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A scale-independent analysis of the performance of the Chinese innovation system

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ABSTRACT

In this paper we use scale-independent indicators to explore the performance of the Chinese innovation system from an economic and from a science and technology point of view, and compare it with 21 other nations. Some important developments in the Chinese innovation system, hidden by rankings by conventional performance indicators, were revealed. We find that gross domestic expenditure on R&D (GERD) & gross domestic product (GDP) and GDP & POP (population) all exhibit strong 'Matthew effects', measured by their scaling factors. This means that the Chinese R&D intensity (GERD/GDP) and national wealth (GDP per capita) are growing significantly with the increase of the GDP. Also pairs such as citations & papers, papers & GDP, citations & GDP, and paper & GERD exhibit these 'Matthew effects'. This observation points to the fact that in China scientific outputs and impacts are growing faster than economic growth and research investment. However, according to another scale-independent indicator, namely the adjusted relative citation impact (ARCI), China ranks on the bottom of the list, but the growth rate of the ARCI is the highest among these countries (comparing the periods 1995–1999 and 2001–2005). To sum up, we interpret these findings to mean that the scientific outputs and impacts of China show a real tendency of catching up with its economic growth. It is expected that with an increase of its GDP and R&D intensity China will show a sustained increase in indicators related to science and technology. Similarly, there are very strong 'Matthew effects' between the outputs of technology (patents) and economic growth and research investment. This means that the outputs of technology are expected to increase considerably with an increase of GDP and R&D expenditure. Furthermore, in the Chinese innovation system the government intramural expenditure on R&D (GOVERD) has a stronger non-linear impact on patent productivity than business enterprise expenditure on R&D (BERD). This shows that in China research institutions financed by the government play a more important role than enterprises.

1. Introduction

An innovation system is a social construct, composed of individuals and organizations that directly and indirectly invest time and energy in the production of scientific and technical knowledge (Katz, 2006). The innovation capacity of a country is widely regarded as the principal driving force behind its competitiveness and economic growth. However, for different

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nations it takes a different time to reach the technological frontier where innovation becomes a basic driving force. Innovation in the case of latecomer countries needs to be understood in a way that is rather different from innovation in the case of leaders (Hu & Mathews, 2005).

Most, if not all, complex systems have a propensity to exhibit scaling properties. A scaling property is characterized by a power law correlation or distribution, and is common to physical systems, natural systems and social systems (Christensen, Danon, Scanlon, & Bak, 2002; Katz & Katz, 1999; Newman, Watts, & Strogatz, 2002; van Raan, 2008a; Wagner & Leydesdorff, 2005). A power law is one of the signatures of non-linear dynamical processes and is also indicative of the existence of scale-independence or self-similarity. Like most complex systems, innovation systems display characteristic power law correlations or distributions (Jin & Rousseau, 2005a; Katz, 1999, 2000; Katz & Cothey, 2006; van Raan, 2008b). These scaling correlations can be used to construct scale-independent indicators that are properly normalized for the sizes of the members of the system (Katz, 2000, 2006). The differences between the ranks by scale-independent indicators and by conventional (scale dependent) indicators can result in a shift in perspective about the performance of members of an innovation system.

Since 1978 China has undergone profound economic and organizational reforms. One objective of the reforms is to increase efficiency by replacing the central planning system of resource allocation by a free market mechanism. Significant achievements have been made in the latest three decades. The government has decentralized fiscal and managerial control, redefined public and private ownership, and encouraged new linkages between research and industry. Organizational boundaries related to innovation activities have changed considerably, and primary actors in innovation activities have become more autonomous and functionally diversified (Liu & White, 2001). Typical aspects of China's innovation system continue to emerge from the interactions between its regional innovation systems and other ones.

Quantitative and qualitative measures of input and output are frequently applied to construct performance indicators used to inform decision makers. However, some of these performance indicators derived from ratios, are not normalized for size. As a result, some important developments are kept hidden from view, and decision makers can be misled. For example, King (2004) used performance indicators derived from ratios, such as 'wealth intensity' (GDP per person), 'citation intensity' (citation per GDP), scientific impact (citation/paper), publications per researcher, etc., to measure the quantity and quality of science in different nations. In his rankings China lags behind scientific giants such as the US, UK, Germany and Japan. But he also points out that simple citation rankings can hide important developments, particularly in countries such as China and India, which have developed their science base rapidly and effectively over the past years. This paper focuses on finding important developments in China's innovation system which are otherwise hidden by rankings based on conventional performance indicators. This goal is reached by using a scale-independent approach. Further, based on these scale-independent indicators, the performance of China's innovation system will be illustrated and compared with 21 other countries.

