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Evolutionary patterns of national disciplinary profiles in research: 1996–2015

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Abstract This paper presents an empirical study of the evolutionary patterns of national disciplinary profiles in research using a dataset extracted from Scopus covering publications from 45 nations for the period 1996–2015. Measures of disciplinary specializations and statistical models are employed to examine the distribution of disciplinary specializations across nations, the patterns of structural changes in the world's disciplinary profiles, and the evolutionary patterns of research profiles in individual nations. It is found that, while there has been a continuous process of convergence in national research profiles, nations differ greatly in their evolutionary patterns. Changes in national disciplinary profiles are decomposed into the regression effect and the mobility effect and both effects are analyzed for individual nations. The G7 and the BRICs countries are used as cases for the in-depth scrutiny. Policy implications based on the findings and directions for future research are discussed.

Keywords Evolutionary patterns · Disciplinary profiles · Specialization · Convergence

Introduction

A clear picture of the dynamics of national disciplinary profiles helps identify the strengths and weaknesses in research fields of a nation and is thus key to science policy-making, especially with regards to allocation of funding. Recent years have seen an emerging strand of research in scientometrics focusing on quantitative investigations of disciplinary distributions of national research capacity measured by bibliometric indicators. The approaches of this research strand have mainly been either a comparative study of national

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research profiles, a time series analysis of the evolutionary patterns of national disciplinary specializations, or a combination of both.

The comparative studies have provided insightful information. King (2004) compares the disciplinary strength and weakness of the G8 nations using disaggregated citation share as the indicator and identifies some marked asymmetries in national disciplinary profiles, i.e., the relative strength in the physical sciences and engineering for Russia and Japan, and in the medical, life, and environmental sciences for the United States and United Kingdom. Hu and Rousseau (2009) assess research performance in selected Western and Asian countries and find that Western countries outperform their counterparts in Asia in most biomedical fields. Yang et al. (2012) evaluate the similarity and balance of disciplinary structures of the G7 countries as opposed to the BRIC nations and assert the G7 countries have more balanced disciplinary structures than the BRIC nations but the latter are catching up. They also find that the G7 countries are specialized in life sciences and the BRIC nations have relative strength in physics, chemistry, mathematics, and engineering.

Evolutionary patterns are investigated at both national and regional levels, with mixed research findings. Glänzel and Schlemmer (2007) analyze research profiles of the EU nations and confirm that while a converging process is in place, the process is slow and EU member countries have maintained their individual peculiarities and preferences. Horlings and van den Besselaar (2013) verify that there has been a process of convergence in both the level and structure of scientific outputs. It is found that convergence is more evident within each of the nine convergence clubs of nations grouped according to their socio-economic and political nature. Radosevic and Yoruk (2014) investigate whether the catching-up/transition regions have converged with the world frontier regions in their research profiles and find an overall pattern of persistence in regional disciplinary structures.

In addition, there have been noteworthy scholarly efforts devoted to the development of methodologies for the study of national disciplinary profiles. Zhou et al. (2012) propose a general framework for describing the degree of inequality within systems and similarity between systems. They suggest that the Gini coefficient and the Herfindahl–Hirschman index be used for measuring diversity within systems and the Salton's Cosine measure for measuring structural similarity. Bongioanni et al. (2014a, b) propose a different measure of structural similarity—the spin glass model of the physics of complex systems—to analyze national research systems' disciplinary orientations based on the percentage of publications in various research fields. This model is applied to European countries as well as a sample of 40 nations. Their studies confirm the existence of a converging process in the disciplinary profiles across nations.

While existing literature has revealed important findings, more in-depth investigations are still in demand to reveal insights of structural changes in national research profiles in at least two aspects. First, it is desired that research of this topic keep focusing on the evolutionary patterns of national disciplinary profiles. National research systems are ever changing; their disciplinary profiles can only be better assessed if the changes over time are taken into account. Second, given that the approaches utilized in studies of research profiles are often descriptive in nature, appropriate inferential statistical methods need to be applied to testing the stability and mobility of national disciplinary structures.

This paper contributes to the literature in the two aforementioned aspects by providing an empirical study of the evolutionary patterns of national research systems in terms of their disciplinary profiles. The nations examined cover the 45 top producers of publications around the world during a period spanning two decades from 1996 to 2015. For every nation, the level of specialization for each discipline is measured and the level of

dispersion among disciplinary specializations is calculated. Significance of the structural changes is tested through simple regression models. Three related issues are examined: (1) the distribution of disciplinary specializations across nations; (2) the patterns of structural changes in the world's disciplinary profiles across nations, i.e., whether there has generally been a convergent process in national disciplinary structures towards a unique profile defined as the global disciplinary distribution of publications; and (3) the evolutionary patterns of research profiles in individual nations.

Data and methodological issues

The number of publications from each nation extracted from Scopus is used as the measure of national research outputs. Changes of structural changes in national research profiles are to be analyzed through descriptive tools and inferential statistics such as regression models. However, the research design should be applied with caution, as using publication counts extracted from bibliometric databases as a measure of scientific outputs is subject to biases that may lead to questionable research findings. In this section, relevant reliability and validity issues are discussed and steps taken to reduce the problems are described, including the approach to better meet the assumptions of regression analysis. Methods for interpreting regression results are also elaborated.

The reliability and validity of bibliometric analysis are of central importance in the study of national research system (Nederhof 1988; Tijssen 1992) and relevant issues need to be identified and tackled. First, coverage of the database constrains the quality of data in representing the world scientific outputs, causing reliability issues to the studies that involve comparing across nations and/or disciplines and between different time periods. On one hand, every bibliometric database, even the largest one, has its own selection policies and there is no one single database that covers every valuable piece of the research literature in the world. Issues linked with the balance of subject areas and with languages bias have been identified: (1) some subject areas in social sciences and humanities are less represented; and (2) major bibliometric databases have strong presence of publications from the Anglo Saxon world (van Leeuwen 2004; van Raan 2004, 2014). On the other hand, time-series studies encounter problems with the inconsistence of database coverage. Both the selection policy and the strategic expansion of databases may lead to significant changes in coverage. The level of influence of inclusion and/or exclusion of journals in bibliometric databases differs more or less across subject areas. Second, using publication counts as the unit for quantitative analysis of national research profiles has critical validity concerns. For comparative purposes, an essential assumption is often made—all publications included in the database are of equal values in measuring scientific outputs. In the real world, however, values of papers differ greatly. Furthermore, many quantitative studies employ statistical techniques that require normality of the distributions of variables but the distribution of publication counts is very likely highly skewed (van Raan 2006).

Problems with the reliability and validity issues described above may lead to invalid or partially valid findings and these problems need to be carefully addressed. A common practice in reducing these problems is to use macro-level bibliometric data. Nederhof (1988) argues that comparative studies become more reliable when the unit of study becomes more aggregated. This is because in general a more aggregated unit of study means a larger sample size and a larger sample size reduces uncertainty caused by random errors. This paper follows this common practice of addressing issues related to database

coverage in four aspects. First, data for analysis are extracted from a bibliometric database of large scale. The present study uses data from SCImago Journal & Country Rank (SCImago 2007), a free access portal that provides country level scientific indicators developed from the Scopus database. Launched in 2004, with new titles added in each year, Scopus now contains over 60 million records of bibliometric data, including 14,200 journals. Although Scopus does not backfill content for newly added journals, the database does add cited references going back to 1996. Through the Cited Reference Expansion project, Scopus was 99% complete for titles originally included in the database back to 1996 by the end of 2015 (Scopus 2016). Therefore, the post-1995 publication counts from Scopus is more reliable than the pre-1996 counts.

Second, this study sets a relatively higher threshold for sample selection. Changes in coverage from inclusion or exclusion of journals tend to have higher impact on small countries with less scholarly outputs. Characteristics of disciplinary distribution are only best measured if a nation reaches a certain level in its total publications. Inclusion of too many nations may result in distortion of analyses, as relative indicators may become statistically unreliable when a country only has a small number of publications (Schubert et al. 1989). This study sets 100,000 total publications as the threshold for sample selection. Above the threshold are 45 nations representing 96% of the world's research outputs (see Table 1).

Third, in measuring individual nation's research profile, instead of relying on publication counts for each year, this paper divides the time span of 1996–2015 into three 6-year periods and uses measures for each period as the unit of analysis. The more aggregated data reduce the impact of sudden fluctuations that may happen to individual nations. The three 6-year periods are defined as Period I—1996 to 2001, Period II—2003 to 2008, and Period III—2010 to 2015. There is a 7-year gap between the consecutive periods and a 14-year gap between the starting and the ending periods. In the traditions in public policy studies (Johns and Inwood 2014) as well as in financial management (Brigham and Houston 2016), a long term is defined as a period of more than 10 years and a medium term as 5–10 years. Therefore, comparison between the three periods allow exploration of both medium-term and long-term changes in national disciplinary structures.

Fourth, this paper makes an attempt to decide on the appropriate level of classification system. In the Scopus database, publications are grouped into 4 board areas, 27 subject areas, and 313 specific subject categories. A more detailed classification may provide more insights, but using disaggregated data may cause the concerns of reliability. Meanwhile, if the more aggregated classification is chosen, then it is at the price of sacrificing insightful information in particular disciplines. Therefore, the 27 Scopus subject categories are chosen for analysis of disciplines. Table 2 shows that there is a high level of distributive disparity of publications across the 27 disciplines, ranging from 0.54% (Veterinary) to 16.70% (Medicine). Note that due to double counting, there is a large difference between the number of world total publications in Tables 1 and 2.

It is believed that the aforementioned four steps taken to reduce the problems associated with the reliability issues caused by the database coverage should be effective. Nonetheless, as this study uses Scopus as the sole source of data, the analysis is still subject to the biases inherent to this particular database, although to a much lesser extent.

The validity problems in the study are addressed through the selection of a more appropriate indicator for analyzing national patterns in disciplinary specializations. The process is elaborated in the following discussions on the statistical methods employed in this paper.

