. This discrepancy may be induced from the aforementioned JPO practice of splitting patents into more applications, resulting in more patent citations for Asiatic countries relying on this office as compared to other nations with similar scientific success. Note also the position of China, which has low scientific success because of the intensive nature of the index (China still has a low citation ratio in science) as well as a low technological success also due to the lack of the CTPO in our dataset. Panel (b) shows instead the trajectories of the different nations in the plane of scientific and technological success. To understand the plot, we first notice that both the success measures are based on citation shares over document shares, and since the world's shares are necessarily equal to one, the success indices cannot grow for all nations at the same time. Most of the nations, especially those in the center of the diagram, show a positive trend both for scientific success, compensated by the notable exception of the USA, and for technological success, compensated instead by the decrease of some under-developed countries (not shown in the plot), as well as by that of Japan and Korea at the end of the time span considered. We then see that developing nations do move towards regions of higher success, but in a chaotic manner (except for China that moves smoothly). On the contrary, the motion of Western countries towards the highest scientific and technological success is more laminar (and an extraordinary improvement is observed for Singapore). Notably, this heterogeneous dynamics reflect those found in the study of economic development [42, 43].

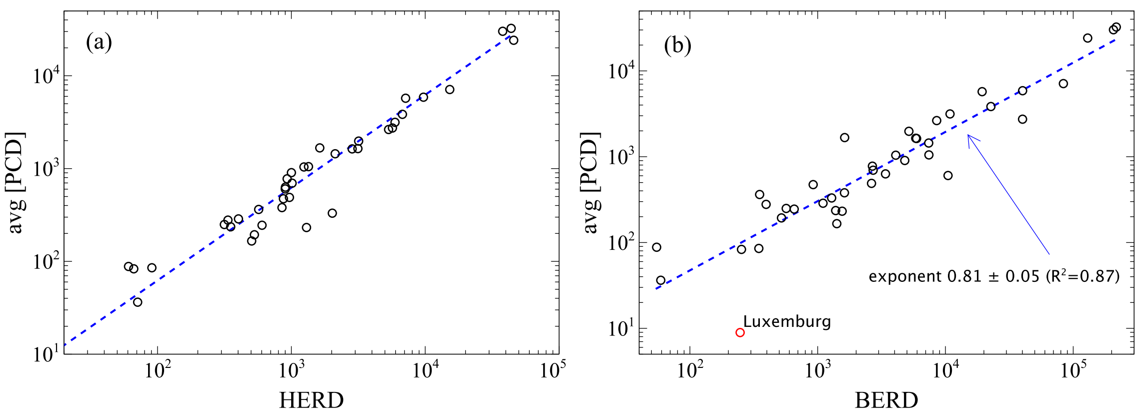

FIG. 3. Scatter plot of HERD (panel (a)) and BERD (panel (b) R&D funding versus the amount of patent-cited scholarly output, averaged over years 1996 − 2008. Points correspond to different nations, and the blue dashed lines mark the best regressions (linear with $R^2 = 0.84$ for HERD, power-law with exponent 0.81 ± 0.05 and $R^2 = 0.87$ for BERD).

We conclude with an analysis of patent citation statistics with respect to national expenditures in R&D. In particular, we consider HERD as usually done in studies focused on bibliometric scientific outputs, as well as BERD which is supposedly more related to patenting activity—and thus important for innovation and economic growth. We exclude GOVERD as it is related to the government research sector, which is often mission-oriented [34, 44] and therefore less related to scientific productivity, be it patent-cited or not. Figure 3 shows scatter plots of the patent-cited scholarly output versus these R&D expenditures, both averaged from 1996 to 2008, for several nations. When HERD is considered (panel (a)), we observe a succession of points which is perfectly fitted with a straight line. This result is expected if we assume that the number of scientific documents cited by patents is an homogeneous subset of the scientific output of each nation, while overall scientific production scales linearly with HERD [45]. More interestingly, when we consider BERD (panel (b)) and we exclude Luxembourg (the red outlier in the figure), the point are even more correlated with respect to HERD. However, the least square regression returns a power-law relation with exponent 0.81 ± 0.05. This sublinear behavior suggests that the nations with the larger scientific production make more fundamental research and are thus at the boundary of knowledge—with only future applications and less possibility to induce immediate innovations through patenting activity.