The paper is organized as follows. In Section 2, a description of the data source and the methodology is provided. Based on scale-independent indicators, a thorough investigation of many aspects of the Chinese innovation system including economic, scientific and technological aspects is presented in Section 3. The policy relevance of the findings is summarized in the final section.

2. Data source and methodology

This section will explore the data source and the methodology that is applied in this research.

2.1. Data source

In this paper we make a comparison between China and 21 countries (the comparator group) including the G7 group (italicized) and the 15 countries of the European Union (EU15). The countries are: Austria, Australia, Belgium, *Canada*, Denmark, Finland, *France*, *Germany*, Greece, India, *Italy*, *Japan*, the Netherlands, Portugal, Ireland, South Korea, Spain, Sweden, Switzerland, *the United Kingdom* and *the United States*. Except for China and India, the other countries are all OECD countries, and most of them can be described as innovation-typed countries. We note that over the past years China and India have been engaged in technology based economics growth, competing with each other in many sectors (Bhattacharya, 2004). Therefore, we consider it of interest to include and compare the innovation systems of these two important emerging economies.

The following measures are used to construct scale-independent indicators: GDP, gross domestic expenditure on R&D (GERD), higher education expenditure on R&D (HERD), business enterprise expenditure on R&D (BERD), government intramural expenditure on R&D (GOVERD), population (POP), number of scientific papers, citations to papers and patents. The above measures can be roughly classified into three groups: economic indicators (GDP, GERD, HERD, BERD, GOVERD, POP), output and impact of science research (scientific papers and citation to papers), and the output of technological innovation (patents). Here the term "scientific papers" refers to publications covered by the *Science Citation Index* (SCI) and the *Social Science Citation Index* (SSCI). The SCI and SSCI provide reasonably comprehensive coverage of the significant contributions in most scientific areas. As for patents, three categories are identified for each country: the number of patent applications to the US Patent and Trademark Office (USPTO), the number of patent applications to the European Patent Office (EPO) and the number of triadic patent families (TPF).

As we use a broad range of measures in this paper, the corresponding data sources are also relatively complicated. The economic data for China and 20 OECD countries come from the *Main Science and Technology Indicators* (1998–2007) produced by the OECD. The data for India are obtained from the International Monetary Fund (IMF) and the Asian Development Bank. For analysis purpose, an exponential growth trend is used to interpolate over missing data. The above economic data for 22 countries have been converted to purchasing power parity at current prices in US dollars (PPP $US). The number of scientific papers for each year is obtained from the SCI and SSCI databases. Unlike in Katz's case (1999), publication and citation counts obtained using a fixed citation window were not available to us. So we substitute this piece of information by publication and citation counts provided by the *Essential Science Indicators* (ESI). The ESI is based on journal article publication counts and citation data from Thomson/Reuters' databases, and are available as 10-year rolling files each giving using a moving five-year time window. Finally, the three types of patent data are obtained from the USPTO and the *Main Science and Technology Indicators* published by the OECD.

2.2. Methodology

An innovation system consists of, among other things, an evolving network of interactions between individuals and groups from all sectors of society (Katz, 2006). Measures such as GDP, GERD, numbers of scientists and engineers, citations to papers and patents are frequently used to create indicators of the activities of an innovation system (Godin, 2005).

The paper is based on time series data showing the evolution or trajectory of the corresponding data. It has been observed that measures such as GDP, GERD, publications and citations tend to grow exponentially over time, although growth is rarely perfectly exponential. A pair of exponential processes that are coupled through a common variable such as time exhibit a power law correlation (Katz, 2000). A power law is readily identifiable when it is plotted on a log–log scale because it appears linear. The exponent alpha of a power law is called its scaling factor. It is obtained as the slope of the linear regression line drawn through the log values (Katz, 2006). A scaling factor can be used as a scale-independent indicator comparing the relative growth rate of variables within one system or between systems. For simplicity and clarity, the scaling factor for each nation is presented in a compressed form using footprint plots (also known as spider or radial plots) for comparison.