Table 1 Sample nations and number of publications 1996–2015. *Data source*: SCImago

Rank	Nation	Code	Region	Number of publications	% of world total	Cumulative % of world total
1	United States	USA	North America	9,360,233	23.1	23.1
2	China	CHN	Asia Pacific	4,076,414	10.1	33.2
3	United Kingdom	GBR	Western Europe	2,624,530	6.5	39.6
4	Germany	DEU	Western Europe	2,365,108	5.8	45.5
5	Japan	JPN	Asia Pacific	2,212,636	5.5	50.9
6	France	FRA	Western Europe	1,684,479	4.2	55.1
7	Canada	CAN	North America	1,339,471	3.3	58.4
8	Italy	ITA	Western Europe	1,318,466	3.3	61.7
9	India	IDN	Asia Pacific	1,140,717	2.8	64.5
10	Spain	ESP	Western Europe	1,045,796	2.6	67.0
11	Australia	AUS	Asia Pacific	995,114	2.5	69.5
12	South Korea	KOR	Asia Pacific	824,839	2.0	71.5
13	Russian Federation	RUS	Eastern Europe	770,491	1.9	73.4
14	Netherlands	NLD	Western Europe	746,289	1.8	75.3
15	Brazil	BRA	South America	669,280	1.7	76.9
16	Switzerland	CHE	Western Europe	541,846	1.3	78.3
17	Taiwan	TWN	Asia Pacific	532,534	1.3	79.6
18	Sweden	SWE	Western Europe	503,889	1.2	80.8
19	Poland	POL	Eastern Europe	475,693	1.2	82.0
20	Turkey	TUR	Middle East	434,806	1.1	83.1
21	Belgium	BEL	Western Europe	407,993	1.0	84.1
22	Iran	IRN	Middle East	333,474	0.8	84.9
23	Israel	ISR	Middle East	295,747	0.7	85.6
24	Austria	AUT	Western Europe	295,668	0.7	86.4
25	Denmark	DNK	Western Europe	290,994	0.7	87.1
26	Finland	FIN	Western Europe	257,159	0.6	87.7
27	Greece	GRC	Western Europe	246,202	0.6	88.3
28	Czech Republic	CZE	Eastern Europe	237,910	0.6	88.9

Table 1 continued

Rank	Nation	Code	Region	Number of publications	% of world total	Cumulative % of world total
29	Mexico	MEX	South America	232,828	0.6	89.5
30	Norway	NOR	Western Europe	229,276	0.6	90.1
31	Hong Kong	HKG	Asia Pacific	219,177	0.5	90.6
32	Singapore	SGP	Asia Pacific	215,553	0.5	91.1
33	Portugal	PRT	Western Europe	214,838	0.5	91.7
34	South Africa	ZAF	Africa	188,104	0.5	92.1
35	Malaysia	MYS	Asia Pacific	181,251	0.4	92.6
36	New Zealand	NZL	Asia Pacific	180,340	0.4	93.0
37	Argentina	ARG	South America	159,172	0.4	93.4
38	Ireland	IRL	Western Europe	150,552	0.4	93.8
39	Hungary	HUN	Eastern Europe	147,901	0.4	94.1
40	Ukraine	UKR	Eastern Europe	145,332	0.4	94.5
41	Romania	ROU	Eastern Europe	141,731	0.3	94.9
42	Egypt	EGY	Middle East	137,350	0.3	95.2
43	Thailand	THA	Asia Pacific	123,410	0.3	95.5
44	Saudi Arabia	SAU	Middle East	111,117	0.3	95.8
45	Chile	CHL	South America	101,841	0.3	96.0
	World total			40,519,542		

To reveal insights of the evolutionary patterns of individual nation's research profiles, both descriptive tools and inferential statistical techniques are utilized in the present study. As for statistical analysis, research methods are borrowed heavily from the tradition in the studies of sectoral specialization in two related fields: international competitiveness and technological development (see Cantwell 1989; Dalum et al. 1998; Amendola et al. 1998). This borrowing of research methods encounters little obstacle because the quantitative studies of disciplinary profiles are analogous to these two research fields in that they all deal with compositional data. In fact, the three fields share the same measures of specialization with different terminologies. Activity Index (AI), the commonly used measure of disciplinary specialization, is calculated in the same way as the Revealed Comparative Advantages (RCA), the most popular measure of specialization in trade and technology policy. Specifically, the formula for AI in subject field i of country j is:

$$\text{AI}_{ij} = \frac{P_{ij} / \sum_i P_{ij}}{\sum_j P_{ij} / \sum_i \sum_j P_{ij}}$$

where P_{ij} represents publications in field i from country j. The numerator is the percentage share of a given field in a nation's total publications, and the denominator is the percentage

Table 2 Distribution of world publications across disciplines: 1996–2015. *Data source*: SCImago

Research fields	Number of publications	Percent (%)
Agricultural and Biological Sciences	3,219,887	4.84
Arts and Humanities	1,105,438	1.66
Biochemistry, Genetics and Molecular Biology	5,434,223	8.16
Business, Management and Accounting	674,311	1.01
Chemical Engineering	1,615,325	2.43
Chemistry	3,720,534	5.59
Computer Science	4,151,679	6.24
Decision Sciences	354,846	0.53
Dentistry	193,810	0.29
Earth and Planetary Sciences	2,095,734	3.15
Economics, Econometrics and Finance	494,776	0.74
Energy	1,003,208	1.51
Engineering	7,576,230	11.38
Environmental Science	1,953,669	2.94
Health Professions	581,021	0.87
Immunology and Microbiology	1,368,311	2.06
Materials Science	4,304,398	6.47
Mathematics	2,822,938	4.24
Medicine	11,112,099	16.70
Multidisciplinary	399,879	0.60
Neuroscience	1,149,671	1.73
Nursing	550,490	0.83
Pharmacology, Toxicology and Pharmaceutics	1,378,829	2.07
Physics and Astronomy	6,000,042	9.01
Psychology	821,705	1.23
Social Sciences	2,118,501	3.18
Veterinary	356,521	0.54
Total	66,558,075	100

share of a given field in the world total publications. Therefore, the AI values compare national disciplinary profiles against the world research profile. For a given discipline of a nation, if AI > 1, the nation is said to be specialized in that discipline and vice versa if AI < 1.

Statistical tests of the stability of the national disciplinary profiles are to be conducted through simple regression models, following the methods utilized by Cantwell (1989) and Dalum et al. (1998). Theoretically, a simply regression analysis makes key assumptions of linear relationship, multivariate normality, no autocorrelation, and homoscedasticity (constant variance) of the errors. The major concerns in this study are multivariate normality and auto-correlation issues.

Using simple regression models with AIs as the variable invokes a risk of violating the assumptions of normality. The value of AIs falls between 0 and infinity with an average of 1 (or very close to 1) and it is likely that the distribution of AIs is skewed. One possible fix

of the problem is to use an alternative indicator—the Relative Specialization Index (RSI), a widely adopted indicator in the study of national disciplinary profiles (Aksnes et al. 2014). An RSI is calculated as $(AI - 1)/(AI + 1)$, and takes a value between -1 and $+1$. For a discipline, if $AI > 1$, then $RSI > 0$; if $AI < 1$, then $RSI < 0$. For a nation in a given subject discipline, a positive RSI indicates that the nation has a higher-than-average activity, or is specialized in that discipline; a negative RSI means the nation has a lower-than-average activity, and a zero RSI reflects the nation has equal-to-average activity or is completely balanced. As RSI values fall between -1 and $+1$, distribution of RSIs tends to be symmetric, with better normality than AIs. This notion is supported by studies of trade specialization. Dalum et al. (1998) and Laursen (2015) propose using *RSCA* (Revealed Symmetric Comparative Advantage) rather than *RCA* in their regression models and an *RSCA* is calculated in the same way as an RSI.

As to the autocorrelation issue, the fact that scientific disciplines are interrelated raises concerns about independence between consecutive observations. The effects of interrelatedness between disciplines are complicated and hard to estimate. On one hand, research project in one subject field may trigger related projects in other closely related fields, i.e., in life sciences. On the other hand, competing for research funds between two subject fields may result in an increase of publications in one field and a decrease in another.

To diagnose the possible violations of the assumptions for regression analysis, this paper employs the Shapiro–Wilk test for normality and the Durbin–Watson test for autocorrelation. The purpose of the test is to verify whether RSI is a more appropriate indicator for regression analysis then AI. Hence, the following regression models are to be tested and compared:

$$AI_{ij}^{t_2} = \alpha_i + \beta_i AI_{ij}^{t_1} + \varepsilon_{ij} \qquad \text{(Model I)}$$

and

$$RSI_{ij}^{t_2} = \alpha_i + \beta_i RSI_{ij}^{t_1} + \varepsilon_{ij} \qquad \text{(Model II)}$$

where AI_{ij} stands for Activity Index for discipline i of nation j, RSI_{ij} stands for Relative Specialization Index for discipline i of nation j, and t_1 and t_2 refer to the initial time period and the final time period, respectively. α and β are linear regression parameters and ε is the residual term. For the Shapiro–Wilk test, test values are calculated for each nation and for each period for both AI and RSI. For the Durbin–Watson test, simple regressions are performed for both AI and RSI for the changes over three time-spans: Periods I–II, Periods II–III, and Periods I–III. The results are reported in Table 3 and both tests confirm that RSI is more appropriate than AI. Overall, of problems associated with the no-autocorrelation and normality assumptions, the latter deserves more serious concerns. It shows the normality of the error terms can be rejected for 54 out of 135 cases (45 nations for 3 periods) when using AI, and for 27 out of 135 cases when using RSI. That is, using RSI instead of AI reduces the violation of normality from 40 to 20% of the cases. Using RSI rather than AI in the regression model also reduces the problems of autocorrelation. Results of the Durbin–Watson test indicate that 23 out of 135 regressions when using AI and 18 out of 135 regressions when using RSI violate the no-autocorrelation assumption.