IV. CONCLUSION

In this work, using citation data from scientific papers as well as from patents, we have investigated the impact of the scientific production of nations (developed and developing) on science and technology at the global scale. We designed a novel technology impact indicator, in line with existing impact metrics for science, and show that a relation exists between scientific and technological successes, which grow together for most of the nations considered in our study. This feature points to the positive feedback between knowledge production, discoveries and innovation.

Geographical and cultural patterns emerge from the joint analysis of paper and patent citations. For instance we find that Northern European countries (including Switzerland) have an efficient scientific system, along the observation made by Cimini *et al.* [27], and their scientific production has an even larger impact on the patent literature. We also observe a gap between Western Europe and USA that does not emerge by looking at scientific citations alone, and which can be due to a more optimized and integrated national innovation system in the USA. Moreover, we find that the amount of national scientific production having technological relevance (*i.e.*, cited by patents) strongly correlates with the total expenditure in R&D by business institutions and enterprises. A possible explanation for the sub-linear behavior observed in this case may be that the larger such expenditures, the larger the research efforts in the private sector aimed at fundamental research with no immediate technological spin-offs.

Our study represents a preliminary and exploratory step in the understanding of the coupling and co-evolution of science and technology as different but interacting compartments of the innovation system. The future challenge will be that of identifying the micro-determinants describing the complex interplay between scientific advancement, technological progress, economic development and societal changes within the multi-layered space of innovation and development.

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SUPPLEMENTARY MATERIALS

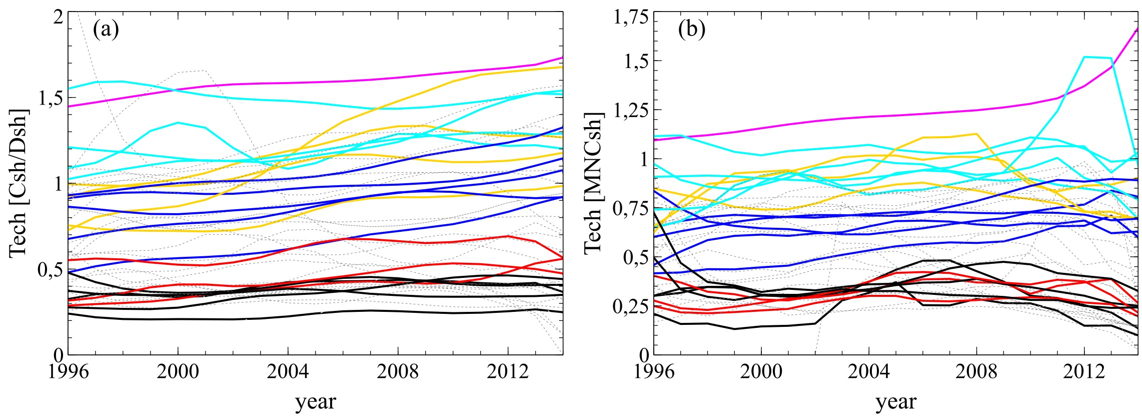

FIG. S1. Technological successes of nations, measured by the *citation share over document share* of eq. (2) of the main text (left panel) and by the field-normalized *mean normalized citation share* defined in Cimini *et al.* [27] (right panel): $Tech\ [MNCsh]_i(t) = N_d^{-1} \sum_\alpha \left(\frac{[PCC]_{i\alpha}(t)}{\sum_j [PCC]_{j\alpha}(t)} \right) \Big/ \left(\frac{[DOC]_{i\alpha}(t)}{\sum_j [DOC]_{j\alpha}(t)} \right)$.