A power law relationship between a pair of variables also provides a tool for developing another type of scale-independent indicator. This indicator takes the size effect into consideration: it is a relative magnitude indicator (Katz, 2000). As this relative magnitude indicator has been normalized by the scaling relationship it can be used to compare groups of vastly different sizes. Throughout this paper we focus on the above two types of scale-independent indicators. In this way a comparative analysis of the performance of China's innovation system will be conducted from an economic, scientific and technological point of view.

Using these properties scale-independent indicators are constructed which account for a non-linear size effect. They can more accurately inform decision makers how much groups of different sizes contribute to an innovation system, and help them draw up a more reliable public policy.

3. Results and discussion

3.1. Scaling from economic systems

The following examples explore scaling correlations between GERD & GDP and GDP & POP for the Chinese innovation system, as compared to 21 other countries.

3.1.1. Scaling correlations between GERD and GDP

Fig. 1 gathers the GERD–GDP scaling factors for China, India and the G7 group into a footprint plot. The distance from the origin to the data point is equal to the value of the respective scaling factor. The larger the national footprint, the stronger the non-linear impact of GDP on GERD. For China, it shows that the GERD–GDP scaling factor is 1.646, which is greater than 1.0. This means that over the 15-year period the Chinese GERD is growing faster than the GDP. Moreover, this value also shows that in the same period the Chinese GERD tended to grow 3.13 ($2^{1.646}$) times every time the GDP doubled ($2^{1.0}$). In other words, the Chinese GERD grew quite non-linearly with GDP. Within the G7 group, the GERDs for Canada, United Kingdom and United States are growing slower than the GDP while the reverse is true for the other four nations. The GERDs for United States grow almost linearly with GDP, and the GERDs for three Asian countries, i.e. China, India and Japan, grow quite non-linearly with GDP. Among this group the non-linear effect is the strongest for China.

Furthermore, we focus on the innovation systems of two developing countries in Asia: China and India. As the Chinese and Indian systems have exponentially growing trends in GDP and are coupled in time, they exhibit a scaling correlation. Therefore, intersystem scale-independent indicators can be produced. The scaling relationship between the Chinese GDP (GDP_C) and the Indian GDP (GDP_I) has a scaling factor equal to 1.39 ± 0.03. The $GERD_C$–$GERD_I$ scaling factor has a value of 1.51 ± 0.08. These indicators show that between 1991 and 2005 the Chinese GDP and GERD grew faster than the Indian one. According to these scaling relationships, if the Indian GDP and GERD doubled the Chinese GDP and GERD would be expected to increase 2.62 ($2^{1.39}$) and 2.85 ($2^{1.51}$) times, respectively.

If GERD and GDP exhibit a scaling relationship then the R&D intensity (GERD/GDP) also exhibits a scaling relationship with GDP. Using this relationship the R&D intensity indicator for the Chinese innovation system is predicted to scale with GDP with a scale factor of 0.660, which should be compared with the observed value of 0.646 ± 0.078. This result shows that the R&D intensity for the Chinese innovation system exhibits a tendency to increase 1.56 times ($2^{0.646}$) when GDP doubled.

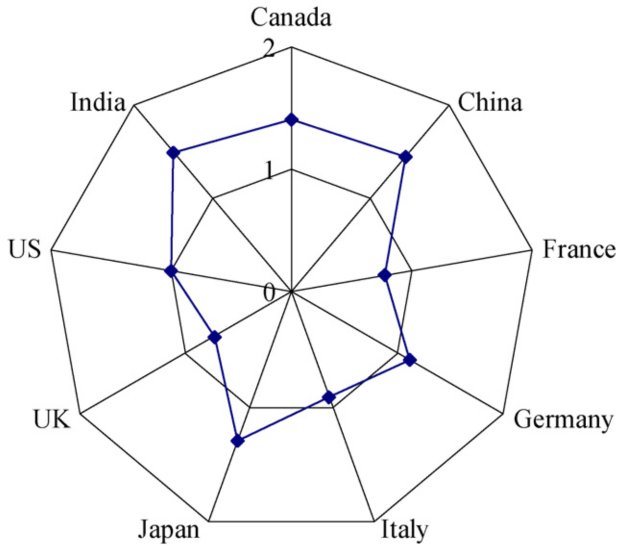

Fig. 1. GERD–GDP scaling factors for China, India, and the G7 group.