Thus, Model II, with RSI at different periods as the dependent and independent variables, will be used for analysis. Note that Model II is for the test of the stability of research profiles in individual nations. When the subscript j is removed, it becomes:

Table 3 The Shapiro–Wilk test for normality and the Durbin–Watson test for autocorrelation

Code	Shapiro–Wilk test sig. for AI			Shapiro–Wilk test sig. for RSI			Durbin–Watson's d for AI			Durbin–Watson's d for RSI		
	Period I	Period II	Period III	Period I	Period II	Period III	Periods I–II	Periods II–III	Periods I–III	Periods I–II	Periods II–III	Periods I–III
USA	0.102	0.073	**0.022**	0.396	0.344	0.141	1.806	2.193	2.068	1.691	2.181	1.965
CHN	**0.004**	**0.013**	0.170	**0.010**	**0.031**	0.067	1.925	1.738	2.024	2.120	1.714	2.427
GBR	**0.035**	0.083	0.052	0.085	0.222	0.382	2.045	1.719	1.910	1.992	1.884	1.853
DEU	0.685	0.459	0.088	0.517	0.855	0.382	2.249	1.804	1.862	2.321	1.772	1.854
JPN	**0.037**	0.065	0.257	**0.020**	**0.025**	**0.026**	2.233	1.849	2.303	1.816	1.928	2.167
FRA	0.331	0.069	0.357	**0.015**	**0.001**	**0.005**	**2.548**	**2.615**	**2.706**	**2.499**	**2.699**	**2.730**
CAN	0.467	0.567	0.096	0.263	0.435	0.330	1.799	2.010	1.553	1.820	2.000	1.588
ITA	0.510	0.236	0.890	0.237	0.063	0.810	**1.168**	1.969	1.582	**1.381**	2.012	1.770
IDN	**0.007**	0.066	**0.026**	0.757	0.382	0.155	1.899	2.018	2.163	**2.544**	2.081	2.441
ESP	0.751	0.494	0.795	0.553	0.065	0.081	2.043	1.786	1.928	2.058	1.791	1.944
AUS	**0.041**	0.060	**0.013**	**0.034**	0.071	**0.048**	1.981	**1.336**	1.798	2.166	1.522	1.873
KOR	**0.017**	0.058	0.693	0.065	0.167	0.287	2.022	2.088	2.140	2.053	1.986	2.074
RUS	**0.001**	**0.001**	**0.012**	**0.027**	0.055	0.746	2.009	2.344	2.170	1.682	2.273	2.149
NLD	0.350	0.314	0.147	0.107	0.171	0.529	2.027	**1.287**	1.612	2.042	2.042	1.512
BRA	0.112	**0.000**	**0.000**	0.188	0.057	**0.001**	2.245	1.772	1.962	1.905	1.721	1.591
CHE	0.375	0.272	0.373	0.496	0.597	0.458	1.617	**1.473**	**1.495**	1.601	**1.447**	**1.399**
TWN	**0.026**	**0.037**	0.066	0.861	0.823	0.451	2.366	1.848	2.155	2.209	1.761	2.037
SWE	**0.000**	**0.002**	0.082	**0.002**	**0.049**	0.126	1.814	2.367	2.043	2.177	2.415	2.200
POL	0.125	**0.018**	0.069	0.074	0.458	0.940	1.770	1.763	1.828	2.277	1.839	2.021
TUR	**0.001**	**0.000**	**0.000**	0.641	**0.038**	**0.000**	1.904	1.753	1.884	1.563	1.560	1.585
BEL	**0.000**	0.054	0.102	0.155	0.944	0.783	1.775	1.501	1.672	1.754	**1.351**	1.646
IRN	**0.033**	0.454	0.189	0.193	0.116	0.117	1.848	2.119	2.181	1.826	2.116	2.112
ISR	0.092	0.160	0.092	0.851	0.494	0.821	**1.476**	1.836	**1.363**	1.534	1.658	**1.240**
AUT	0.795	0.591	0.344	0.668	0.813	0.222	2.214	2.128	2.216	2.266	1.942	2.101

Table 3 continued

Code	Shapiro–Wilk test sig. for AI			Shapiro–Wilk test sig. for RSI			Durbin–Watson's d for AI			Durbin–Watson's d for RSI		
	Period I	Period II	Period III	Period I	Period II	Period III	Periods I–II	Periods II–III	Periods I–III	Periods I–II	Periods II–III	Periods I–III
DNK	0.074	0.410	0.149	0.508	0.530	**0.049**	1.970	1.953	1.810	2.075	1.922	1.819
FIN	**0.002**	0.983	0.097	0.566	0.558	0.775	2.143	2.297	2.289	2.107	2.442	2.273
GRC	0.918	0.132	0.213	0.491	0.189	0.450	2.239	2.088	2.153	2.321	2.048	2.135
CZE	0.536	0.390	0.309	**0.045**	**0.013**	**0.002**	1.849	1.809	**1.320**	1.945	2.263	1.681
MEX	0.286	0.259	**0.008**	0.998	0.879	0.733	1.777	**1.028**	**1.014**	1.819	**1.184**	**1.073**
NOR	**0.026**	0.201	0.127	0.781	0.062	0.051	2.419	2.318	2.465	2.302	2.231	2.414
HKG	**0.001**	**0.002**	**0.003**	0.900	0.768	0.751	1.937	**2.521**	2.356	1.530	2.123	2.022
SGP	**0.000**	**0.021**	0.773	**0.044**	0.355	0.174	1.782	1.851	**1.458**	1.686	1.728	**1.202**
PRT	0.150	0.504	0.991	**0.020**	0.173	0.556	1.706	1.849	2.058	1.623	1.733	1.523
ZAF	**0.000**	**0.005**	**0.002**	0.066	0.146	0.376	2.112	2.308	2.284	2.273	1.822	1.946
MYS	0.504	0.229	**0.000**	**0.011**	0.378	0.996	2.085	1.825	2.370	2.160	2.119	2.425
NZL	**0.030**	0.092	**0.019**	0.734	0.159	**0.028**	2.261	2.169	2.245	2.314	2.384	2.334
ARG	0.057	**0.002**	**0.002**	0.505	0.367	0.227	1.659	**1.245**	**1.083**	2.001	**1.460**	**1.467**
IRL	0.120	0.998	0.264	0.955	0.343	0.993	2.085	1.536	2.018	2.037	**1.485**	1.908
HUN	**0.001**	0.295	0.401	0.758	0.646	0.585	**1.412**	2.015	**1.472**	**1.276**	2.013	1.591
UKR	**0.000**	**0.000**	**0.000**	**0.005**	**0.015**	0.053	**2.620**	**1.281**	1.539	2.280	**1.373**	1.609
ROU	**0.000**	**0.001**	0.395	**0.006**	0.097	0.736	1.919	2.232	2.344	2.091	1.896	2.203
EGY	0.101	0.305	**0.036**	0.198	0.169	0.445	**1.478**	1.809	1.814	1.605	1.568	**1.432**
THA	**0.003**	0.265	0.070	0.509	0.328	0.299	2.248	**1.412**	2.226	2.209	1.883	2.317
SAU	**0.001**	**0.000**	0.210	0.951	0.942	0.423	2.490	1.939	2.197	2.172	2.004	2.292
CHL	**0.000**	**0.000**	**0.006**	0.597	0.497	0.421	1.683	1.984	1.680	1.868	1.898	1.542

Shapiro–Wilk test: values above 0.05 confirm normality

Durbin–Watson test: values of $1.5 < d < 2.5$ show no autocorrelation

Bold types indicate violation of normality or no-autocorrelation assumptions

$$\mathrm{RSI}_i^{t_2} = \alpha_i + \beta_i \mathrm{RSI}_i^{t_1} + \varepsilon_i \qquad\qquad (\mathrm{Model\ III})$$

Here, RSI_i stands for Relative Specialization Index for discipline i of a nation for all nations in the sample. Since this study covers 45 nations that collectively represent 96% of the world's total research output, it is proper to use Model III to test the stability of the global disciplinary profiles across nations.

The degree of dispersion of a nation's disciplinary specialization measure by RSIs corresponds to the extent to which the nation's research capacity is more concentrated or diffused across disciplines. A high degree of dispersion means strong specialization or a highly polarized disciplinary structure. A lower degree of dispersion indicates a relatively more balanced disciplinary profile. Furthermore, measures of dispersion presented for different time periods help determine whether a nation has experienced a converging, diverging, or a mixed process in reference to the world's overall disciplinary profile. An increase in variability means a nation has become more specialized or polarized; a decrease is an indication that a nation has become more balanced or converged with the world research profiles.

This study uses Standard Deviation (SD) as the measure of dispersion across RSIs in different disciplines. Although SD is an absolute measure for dispersion, given the fact that RSI is a bounded relative indicator without unit, SD is suitable for comparison. SD has the property of being very sensitive to extreme values or outliers, allowing the analysis to sensitively reflect changes of nations in disciplines with high level of specialization or in disciplines with relatively very low level of outputs.

Also noteworthy is that using SD as the measure links the present analysis to the literature on growth in which the convergence/divergence issues have been thoroughly discussed. The growth literature specifies two kinds of convergence: β-convergence and σ-convergence. According to Sala-i-Martin (1996), β-convergence is the phenomenon that poor economies grow faster than rich ones and σ-convergence results from the decrease of the dispersion of nations' real per capital GDP levels over time; β-convergence shows the mobility of individual economies and σ-convergence captures the features of distribution of the group in question as a whole. Sala-i-Martin (1996) also demonstrates that a σ-convergence must result in β-convergence, but β-convergence does not necessarily lead to σ-convergence. Apparently the analysis of disciplinary structures in this paper has much in common with σ-convergence. Let σ be the dispersion of the numbers of publications across disciplines, if $\sigma_{t_2} < \sigma_{t_1}$, where t_1 and t_2 refer to the initial and the final time periods, then there is σ-convergence. In this study, σ is the SD.