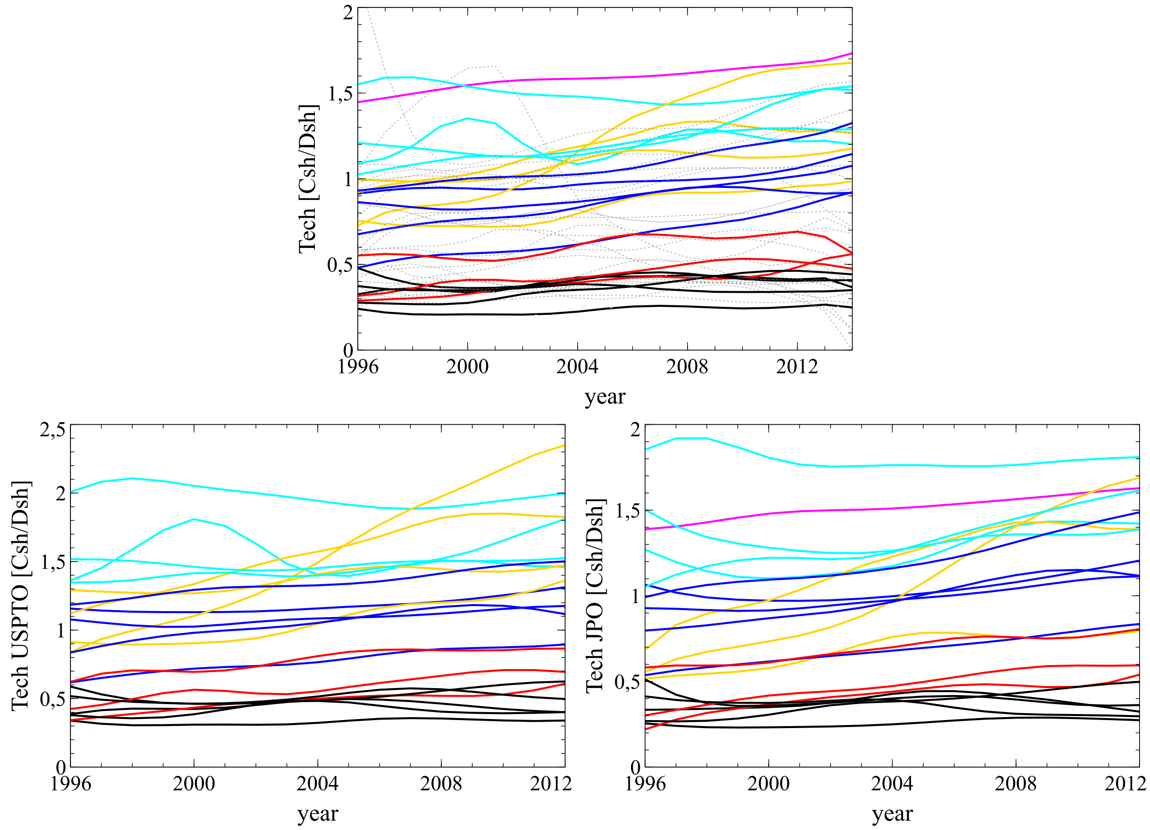

FIG. S2. Technological successes of nations using patent data from all five patent offices (top panel), from USPTO (bottom left panel) and from JPO (bottom right panel). In the last two cases, the home country of the considered patent office is not included in the analysis. While we see that home countries of patent offices do benefit from home advantage (*e.g.*, USA gets close to Europe when only JPO is considered), in general we observe similar trends and a robust ranking. For instance, Switzerland (and also USA) still occupies top positions, and Singapore enjoys a rapid ascend in success (which is striking in the USPTO case).