This is a relatively strong non-linear tendency. For India, the R&D intensity tended to increase $1.40(2^{0.487})$ times every time the GDP doubled.

The R&D intensity indicator is not normalized for size. A relative GERD indicator that has been adjusted can be used instead of the R&D intensity to compare countries of different sizes. Table 1 gives the average R&D intensity and relative GERD, sorted in descending order of the relative GERD, for China and the comparator group over the period 1991–2005. This table furthermore shows data for 1995, 2000, 2005, showing the general trend more clearly. The value between brackets is the rank determined using the corresponding indicator. Clearly, in the l990s the R&D intensity for China grew slowly, but this figure has been increasing rapidly since the year 2000. For this reason we chose the years 1995, 2000 and 2005 for comparison.

Our data show that of the G7 nations, Japan heads the table, followed by the United Stated, Germany and France. Among the EU15 nations, Sweden is first on all the two measures. Of 22 nations, China and India are ranked on the bottom of the lists, at the 19th and 21st position, respectively. This means that there is still a large gap in the relative GERD between China and

Table 1
Comparison of R&D intensity and relative GERD indicators for China and the comparator group.

Country	1991–2005		1995		2000		2005	
	RGERD	R&DI	RGERD	R&DI	RGERD	R&DI	RGERD	R&DI
Sweden	2.29	3.66 (1)	2.30 (1)	3.59	2.28 (1)	3.96	2.17 (1)	3.89
Denmark	2.16	2.14 (9)	1.23 (11)	1.91	1.33 (8)	2.30	1.36 (8)	2.45
Finland	1.86	2.88 (3)	1.52 (6)	2.35	1.98 (2)	3.40	1.90 (2)	3.40
Japan	1.74	2.98 (2)	1.80 (2)	2.98	1.64 (3)	2.96	1.87 (3)	3.33
Switzerland	1.7	2.7 (4)	1.73 (3)	2.70	1.48 (4)	2.57	1.54 (5)	2.75
Korea	1.52	2.5 (6)	1.67 (4)	2.68	1.35 (7)	2.39	1.67 (4)	2.98
US	1.51	2.65 (5)	1.55 (5)	2.61	1.48 (5)	2.72	1.47 (6)	2.62
Germany	1.46	2.46 (7)	1.40 (8)	2.30	1.39 (6)	2.49	1.39 (7)	2.48
France	1.35	2.27 (8)	1.44 (7)	2.34	1.22 (9)	2.18	1.19 (10)	2.13
Netherlands	1.2	1.95 (10)	1.31 (9)	2.07	1.08 (10)	1.90	0.97 (14)	1.73
UK	1.15	1.93 (11)	1.24 (10)	2.02	1.04 (13)	1.85	1.00 (13)	1.78
Austria	1.15	1.83 (12)	1.02 (13)	1.59	1.07 (12)	1.86	1.35 (9)	2.42
Canada	1.08	1.78 (13)	1.01 (15)	1.62	1.08 (11)	1.92	1.10 (11)	1.98
Belgium	1.03	1.66 (14)	1.01 (14)	1.59	0.91 (14)	1.59	1.04 (12)	1.86
Australia	0.99	1.61 (15)	1.04 (12)	1.65	1.07 (12)	1.86	0.92 (15)	1.64
Ireland	0.78	1.21 (16)	0.91 (16)	1.39	0.67 (16)	1.15	0.70 (17)	1.26
Italy	0.66	1.1 (17)	0.62 (17)	1.01	0.60 (17)	1.07	0.62 (19)	1.10
Spain	0.57	0.94 (18)	0.53 (18)	0.85	0.53 (19)	0.94	0.63 (18)	1.12
China	0.48	0.87 (19)	0.36 (20)	0.60	0.55 (18)	1.00	0.75 (16)	1.34
Portugal	0.45	0.71 (20)	0.37 (19)	0.58	0.46 (21)	0.80	0.45 (20)	0.81
India	0.41	0.7 (21)	0.34 (21)	0.55	0.47 (20)	0.85	0.43 (21)	0.77
Greece	0.34	0.54 (22)	0.32 (22)	0.49	0.38 (22)	0.66	0.28 (22)	0.51
EU15	1.07	1.87	1.07	1.82	1.02	1.88	1.05	1.88

Note: R&DI is short for R&D intensity, i.e. GERD/GDP (%); RGERD is short for relative GERD; it is normalized for size.