For statistical testing of structural stability, the β value should be tested against zero for each regression function. If $\beta = 0$ cannot be rejected at a certain significance level, then no relationship is found between the initial and ultimate values of RSIs across disciplines. In the cases that there is a linear relationship between the initial and ultimate RSIs, if β is significantly below zero, the ranking of publication activities across disciplines has been deeply changed or even reversed (the case of $\beta = -1$), meaning disciplines with lower-than-average activities became higher-than-average and vice versa. If β is significantly above zero, then the null hypothesis of $\beta = 1$ should be tested. For interpretation of the regression coefficient, $\beta = 1$ corresponds to perfect stability in the profile of a nation's research specialization; $\beta > 1$ means the nation has become more specialized in disciplines where specializations were in place or became even lower in disciplines with previously lower-than-average activities; $0 < \beta < 1$ indicates the nation has decreased in the degree of specialization in disciplines with higher-than-average activities and became higher in previously lower-than-average disciplines in terms of publication activity. Therefore, if the

alternative hypothesis of $\beta \neq 1$ is accepted, then the signs and values of $\hat{\beta}$, the estimated value of β, signal the degree and direction of disciplinary structural changes for a nation revealed by regression. Thus, the magnitude of $(1 - \hat{\beta})$ can be treated as the estimated measure of the "regression effect", an indicator of the degree of structural change explained by the regression model.

The process of convergence or divergence can be confirmed by comparing the β value against the Pearson correlation coefficient value (R). With reference to Cantwell (1989, p. 30):

$$(\sigma_i^{t_2})^2/(\sigma_i^{t_1})^2 = \beta_i^2/R_i^2. \quad \text{Thus } \sigma_i^{t_2}/\sigma_i^{t_1} = |\beta_i|/|R_i|$$

Since σ measures the level of dispersion, using the estimated values, when $|\hat{\beta}| = |R|$, the dispersion of a given distribution is unchanged; $|\hat{\beta}| > |R|$ indicates an increase in the dispersion, equivalent to a process of divergence or specialization; $|\hat{\beta}| < |R|$ implies a decrease in the dispersion, equivalent to a process of convergence or de-specialization. Furthermore, the value of coefficient of determination (R^2) represents the percentage of the total variation that is explained by the regression model, and the value of $(1 - R^2)$ is the percentage of total variation caused by random errors. Thus, the magnitude of $(1 - |R|)$ can be used as a measure of random variation. Cantwell (1989) terms the value of $(1 - |R|)$ as the measure of the "mobility effect". If $|R|$ is close to 1, then the relative position of disciplines has been fairly stable. If the $|R|$ value is low, then the linear relationship between RSIs in t_1 and t_2 are relatively weak and the mobility effect is more significant. This is caused by the changes in the ranking of disciplines—some disciplines are moving closer together and others are moving further apart.

Hence, the dispersion in a nation's disciplinary profiles is decomposed into a "regression effect" $(1 - |\beta|)$ and a "mobility effect" $(1 - |R|)$. Structural changes in research profiles of different nations result from a variety of combinations of the two types of effects. Since the condition of $(1 - |\beta|) > (1 - |R|)$ is equivalent to that of $|\beta| < |R|$, a convergence process in a nation can be explained as the case when the regression effect outweighs the mobility effect.

Findings and discussions

This section is devoted to the exploration of the characteristics of specialization patterns in national research profiles. The exploration starts with observations on important patterns. Then, the statistically significance of these observations is verified through regression models described in the previous section. Structural changes in national specialization patterns are interpreted through the decomposition of dispersion in the regression effect and the mobility effect. This section proceeds with an in-depth comparative study of the he G7 and the BRIC countries.

### Observations on important patterns

Figure 1 shows the SDs of RSIs for each nation during 1996–2015 as an overall picture exhibiting the degrees of balance in national disciplinary profiles. Clearly, the level of balance differs greatly from nation to nation. *SD*s of RSIs across disciplines range from 0.08 to 0.44. The 45 nations are divided into three groups based on their SD values—Group

One: SD < 0.2; Group Two: 0.2 < SD < 0.32; and Group Three: 0.32 < SD < 0.44. 21 nations belong to Group One and all are members of OECD. The top 17 nations in Group One are all developed countries located either in Western Europe or in North America. The top 5 nations are Germany, Austria, Spain, Switzerland, and Italy, all located in continental Europe. 21 nations belong to Group Two, representing the moderate level of balance. Most Asia Pacific economies (such as Japan, Korea, Taiwan, Singapore, Hong Kong, Malaysia, Thailand, India, and New Zealand), and countries of South America (Brazil, Chile and Argentina), Middle East (Iran, Egypt, and Saudi Arabia), and Eastern Europe (Hungary, Poland, Czech Republic, and Romania) belong to this group. 3 countries—Ukraine, Russia, and China—stand out as Group Three, the one with the highest level of disciplinary polarization. History of these counties significantly matters, notably the great influence of former Soviet Union. Observations from Fig. 1 suggest that factors such as a nation's level of development, geographical location, and history might have significant impacts on its research profiles. However, determinants of whether a nation is more balanced or polarized in its disciplinary profiles are complex and a better understanding of how these factors play their roles requires more systematical studies.

The dynamic patterns of the structural changes in national disciplinary profiles are illustrated by Fig. 2 in which the heights of column represent SD values of the three 6-year periods. Comparison of the heights of the three columns for each nation offers very suggestive observations. First, for the vast majority of nations, the heights of the white columns representing Period I are the greatest and the heights of the dark columns representing Period III are the shortest among the three columns. This indicates a prevailing trend of convergence in national disciplinary profiles. Second, differences in height among the three columns for a nation may illustrate the extent to which structural changes have been made. However, while there are observable variations among individual nations in their dynamics of dispersion across disciplines, Fig. 2 along does not provide enough information for explaining these variations. This paper relies heavily on the statistical analysis approach for a more in-depth exploration.
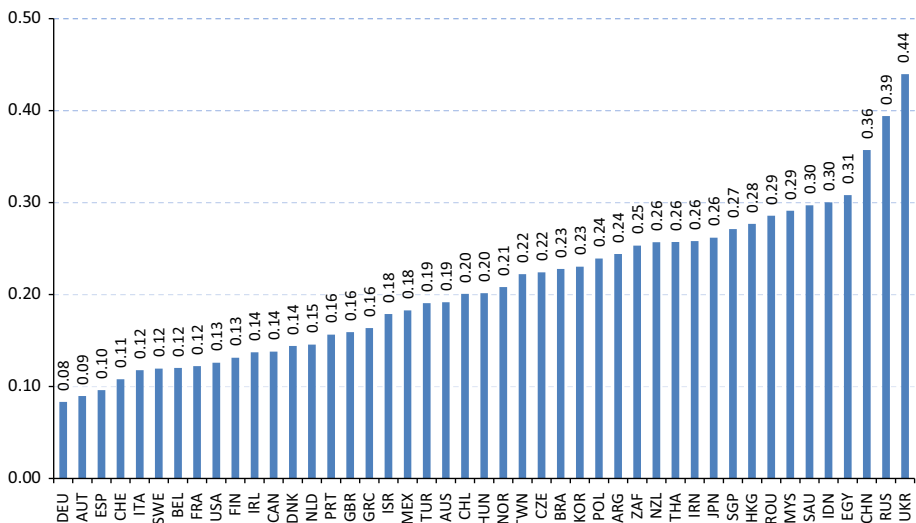
Fig. 1 Standard deviations of RSIs for selected nations: average of 1996–2016
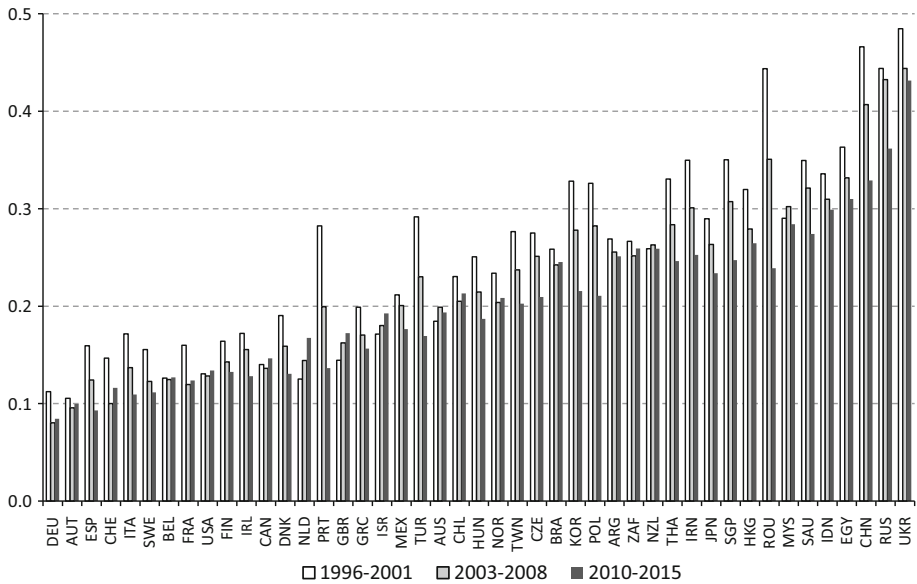
Fig. 2 Standard deviations of RSIs for selected nations: comparison of three periods

Statistical analyses

The statistically significance of the observations made from Figs. 1 and 2 is verified using regression models as for whether there has been an overall pattern of convergence in national disciplinary profiles and whether all individual nations have experienced significant structural changes converging towards more balanced research profiles. Findings are discussed through the analysis of the regression effect as opposed to the mobility effect.

The overall pattern of convergence is tested using regression Model III with the dataset that covers RSI values for all sample nations for each of the three periods. Regression analysis is conducted for three pairs of values: RSIs of Period II on Period I, of Period III on Period II, and of Period III on Period I. Regression results are provided in Table 4. For all three regressions, the $\hat{\beta}$-values are significantly different from 0 and from 1, meaning there have been statistically significant changes in the global disciplinary structure across nations for both medium and long terms. The $\hat{\beta}$-values are all between 0 and 1, indicating that, in general, nations have decreased in the degree of specialization in disciplines with higher-than-average activities and became higher in previously lower-than-average disciplines in terms of publication activity. Further, values of $\left|\hat{\beta}\right|/|R|$ are all below 1, confirming a process of convergence in national disciplinary profiles. Note that since the RSI values are calculated in reference to the world's disciplinary distribution of publications, the convergent process implies the changes of national research profiles toward the global structure of disciplines. Also noteworthy here is the cumulative effect. It seems that the long-term change between Period I and Period III results from a sort of additive of the changes during Period I–Period II and Period II–Period III. That the values of $\hat{\beta}$ are among the lowest for regression of Period III on Period I among the three regressions suggests a continuous convergence process.