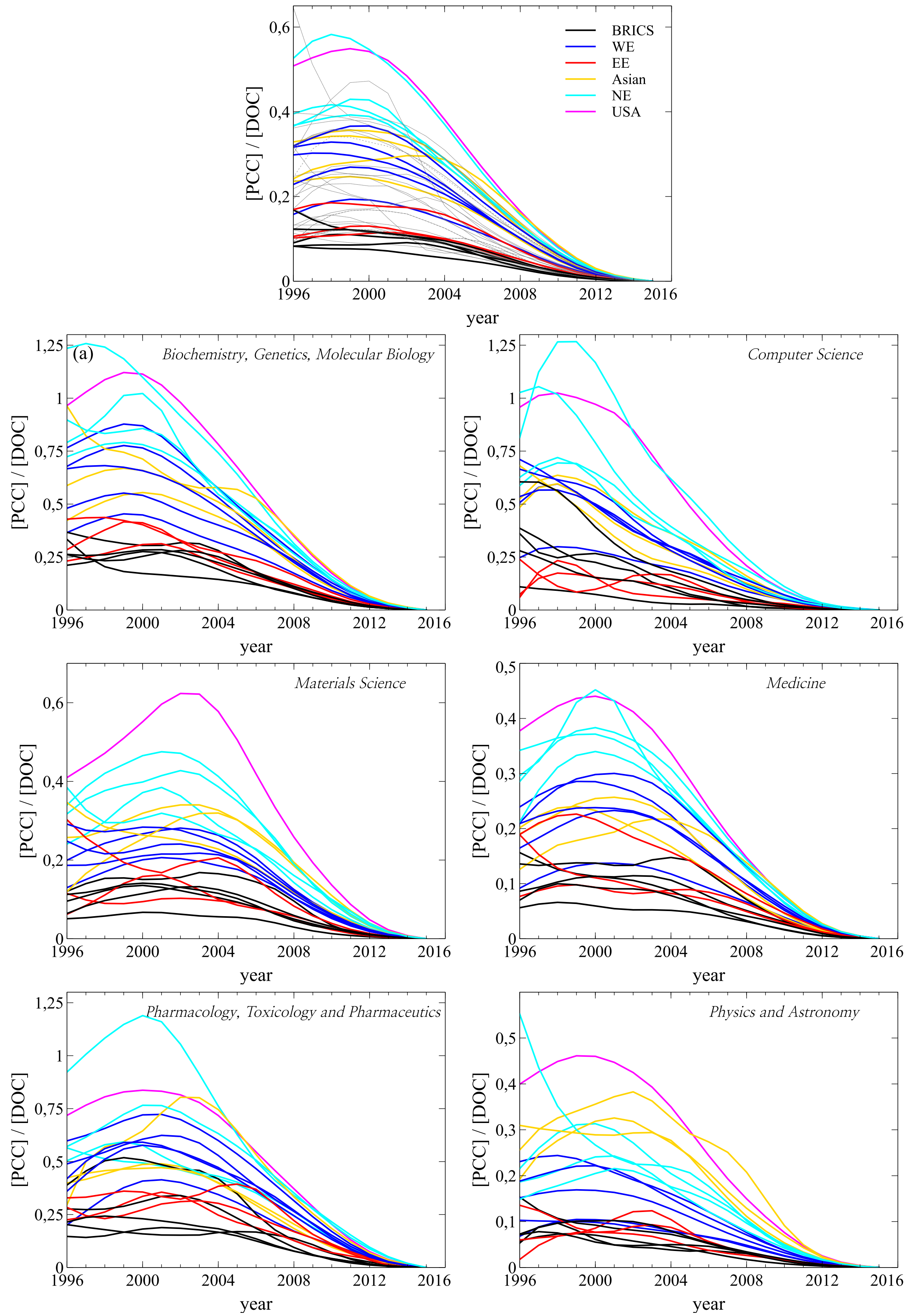

FIG. S3. PCC/DOC ratios (and PCD/DOC in the insets) computed on all scientific sectors (top panel) and on selected sectors: *Biochemistry, Genetics, Molecular Biology* (upper left panel), *Computer Science* (upper right panel), *Materials Science* (middle left panel), *Medicine* (middle right panel), *Pharmacology, Toxicology, Pharmaceutics* (lower left panel), *Physics and Astronomy* (lower right panel). We see that each sector possesses its own features, however the separation between USA, Europe and BRICS is persistent.