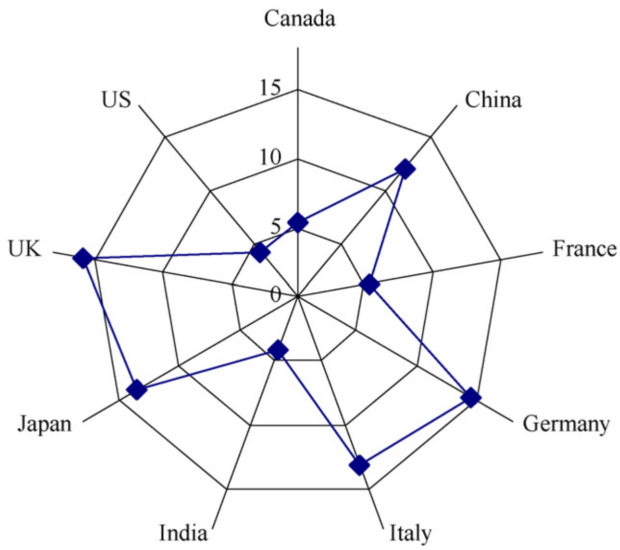

Fig. 2. GDP–POP scaling factors for China, India and the G7 group.

India and advanced countries such as the United States, Japan and Germany. Yet, as shown by the figures for 1995, 2000 and 2005, the relative GERD for the Chinese innovation system exhibited an increasing trend from 0.36 in 1995 to 0.55 in 2000, and further to 0.75 in 2005 or a considerable difference of 0.39. Correspondingly, the ranking by relative GERD rises from 20th in 1995 to 18th in 2000 and further to 16th in 2005. The Indian innovation system does not grow that fast: the relative GERD grew from 0.34 in 1995 to 0.47 in 2000, and 0.43 in 2005. Consequently Indian's ranking did not change. Obviously, the growth rate over the period 1991–2005 of the relative GERD for China is larger than that of India.

3.1.2. Scaling correlations between GDP and POP

The GDP–POP scaling factors for China, India and G7 group are presented by spider plots, shown in Fig. 2. Among the G7 nations, Germany, Italy, Japan and the United Kingdom are characterized by a strong non-linear relationship between GDP and population with a scaling factor above 10, while Canada, France and the United States have a weaker non-linear relation with a score of about 5. This means that the non-linear impact of POP on GDP for the former group is far stronger than for the latter one.

The GDP–POP scaling factor for China is equal to 12.12. This value tells us that the growth rate of the Chinese GDP far exceeds that of the population over the 15-year period. Stated otherwise, a doubling of the population would be expected to increase GDP by nearly 4450 times ($2^{12.12}$) in China. In the Chinese innovation system there is a strong non-linear relationship between GDP and population. For India, the GDP–POP scaling factor is 4.12. This means that the Indian GDP tended to grow about 17 times ($2^{4.12}$) each time the population doubled ($2^{1.0}$), but for China this is nearly 4450 times ($2^{12.12}$). The larger difference in the scaling factors can be explained by the fact that the GDP_C–GDP_I scaling factor is 1.39 and the POP_C–POP_I is measured to be 0.47. These indicators show that the Chinese GDP grew faster than the Indian GDP between 1991 and 2005, but the Chinese population increased slower than the Indian. Furthermore, the GDP–POP scaling factors for China and India also indicate that GDP per capita is expected to increase about 2225 ($2^{11.12}$) and 9 ($2^{3.12}$) fold, respectively, each time the POP doubles.

3.2. Scaling from science systems

The science system is an indispensable part of the national innovation system. Its performance plays an important role in the set of innovation activities. The ability to judge a nation's scientific standing is vital for governments, businesses and trusts that must decide scientific priorities and funding (King, 2004). In this section, we will use several scale-independent indicators to compare the research impact of China and the 21 other nations. Our analysis provides some important insight into the performance of the Chinese science system.