Table 4 Regression results for disciplinary profiles in the world across nations ($N = 1215$)

	$\hat{\beta}$	t	R^2	$\left|\hat{\beta}\right|/|R|$	Durbin–Watson
Period I–Period II	0.826	−16.711***	0.838	0.902	1.777
Period II–Period III	0.775	−20.206***	0.801	0.867	1.778
Period I–Period III	0.597	−27.803***	0.583	0.782	1.779

All β-values are significantly different from zero at the 1% level

t-statistics refer to the hypothesis H_0: $\beta = 1$ and *** denotes significant different from 1 at the 1% level

The detailed regression results for individual nations are displayed in Table 5. For all but two cases (Spain and Malaysia, regression of Period III on Period I), there is a linear relationship between RSIs across subject areas of the initial and ending periods for each nation and for both medium and long terms. The two outliers should have experienced some turbulence in their research profiles—some disciplines lost while others gained specializations, resulting in some tremendous changes in their disciplines' ranking as well as RSI values.

As to whether there have been significant structural changes with individual nations, the findings are mixed. The 45 nations are grouped into various categories based on two dimensions: whether it is about the medium or long term structural change and whether a nation has experienced significant changes (see Table 5). Of the 45 nations, 76% had significant structural changes during the First Medium Term (Periods I–II), 67% during the Second Medium Term (Periods II–III), and 87% during the Long Term (Periods I–III). 5 nations (Australia, Canada, Israel, New Zealand, and the United States) have experienced no significant changes in research profiles both for the medium term and the long term. 4 of the 5 nations have English as their official languages, and among them 2 are neighboring countries in North America and 2 are neighbors in Oceania. In fact, the UK, as another English speaking country, also has fairly stable research profiles. Neither of the two medium terms has seen significant structural changes for the UK. The structural change for UK is only significant for the Long Term, showing the nation has become slightly more polarized with a $\hat{\beta}$ value of 1.115. The Netherlands only shows significant change for the Second Medium Term when it also became slightly more polarized ($\hat{\beta} = 1.115$). Like the UK, Belgium also only shows significant changes for the Long Term. However, changes in Belgium are more dramatic than in the UK as indicated by the $\hat{\beta}$ value (0.642). Note that the UK, the Netherlands, and Belgium are also geographical neighbors.

While nations with no structural changes or with relatively less changes exhibit some relationships, such as having English as the commonly spoken language and the geographical closeness between nations, those experienced continuous changes in their research profiles do not show a clear pattern. 26 nations had significant structural changes during both the First and the Second Medium Terms (see Table 6). Nations in this category includedeveloped countries with both large size (i.e., Japan and Italy) and relatively small size (i.e., Denmark, Finland, Greece, and Portugal) of economies, historically Newly Industrialized Ecomies (NIEs—Korea, Hong Kong, Singapore and Taiwan), Eastern European countries (such as Czech Republic, Romania and Hungary), current Newly Industrialized Countries (NICs—China, India, Thailand, and Brazil), and Middle East countries (such as Iran, Saudi Arabia, and Turkey).

Table 5 Regression results for national disciplinary profiles ($N = 27$)

Nation code	Period I–Period II				Period II–Period III				Period I–Period III			
	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$
USA	0.945	−1.018	0.926	0.983	1.004	0.064	0.924	1.044	0.903	−0.996	0.775	1.026
CHN	0.837	−3.290***	0.919	0.873	0.786	−5.586***	0.944	0.809	0.662	−6.917***	0.880	0.706
GBR	1.084	1.427	0.932	1.123	1.042	1.057	0.964	1.062	1.115	1.368*	0.875	1.192
DEU	0.589	−5.072***	0.679	0.715	0.889	−0.989	0.716	1.051	0.441	−4.595***	0.344	0.751
JPN	0.902	−4.164***	0.983	0.910	0.869	−3.573***	0.957	0.888	0.781	−5.304***	0.935	0.808
FRA	0.589	−4.442***	0.619	0.749	0.975	−0.368	0.888	1.034	0.479	−4.280***	0.383	0.774
CAN	0.934	−1.216	0.921	0.973	1.034	0.574	0.924	1.076	0.937	−0.672	0.802	1.047
ITA	0.689	−3.849***	0.744	0.799	0.699	−3.883***	0.764	0.799	0.387	−6.039***	0.367	0.638
IDN	0.871	−2.127**	0.892	0.922	0.888	−1.481*	0.846	0.965	0.705	−2.714**	0.626	0.890
ESP	0.673	−4.171***	0.747	0.779	0.435	−4.641***	0.338	0.748	**0.192**	**−7.344***	**0.108**	**0.583**
AUS	1.041	0.721	0.932	1.078	0.932	−1.225	0.919	0.972	0.945	−0.604	0.814	1.048
KOR	0.803	−3.653***	0.898	0.847	0.634	−4.102***	0.670	0.775	0.454	−5.756***	0.478	0.657
RUS	0.951	−1.156	0.954	0.974	0.770	−3.518***	0.847	0.836	0.728	−3.713***	0.798	0.815
NLD	1.063	0.707	0.852	1.151	1.106	1.492*	0.907	1.161	1.077	0.483	0.649	1.337
BRA	0.771	−2.145**	0.677	0.938	0.886	−1.169	0.767	1.011	0.484	−3.164***	0.260	0.948
CHE	0.579	−5.860***	0.723	0.682	1.022	0.203	0.775	1.161	0.490	−4.102***	0.384	0.791
TWN	0.813	−3.389***	0.897	0.859	0.826	−4.054***	0.936	0.853	0.644	−5.097***	0.773	0.733
SWE	0.721	−4.352***	0.834	0.789	0.810	−2.298**	0.794	0.909	0.489	−4.867***	0.466	0.717
POL	0.821	−3.255***	0.900	0.866	0.677	−5.156***	0.824	0.746	0.534	−6.412***	0.684	0.646
TUR	0.696	−4.100***	0.779	0.789	0.664	−5.313***	0.816	0.736	0.424	−7.275***	0.535	0.580
BEL	0.836	−1.554	0.716	0.988	0.931	−0.840	0.839	1.017	0.642	−2.313**	0.408	1.005
IRN	0.682	−3.032***	0.629	0.860	0.776	−3.502***	0.855	0.839	0.479	−4.823***	0.439	0.722
ISR	0.981	−0.246	0.871	1.052	1.041	0.835	0.948	1.069	0.985	−0.142	0.767	1.125
AUT	0.770	−2.395**	0.721	0.907	0.852	−1.239	0.670	1.041	0.497	−3.133***	0.277	0.944

Table 5 continued

Nation code	Period I–Period II				Period II–Period III				Period I–Period III			
	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$
DNK	0.779	−3.699***	0.872	0.835	0.739	−3.634***	0.809	0.822	0.500	−5.328***	0.531	0.686
FIN	0.752	−2.824***	0.746	0.871	0.774	−2.200**	0.695	0.929	0.434	−4.147***	0.288	0.809
GRC	0.769	−3.072***	0.807	0.856	0.875	−2.220**	0.907	0.919	0.628	−3.923***	0.638	0.787
CZE	0.841	−2.236**	0.848	0.913	0.760	−3.493***	0.830	0.834	0.669	−4.549***	0.772	0.761
MEX	0.910	−1.705	0.922	0.947	0.796	−2.730**	0.819	0.879	0.748	−3.433***	0.805	0.833
NOR	0.806	−2.911***	0.853	0.872	0.974	−0.414	0.907	1.023	0.713	−2.677**	0.639	0.892
HKG	0.853	−3.950***	0.955	0.873	0.918	−1.756*	0.939	0.947	0.775	−3.886***	0.877	0.827
SGP	0.826	−2.936***	0.886	0.877	0.726	−3.963***	0.815	0.804	0.562	−5.134***	0.634	0.705
PRT	0.660	−6.833***	0.876	0.706	0.520	−5.383***	0.576	0.685	0.310	−9.299***	0.410	0.483
ZAF	0.839	−1.863*	0.791	0.944	0.943	−0.689	0.838	1.030	0.726	−2.121**	0.558	0.972
MYS	0.562	−2.499**	0.291	1.041	0.793	−2.054*	0.712	0.940	**0.310**	**−3.716***	**0.101**	**0.978**
NZL	0.969	−0.512	0.911	1.015	0.965	−0.891	0.961	0.985	0.902	−1.140	0.814	1.000
ARG	0.872	−1.696	0.842	0.950	0.880	−1.370*	0.802	0.983	0.719	−2.356**	0.593	0.934
IRL	0.779	−2.417**	0.743	0.903	0.701	−3.437***	0.722	0.825	0.629	−4.645***	0.713	0.745
HUN	0.797	−3.258***	0.867	0.856	0.772	−2.815***	0.784	0.872	0.550	−4.466***	0.544	0.746
UKR	0.901	−2.987***	0.967	0.916	0.833	−1.669*	0.735	0.972	0.717	−2.682**	0.650	0.890
ROU	0.721	−4.305***	0.831	0.790	0.553	−5.610***	0.658	0.682	0.391	−8.217***	0.526	0.539
EGY	0.899	−3.154***	0.969	0.913	0.737	−2.289**	0.621	0.935	0.644	−3.178***	0.569	0.854
THA	0.611	−3.230***	0.507	0.858	0.808	−3.011***	0.866	0.869	0.469	−4.584***	0.396	0.745
SAU	0.794	−2.227**	0.746	0.919	0.715	−3.055***	0.702	0.854	0.475	−4.206***	0.366	0.784

Table 5 continued

Nation code	Period I–Period II				Period II–Period III				Period I–Period III			
	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$	$\hat{\beta}$	t	R^2	$|\hat{\beta}|/|R|$
CHL	0.715	−2.688**	0.646	0.890	0.876	−1.106	0.711	1.040	0.472	−3.316***	0.261	0.925

Bold types indicate β-values not significant different from zero at the 5% level

All β-values are significantly greater than zero at the 1% level

t-statistics refer to the hypothesis H_0: $\beta = 1$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 also provides information for individual nations regarding whether their structural changes lead to convergence towards the global disciplinary distribution of publications. Using the $|\hat{\beta}|/|R|$ values as indicators, among the 103 cases of which nations experienced significant structural changes (34 for the First Medium Term, 30 for the Second Medium Term, and 39 for the Long Term), only 4 have their $|\hat{\beta}|/|R|$ values above 1 and thus involve a divergent process: Malaysia during the First Medium Term, the Netherlands during the Second Medium Term, and the UK and Belgium during the Long Term. Of the 45 nations, 33 and 29 had their disciplinary structures converged towards to the global distribution during the Frist and the Second Medium Term, respectively, and among them 26 had continuous converging processes through both medium terms. 37 nations experienced the conrging process through the Long Term.