3.2.1. Scaling correlations between size and recognition

Size (number of published papers), recognition (number of citations to papers), impact (citations per paper), and the relative citation impact (RCI), etc., are frequently used to compare the research impact of groups, institutions and nations in a scientific field. The data related to size (number of published papers) and recognition (number of citations to papers) used in this sub-section are provided by the ESI over the period 1995–2005. The data in the ESI are given in a five-year time window. Each five-year period is self-contained; that is, only citations within a time period to articles within that time

Table 2
Exponents of the power law relationship between size and recognition for China and 21 other nations.

Country	α	SE[a]	R^2	Country	α	SE[a]	R^2
Australia	2.173	0.132	0.975	Italy	1.877	0.048	1.00
Austria	2.363	0.029	0.99	Japan	3.126	0.208	0.97
Belgium	1.935	0.028	1.00	Netherlands	2.217	0.091	0.99
Canada	1.711	0.243	0.88	Portugal	1.475	0.02	1.00
China	1.573	0.024	1.00	Ireland	1.663	0.106	0.97
Denmark	2.698	0.099	0.99	Korea	1.558	0.022	1.00
Finland	2.112	0.076	0.99	Spain	1.833	0.039	1.00
France	3.179	0.192	0.98	Sweden	2.792	0.13	0.99
Germany	2.939	0.157	0.98	Switzerland	1.692	0.064	0.99
Greece	1.63	0.019	1.00	UK	3.18	0.207	0.97
India	2.437	0.113	0.99	US	2.388	0.2	0.95

[a] SE is the standard error for α.

period are counted. For example, the period 1995–1999 counts papers in the database for each full year (1995–1999) and cumulates citations to these papers from all citing items from 1995 to 1999. Thus, each successive time period is defined by a similar five-year time window to form the series. As mentioned by Katz (2000) the values of the recognition–size scaling factors calculated by this type of data may differ from those calculated using a fixed or variable citation window. However, this difference is only due to the way publications and citations are counted, and does not seem to distort basic differences between countries. Hence, it seems reasonable to calculate recognition–size scaling factors using the data obtained from the ESI.

The results displayed in Table 2 illustrate the observed power law relationships in recognition and size for China and the other nations. The exponents suggest that the ‘Matthew effect’ (Merton, 1968) can be quite strong, witnessed by the fact that on average the amount of recognition can increase by 2.78 ($2^{1.475}$) to 9.06 ($2^{3.180}$) times if the size is doubled. In the Chinese science system, each time the size (papers) doubles, on average the amount of recognition (citations) increases by 2.98 ($2^{1.573}$) times; in the Japanese science system, it increases by 8.73 ($2^{3.126}$) times; in the Indian science system, it grows by 5.42 ($2^{2.437}$) times. These findings show that the Chinese science system experiences a non-linear increase in the amount of recognition it receives as its size increases, but this non-linear effect is weaker than Japan’s and India’s.

Table 3 gives the two traditional impact indicators and a scale-independent indicator, i.e., impact (citations per paper), RCI (the relative citation impact, defined as a country’s or region’s impact divided by the world’s impact) and ARCI (adjusted relative citation impact, defined as the actual impact divided by the expected one (Katz, 2000)), sorted in descending order of the RCI among China and the comparator group for 1991–2005, and also, to demonstrate the trend, the figure of ARCI for 1995–1999 and 2001–2005. The value between brackets is the rank determined using the corresponding indicator.

Table 3 shows that among these 22 nations, the three Asian nations, Korea, India and China, are ranked on the bottom of the lists, at the 20th, 21st and 22nd position, respectively. Over recent years China’s total number of publications and citations has

Table 3
RCI and ARCI for China and 21 other nations between 1995 and 2005.