The decomposition of a nation's disciplinary structural changes into a "regression effect" $(1 - \beta)$ and a "mobility effect" $(1 - R)$ enables a more in-depth exploration. Based on the regression results, values of the regression effect and the mobility effect for all nations are plotted in Fig. 3 to show medium term changes and in Fig. 4 for long term changes. Correlation analysis is conducted for each term and a significant linear relationship between the two effects is found for the First Medium Term ($r = 0.71$, $t = 6.62$, $p < 0.001$, $n = 45$), the Second Medium Term ($r = 0.72$, $t = 6.84$, $p < 0.001$, $n = 45$), and for the Long Term ($r = 0.78$, $t = 8.23$, $p < 0.001$, $n = 45$). Thus, in general, the larger the extent to which a nation's disciplinary structural changes are caused by the "mobility effect", the more those changes are influenced by the "regression effect" as well.

Table 6 Medium-term and long-term changes in national research profiles

|	Changes for all three terms	First medium term: periods I–II	Second medium term: periods II–III	Long term: periods I–III
No significant change	**AUS, CAN, ISR, NZL, USA** (5)	ARG, **AUS**, BEL, **CAN**, GBR, **ISR**, MEX, NLD, **NZL**, RUS, **USA** (11)	**AUS**, AUT, BEL, BRA, **CAN**, CHE, CHL, DEU, FRA, GBR, **ISR**, NOR, **NZL, USA**, ZAF (15)	**AUS, CAN, ISR**, NLD, **NZL, USA** (6)
With significant change	**CHN, CZE, DNK, EGT, ESP, FIN, GRC, HKG, HUN, IDN, IRL, IRN, ITA, JPN, KOR, MYS, POL, PRT, ROU, SAU, SGP, SWE, THA, TUR, TWN, UKR** (26)	AUT, BRA, CHE, CHL, **CHN, CZE**, DEU, **DNK, EGT, ESP, FIN**, FRA, **GRC, HKG, HUN, IDN, IRL, IRN, ITA, JPN, KOR, MYS**, NOR, **POL, PRT, ROU, SAU, SGP, SWE, THA, TUR, TWN, UKR**, ZAF (34)	ARG, **CHN, CZE, DNK, EGT, ESP, FIN, GRC, HKG, HUN, IDN, IRL, IRN, ITA, JPN, KOR**, MEX, **MYS**, NLD, **POL, PRT, ROU**, RUS, **SAU, SGP, SWE, THA, TUR, TWN, UKR** (30)	ARG, AUT, BEL, BRA, CHE, CHL, **CHN, CZE**, DEU, **DNK**, EGY, **ESP, FIN**, FRA, GBR, **GRC, HKG, HUN, IDN, IRL, IRN, ITA, JPN, KOR**, MEX, **MYS**, NOR, **POL, PRT, ROU**, RUS, **SAU, SGP, SWE, THA, TUR, TWN, UKR**, ZAF (39)

Number of nations in each category in parentheses

Bold types indicate nations with or without significant structural change for all three terms

Structural Changes in National Research Profiles from Period I to Period II

Structural Changes in National Research Profiles from Period II to Period III
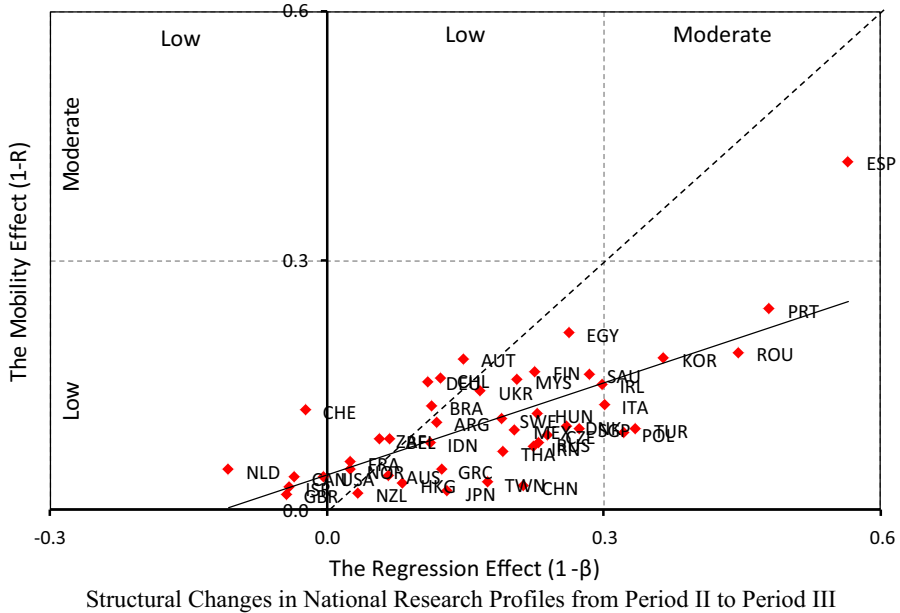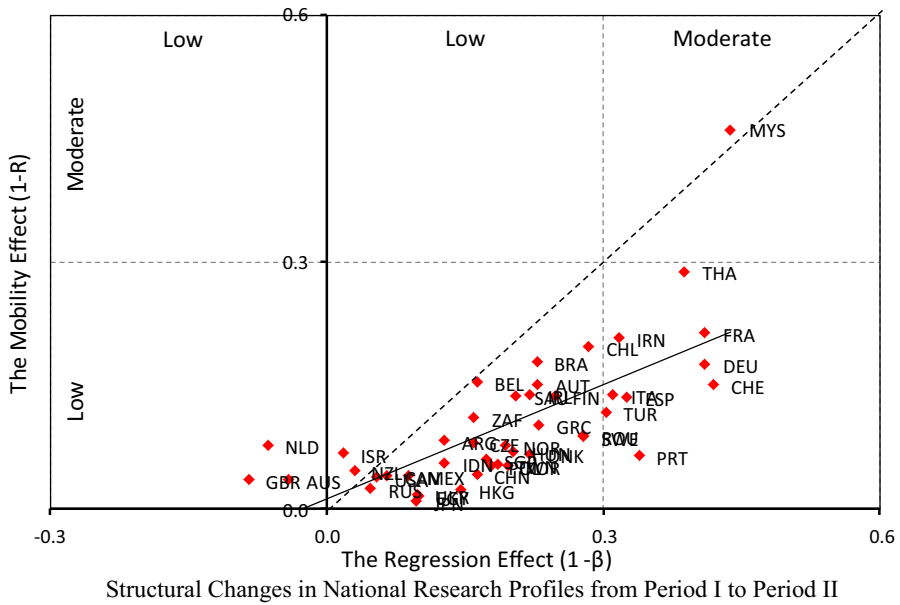
Fig. 3 The regression effect versus the mobility effect: medium term changes

For each chart in Figs. 3 and 4, an estimated regression line is added. In the scatter plots, nations that have experienced higher level of the mobility effect and lower level of the regression effect than the expected levels are located above the estimated regression lines. Figure 3 indicates that Malaysia stood out as an outlier from Periods I–II but returned normal from Periods II–III, and Spain was normal from Periods I–II but stood out as an

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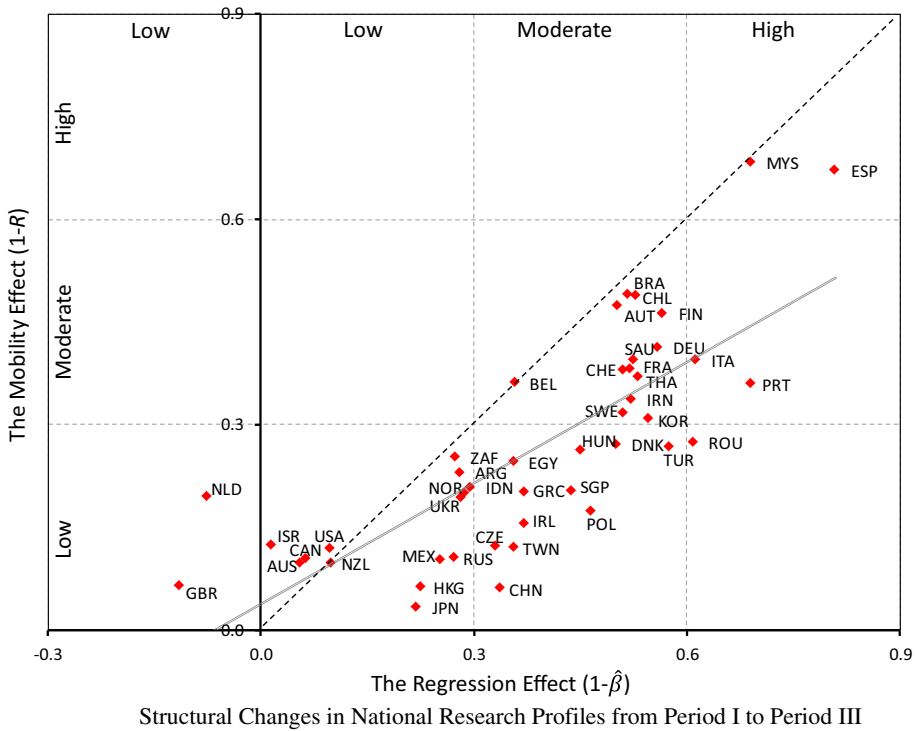
Fig. 4 The regression effect versus the mobility effect: long term changes

outlier from Periods II–III. In Fig. 4, both countries are located relatively further away from the regression line and both are in the area of high regression effect and high mobility effect. Note that Figs. 3 and 4 also indicate that changes in the two nations result more from the mobility effect than the expected levels.