Country	c/p	RCI	ARCI	1995–1999 (ARCI)	2001–2005 (ARCI)
Switzerland	6.45	1.55	1.68 (1)	1.79 (1)	1.53 (1)
US	5.86	1.28	1.23 (8)	1.19 (8)	1.29 (4)
Netherlands	5.46	1.19	1.38 (3)	1.41 (3)	1.34 (3)
Denmark	5.42	1.18	1.47 (2)	1.5 (2)	1.42 (2)
Sweden	5.12	1.12	1.32 (5)	1.38 (5)	1.28 (5)
UK	5.12	1.12	1.18 (10)	1.14 (11)	1.22 (8)
Finland	4.88	1.07	1.33 (4)	1.4 (4)	1.23 (6)
Canada	4.83	1.05	1.17 (11)	1.17 (9)	1.12 (11)
Belgium	4.75	1.04	1.26 (7)	1.35 (6)	1.19 (9)
Germany	4.68	1.02	1.09 (12)	1.04 (12)	1.13 (10)
Austria	4.66	0.97	1.27 (6)	1.26 (7)	1.22 (7)
France	4.39	0.96	1.04 (14)	1.03 (14)	1.05 (13)
Italy	4.27	0.93	1.04 (15)	1.04 (13)	1.03 (15)
Australia	4.16	0.90	1.04 (13)	1.02 (15)	1.04 (14)
Ireland	4.04	0.88	1.19 (9)	1.16 (10)	1.08 (12)
Japan	3.66	0.8	0.84 (18)	0.81 (18)	0.88 (17)
Spain	3.61	0.79	0.91 (16)	0.88 (17)	0.9 (16)
Portugal	2.98	0.65	0.86 (17)	0.9 (16)	0.81 (18)
Greece	2.67	0.58	0.75 (19)	0.79 (19)	0.71 (19)
Korea	2.26	0.49	0.59 (20)	0.54 (20)	0.61 (20)
India	1.70	0.40	0.43 (21)	0.38 (21)	0.47 (22)
China	1.67	0.37	0.42 (22)	0.37 (22)	0.49 (21)

Note: c/p: citation per paper; RCI: relative citation impact; ARCI: adjusted relative citation impact.

been increasing but, on average, its impact is still low. This fact corroborates Jin and Rousseau's findings (2005b). However, a glimpse at the Chinese figure for the ARCI for 1995–1999 and 2001–2005 shows that the scientific impact of China has been increasing considerably: growing from 0.37 in 1995–1999 to 0.49 in 2001–2005. Clearly, China's growth rate in ARCI is the highest among the 22 nations.

3.2.2. Scaling correlations between economic indicators and bibliometric measures

The economic system and the science system are not isolated, but interactive. Funding is a fundamental factor that cannot only influence the publication size of a research group but also its recognition and impact. Also between economic and bibliometric measures a power law relationship exists. Therefore, intersystem scale-independent indicators can be produced. In essence, the intersystem scale-independent indicator is a measure of the complex interplay among such economic and bibliometric factors.

It is important to recognize that there are lags between changes in economic indicators (GDP and GERD) and bibliometric measures (papers and citations). Here, we assume a two-year lag between funding and scientific output. The publication data we use are obtained from the SCI and SSCI databases and refer to the period between 1995 and 2005; the corresponding economic data cover the period between 1993 and 2003. Citation data are gained from the ESI for the period 1995–2005; the corresponding economic data are also defined by a five-year time window and form a series over the period 1993–2003.

In Table 4(a), we investigate the scale correlations between size (papers) and economic indicators such as GDP, GERD and HERD. Among the countries of the G7 group, papers originating from Canada, France, the UK and the US are growing slower than the GDP over the observed period. Especially for the US, the number of papers tends to grow only 1.33 ($2^{0.414}$) times with a doubling in country size measured by GDP. The papers for China grew quite non-linearly with GDP. More precisely, Chinese papers tended to increase 2.84 ($2^{1.508}$) times when the GDP doubled ($2^{1.0}$). For India, papers tended to grow 1.43 ($2^{0.519}$) times each time the GDP doubled. The non-linear effect is weaker for India than for China. According to the paper–GERD scaling factor, the values for France, Japan, the UK, the EU15 and China, are all close to 1.0. This means that for these nations the papers grew almost linearly with GERD. For Canada, the US and India, the paper–GERD scaling factors are all far less than 1.0. In other words, for these nations the number of papers is growing much slower than the GERD. The paper-HERD scaling factor is for most countries, China being an exception, less than 1.0, which means that for these countries, the number of papers is growing slower than the HERD. For China this indicator is 1.002 (very close to 1.0). It shows that the Chinese papers grew almost linearly with the HERD.

Table 4
Scaling factors of papers and citations for China, India, EU15 and the G7 group.