In addition, for each chart, a dashed diagonal line connecting the origin and the upper right corner of the square is added. Structural changes in nations below the lines where $(1 - |\beta|) > (1 - |R|)$ result more from the regression effect than the mobility effect. Since $(1 - |\beta|) > (1 - |R|)$ is equivalent to $|\beta| < |R|$ and, thus, $|\beta|/|R| < 1$, nations below the diagonal lines have experienced a convergence process. Both Figs. 3 and 4 show that the vast majority of nations are located below the diagonal lines, serving as strong evidence to support the statement of an overall phenomenon of converging process. For the two outlier nations, Fig. 3 indicates that the drastic structural changes in Malays during the First Medium Term led the country to the direction of specialization, while in Spain the harsh changes happened during the Second Medium Term, leading the nation to be more balanced.

Take the long term change case as an example for a close look at the patterns of structural changes. In Fig. 4 where the levels of the regression effect and the mobility effect are labelled with low, moderate, or strong, making the chart into a matrix, and in the High Regression Effect-High Mobility Effect category are the aforementioned two outliers, Malaysia and Spain. Nations close to the origin are categorized as Low Regression Effect and Low Mobility Effect. Among them, 6 nations have been fairly stable (β-values not significantly different from 1) in their disciplinary profiles: United States, Canada,

Australia, Netherlands, Israel, and New Zealand. They rank 1st, 7th, 11th, 14th, 23rd, and 36th respectively in terms of number of publications in the world, and together they represent 31.8% of the world's total publications (see Table 2). That is, close to one third of the total publications are produced by nations that did not experience significant changes in their research profiles.

Figure 4 also reveals that, for nations that have experienced significant structural changes in research profiles, the changes in Hong Kong, Japan, Taiwan, China, Russia, Poland, Czech Republic, and Mexico are mainly attributed to the so-called "regression effect." The mobility effect in these nations is limited, implying a high level of stability in the ranking of disciplines. On the other extreme, the nations for which the mobility effect contributes more significantly than the expected level to their changes in national research profiles are Brazil, Chile, Austria, Finland, and Saudi Arabia. No clear geographical or socio-economic pattern among these nations is identified.

The value of $(1 - |\beta|)$ implies the extent to which structural changes have happened in a nation's research systems. Figure 4 shows that, among those that have undergone higher degree of changes are Portugal, Romania, Italy, Finland, Germany, France, Chile, Brazil, Austria, Thailand, Iran, Korea, Sweden, Switzerland, Turkey, and Denmark. This group of nations includes quite a few advanced Western European nations such as Portugal, Italy, Finland, Germany, France, Austria, Sweden, Switzerland, and Denmark, all of which are among nations with homogeneous research profiles.

The convergence patterns revealed above are similar to findings of previous studies. Glänzel and Schlemmer (2007) confirm a convergence process across EU-15 nations but point out that the process is slow. The 45 nations in this paper cover 14 members of the EU-15. For the 14 members, Fig. 3 shows that, from Periods I to II, which corresponds to the time frame of Glänzel and Schlemmer (2007), the UK and the Netherlands had no significant structural changes and all other nations have moved towards convergence, resulting from a combination of low level of mobility effect and low to moderate level of regression effect. The study by Horlings and van den Besselaar (2013) is a more current investigation of the convergence process. The study uses regression and factor analysis for data from Web of Science for 200 nations in 150 subject areas. It confirms a global process of both β-convergence and σ-convergence. Although differing in data source and research methodology, conclusions reached by the Horlings and van den Besselaar (2013) study are in consistent with the findings of the present paper. Furthermore, studies presented in Bongioanni et al. (2014a, b) aggregate data of the 27 subject categories extracted from the Scopus database into 4 broad areas and use multiple indicators for analysis. Both studies confirm the converging process towards a unique disciplinary profile—either towards the European profile among 27 European countries (Bongioanni et al. 2014b), or towards the global profile among 40 nations around the world (Bongioanni et al. 2014a).

A close look at the G7 and the BRIC countries

While due to limited space a careful scrutiny of each of the 45 nations is not feasible, it makes much sense if the present study pays more attention to the G7 and the BRIC countries. The G7 group consists of the world's 7 major advanced economies: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. They also represent a high level of academic research. The BRIC nations are Brazil, Russia, India, and China. They were at a similar stage of economic development and have enjoyed impressive economic growth during the past decades. The BRIC countries also made great achievements in scientific research. As a side note, measured by the total number of

publications from 1996 to 2015, countries belonging to the two groups are all among the top 15. The G7 represents 51.7% of the world's total publications, and the BRIC nations represent 16.5% (see Table 2). What follows is a comparative investigation between the world's biggest developed nations and the biggest catching-up nations.

As illustrated in Figs. 1 and 2, the G7 nations have much lower level of dispersion among RSIs across disciplines than the BRIC countries, with Japan and Brazil as an exception in each group. Statistical analysis shows that during the long term from Period I to Period III there has been no significant structural changes for the United States and Canada, and the UK has become slightly more specialized. Measured by the regression effect $(1 - |\beta|)$, structural changes in the three continental Western European nations are harsh than in three BRIC nations—China, Russia, and India. Structural changes in Japan are much less drastic than those of the three Western European nations of the G7, and changes in Brazil are more significant than the changes in the other three members of the BRICs.

To help analyze evolutionary patterns of structural changes in individual countries, scatter plots are constructed for each of the 11 countries with RSI of Period I as the X-axis and RSIs of Period III as the Y-axis (Fig. 5). Overall, nations with data points more close to the origin have higher level of balance among disciplines than those with data points showing a higher level of variability. For data points located in the four quadrants in each chart, quadrants I and III represents the regression effect and quadrants II and IV represents the mobility effect. Specifically, data points in quadrants II represents disciplines in which a nation did not specialize during 1996–2001 and become specialized during 2010–2015, and data pints in quadrant IV represents disciplines in which a nation specialized during 1996–2001 and lost specialty during 2010–2015. If a nation has more data pints in quadrants II and/or IV, then it has more changes in ranking of disciplines.

Charts for individual nations in Fig. 5 reveal some patterns of differences and similarities among the G7 and BRIC countries. France, Germany, and Italy form the group with the highest level of balance across disciplines. This group is also characterized with the highest level of changes of ranking of disciplines. This leads to the observation that the homogeneity of disciplinary structure makes it easier for disciplines to switch their relative positions in the national research profile. This perception is exemplified in the group of Japan, Russia, India, and China, all of which are with high level of variability of RSIs. Structural changes in these 4 nations to a large extent result from the regression effect and the role of mobility effect has been very limited. Canada, the UK, and the USA are similar in that they all possess very stable and balanced disciplinary structures. Brazil does not belong to any of the three groups as it has a level of variability higher than G7 nations (except Japan) and lower than other BRIC nations and Japan. However, like the group of France, Germany, and Italy, structural changes in Brazil result as much from the regression effect as from the mobility effect.

There is also worth in analyzing how RSIs in each nation have evolved over time. Table 7 lists disciplines that remain in the top 10 most specialized disciplines for all the three periods for the G7 and BRIC nations. Some disciplinary structural similarities among certain nation groups are revealed. Namely, the United States, United Kingdom, and Canada share similar specializations in Psychology, Nursing, Arts and Humanities, Social Sciences, and Health Professions; China, Japan, and Russia in Engineering, Energy, Materials Science, Chemical Engineering, Chemistry, and Physics and Astronomy; Germany, France, Italy, and Russia in Mathematics and Physics and Astronomy. Note that patterns revealed in Table 7 should be interpreted with cautions as levels of data coverage in the Scopus database are not evenly distributed across research areas. Research in arts
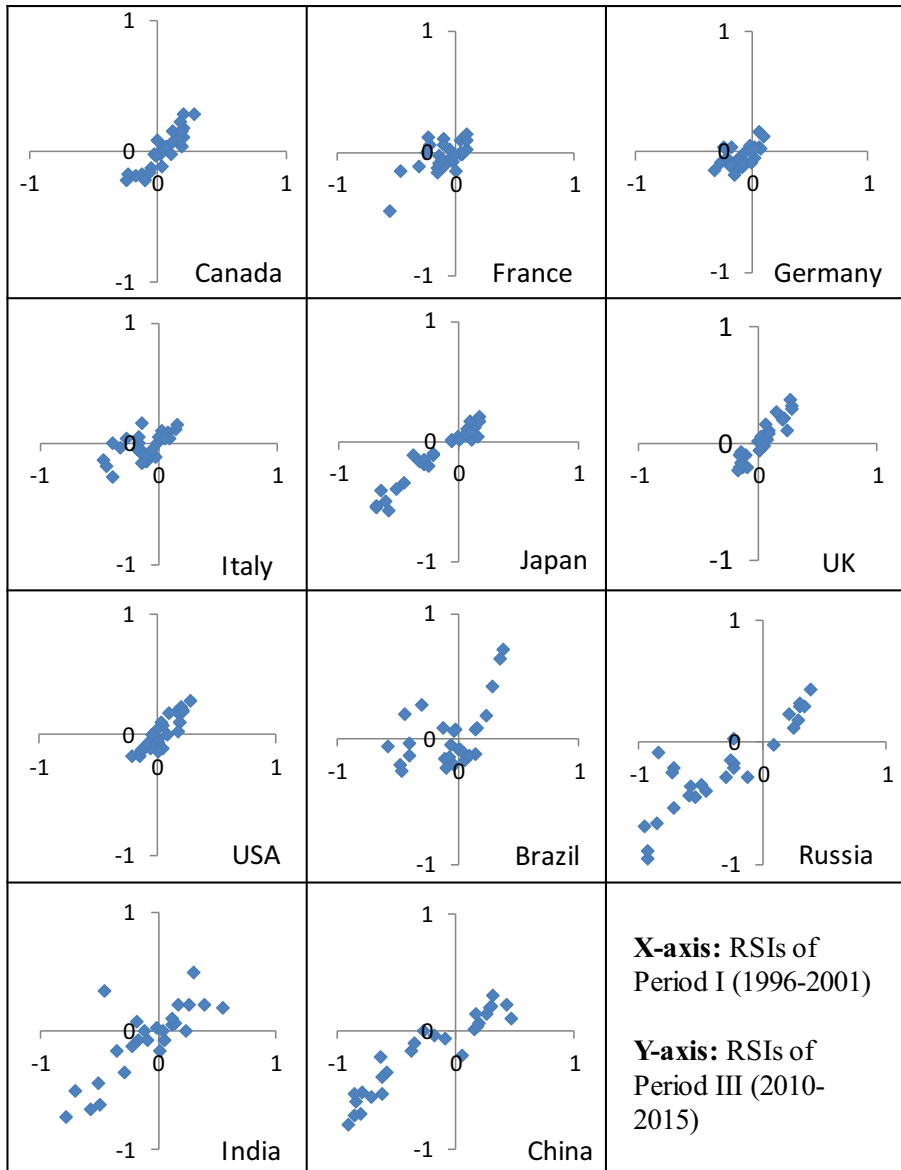
Fig. 5 Long term structural changes in national research profile: G7 versus BRICs

and humanities and social sciences is often more nationally, regionally, and locally engaged and published in languages other than English. These fields are underrepresented in large bibliometric databases, namely Scopus and Web of Science, due to the strong bias towards English-language journals in their coverage (Mongeon and Paul-Hus 2016).

In terms of disciplinary specialization, Yang et al. (2012), using data from Web of Science, find that the G7 is life science dominated and the BRIC members specialize in mathematics–physics–chemistry–engineering. However, this present study reveals two

Table 7 Stability of specialized disciplines in the G7 and the BRIC countries

Countries	Disciplines shared in all three periods (disciplines from the top 10 lists)
Canada	**Health Professions; Psychology;** Neuroscience; **Arts and Humanities;** Social Sciences; Decision Sciences; Environmental Science (7)
France	**Mathematics; Physics and Astronomy;** Earth and Planetary Sciences; Immunology and Microbiology; Medicine (5)
Germany	**Neuroscience; Physics and Astronomy;** Mathematics; Chemistry; Medicine; Biochemistry, Genetics and Molecular Biology; Materials Science (7)
Italy	**Neuroscience; Medicine;** Earth and Planetary Sciences; **Mathematics;** Biochemistry, Genetics and Molecular Biology; Immunology and Microbiology; Pharmacology, Toxicology and Pharmaceutics; Physics and Astronomy (8)
Japan	**Dentistry; Materials Science;** Physics and Astronomy; **Chemistry;** Biochemistry, Genetics and Molecular Biology; Engineering; Chemical Engineering; Pharmacology, Toxicology and Pharmaceutics; Energy (9)
United Kingdom	**Arts and Humanities; Nursing; Social Sciences;** Psychology; Economics, Econometrics and Finance; Business, Management and Accounting; Health Professions; Dentistry (8)
United States	**Psychology; Nursing; Arts and Humanities; Social Sciences;** Health Professions; Neuroscience; Business, Management and Accounting; Economics, Econometrics and Finance (8)
Brazil	**Dentistry; Veterinary; Agricultural and Biological Sciences;** Immunology and Microbiology; Pharmacology, Toxicology and Pharmaceutics; Neuroscience (6)
Russia	**Physics and Astronomy; Earth and Planetary Sciences; Materials Science; Chemistry;** Mathematics; Energy; Chemical Engineering; Multidisciplinary; Engineering (9)
India	**Pharmacology, Toxicology and Pharmaceutics;** Dentistry; **Chemistry;** Multidisciplinary; Chemical Engineering; Veterinary; Materials Science; Computer Science; Environmental Science; Energy (8)
China	**Engineering; Energy; Materials Science;** Chemical Engineering; Chemistry; Computer Science; Multidisciplinary; Mathematics; Physics and Astronomy; Earth and Planetary Sciences (10)

Bold types indicate disciplines shared by the top 5 lists of all three periods

Number of nations in each category in parentheses

patterns within the G7 group (except Japan)—the English speaking nations (USA, UK, and Canada) versus the continental European members (Germany, France, and Italy) plus Russia. It is also found that China, Japan, and Russia share a high level of similarity in their disciplinary structures.

The present study is also closely related to the framework of paradigmatic patterns proposed by Glänzel (2000). This framework identifies four types of models: (1) the Western model: developed Western countries, dominated by clinical medicine and biomedical research; (2) the former socialist model: economies in transition and China, specialized in physics and chemistry; (3) the bioenvironmental model: developing and natural-resource-oriented countries, focusing mainly on biology and earth and space sciences; and (4) the Japanese model: Japan and NIEs, predominant in engineering and chemistry. Findings of the present paper do not fit into this framework very well due to the different classification systems employed. The study by Glänzel (2000) excludes social sciences and arts & humanities, while these two subject areas are included in the present paper. It is also argued that the Western countries differ greatly in their specialized areas, as shown above for the G7 nations.

Concluding remarks and policy implications

This paper provides an empirical study examining the evolutionary patterns of national research systems using a dataset that covers publications of 45 nations across 27 disciplines. Possible reliability and validity concerns associated with the data source and with the research model are addressed and steps have been taken to improve the validity and reliability of the study.

Overall, a converging process is confirmed in the disciplinary structure of worldwide scientific outputs. The time span between 1996 and 2015 has seen a continuous process of convergence towards a unique global profile. It also shows that all of the nations with low level of dispersion or with homogenous disciplinary structures are developed countries. Meanwhile, regression analysis for individual nations reveals that nations differ greatly in their evolutionary patterns of disciplinary structural changes over time. There are nations that have experienced no significant structural changes and nations that have undergone high level changes, while the majority of nations have gone thorough moderate or low degrees of changes. However, there is no clear pattern showing either the level of development of nations or their geographical locations playing a decisive role in the changes of structural specializations.

Causes of changes in disciplinary profiles result from a combination of the regression effect and the mobility effect. In some nations such as Spain and Malaysia, salient alterations in their rankings of disciplines have been the main sources of structural changes in their research profiles, while others such as Japan and China have been very stable in their rankings of disciplines and the evolutions of their national research profiles have shown a continuous process of de-specialization.

Careful scrutiny of the G7 and the BRIC countries reveals some important features. First, France, Germany, and Italy form the group of homogeneity characterized by the highest level of changes of ranking of disciplines. They all specialize in Mathematics and Physics and Astronomy. Second, the group that includes Japan, Russia, and China is of heterogeneity in the variability of *RSI*s. National structural changes result from the regression effect and the role of mobility effect has been very limited. The three nations specialize in Engineering, Energy, Materials Science, Chemical Engineering, Chemistry, and Physics and Astronomy. Third, Canada, the UK, and the USA have very stable and balanced disciplinary structures. They specialize in Psychology, Nursing, Arts and Humanities, Social Sciences, and Health Professions.

The above findings have important implications in science policy. First, as disciplinary profiles differ greatly across nations, there should be no single pattern that fits all nations, and a 'one size fits all' research policy that ignores national differences may not lead to the desired results. Policy-makers must be sensitive to how their respective nations differ from others; particularly, they must possess a good understanding of patterns of structural changes as well as the specialization in their national research profiles. The analytical approaches described in this paper, namely the regression models and the decomposition of the variability of structural changes in national research profiles into the regression effect and the mobility effect, may help individual nations better understand their evolutionary patterns of disciplinary profiles.

Second, for any nation, a notable policy question that needs to be answered is whether the nation will better off if it strives to be more homogenous in its disciplinary structures or if it specializes in just a few disciplines. Unfortunately, the present study does not address this issue. In fact, despite the existence of a general process of convergence across national

research profiles, nations diverge in their evolutionary patterns. Evidence from the comparison between the G7 and the BRIC nations shows that all advanced economies but Japan maintain their research profiles with high level of balance, and the BRIC nations, with the exception of Brazil, retain relative stability in the ranking of their disciplines and move towards a more balanced structure in an incremental way. However, it could be dangerous if this pattern is generalized to other nations for their strategies in scientific research as each nation is unique to some extent and the strategic planning should be made on the case by case basis.

Third, no matter whether a nation sets its development strategy as having a more balanced or more specialized in its discipline profile, the nation may still consider having science policies that take advantage of the overall convergence in national disciplinary profiles. The convergence phenomenon at least results from two contributing factors: one is the indigenous improvement in disciplines with previously lower-than-average publication activities, and the other relates to the international transfer of knowledge through collaborations and mobility of talents. The latter deserves attention. Scientific knowledge, unlike technology know-how, is often regarded as a type of public goods that knows no national borders. This feature eases the process of international transfer of scientific knowledge. Moreover, the movement of globalization speeds up the international exchanges of ideas, goods, and people. Therefore, implementing policies that promote international collaboration and mobility of ideas and talented people not only can facilitate catching-up in disciplines with lower-than-average publication activities but also may strengthen those already specialized fields. Even if a nations aims to become more specialized, it could still benefit from the converging process.

The foregoing interrelated points lead to an important research question: what are the major determinants of a nation's research profile? That is, what leads a nation to be more balanced or to be more specialized and what contributes to the structural changes in the nation's research profile? National differences in research profiles may be caused by direction of persistent investment (i.e., investment in certain fields of R&D), by factor endowments (i.e., big country versus small country), by level of development (developed country versus developing country), by geographical location (continental location, whether adjacent to a large economy, etc.), and by cumulative mastery of knowledge through national culture and traditions, among other factors. It is not clear how the abovementioned factors play their respective roles, nor the relative importance of each factor. This is a promising direction for future research.

It should be emphasized that, although steps have been taken to alleviate problems of reliability and validity, interpretations of the findings of the present study still need to be made with caution. The analysis still suffers to some extent from limitations inherited from the use of the bibliometric databases. In addition, although normality issues have been greatly reduced, the assumption is still not met with 20% of the cases.

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