(a)

Country	Paper–GDP SF			Paper–GERD SF			Paper–HERD SF		
	α	SE[a]	R^2	α	SE[a]	R^2	α	SE[a]	R^2
Canada	0.663	0.062	0.90	0.459	0.053	0.85	0.46	0.051	0.86
France	0.824	0.095	0.85	1.003	0.147	0.78	0.604	0.063	0.88
Germany	1.358	0.139	0.88	1.129	0.152	0.81	0.981	0.099	0.88
Italy	1.734	0.079	0.97	1.58	0.242	0.77	0.81	0.078	0.89
Japan	1.299	0.105	0.92	0.949	0.107	0.86	0.728	0.032	0.98
UK	0.778	0.093	0.84	0.984	0.16	0.74	0.576	0.081	0.79
US	0.414	0.02	0.97	0.41	0.026	0.95	0.334	0.018	0.96
EU15	1.07	0.085	0.93	0.997	0.103	0.88	0.795	0.06	0.93
China	1.508	0.08	0.97	1.025	0.057	0.96	1.002	0.05	0.97
India	0.519	0.048	0.90	0.325	0.044	0.81	–	–	–

(b)

Country	Citation–GDP SF			Citation–GERD SF			Citation–HERD SF		
	α	SE[a]	R^2	α	SE[a]	R^2	α	SE[a]	R^2
Canada	1.045	0.066	0.973	0.693	0.055	0.96	0.564	0.021	0.991
France	1.224	0.030	0.996	1.459	0.09	0.97	0.993	0.037	0.989
Germany	2.023	0.116	0.978	1.443	0.066	0.99	1.626	0.134	0.948
Italy	2.407	0.071	0.994	1.917	0.046	1.00	1.110	0.063	0.978
Japan	2.029	0.158	0.959	1.425	0.148	0.93	1.388	0.049	0.991
UK	1.132	0.04	0.991	1.396	0.096	0.97	0.738	0.043	0.971
US	0.862	0.049	0.977	0.802	0.055	0.97	0.598	0.015	0.996
EU15	1.503	0.029	0.997	1.304	0.031	1.00	1.094	0.03	0.995
China	2.834	0.063	0.997	1.630	0.054	0.99	1.582	0.106	0.97
India	1.890	0.089	0.985	1.136	0.116	0.93	–	–	–

Note: SF: scaling factor; HERD: higher education funding of R&D; HERD data for India is not available, so the corresponding scaling factor can not be calculated.

[a] SE is the standard error for α.

Table 5
Relative paper intensity for China and 21 other nations for the period 1991–2005.

Rank	Country	RPI	Rank	Country	RPI
1	US	3.39	12	Belgium	1.06
2	UK	2.16	13	Ireland	1.05
3	Sweden	1.76	14	Japan	0.93
4	Switzerland	1.7	15	Spain	0.9
5	Canada	1.61	16	Italy	0.87
6	Netherlands	1.45	17	Austria	0.86
7	Australia	1.4	18	Greece	0.66
8	Denmark	1.36	19	Korea	0.49
9	Finland	1.32	20	Portugal	0.42
10	Germany	1.31	21	India	0.33
11	France	1.22	22	China	0.24

Note: RPI: Relative 'Paper Intensity'.

In Table 4(b), we explore the scale correlations between recognition (citations) and the economic indicators GDP, GERD and HERD. For China, each time the GDP doubles, the amount of recognition (citations) increases by 7.17 ($2^{2.834}$) times; for India, it increases by 3.71 ($2^{1.890}$) times. Among the nations listed in Table 4(b) China has the strongest non-linear relation between citations and GDP. This finding shows that although China and India have a low citation intensity (citations per unit GDP) as pointed out by King (2004), their citations are growing much faster than the GDP. In other words, China as well as India tends to increase their citation intensity. According to the citation–GERD scaling factor, Canada and the US exhibit an inverse Matthew effect, while the other countries exhibit a (real) Matthew effect. For China, the amount of citation can increase by 3.10 ($2^{1.630}$) if the GERD is doubled. There is also a strong non-linear effect between citations and GERD for China. Moreover, China performs strongly according to the citation-HERD scaling factor. Stated otherwise, the amount of citations for China shows a tendency to increase about 3 times ($2^{1.582}$) with a doubling in HERD.

Similar to 'citation intensity', we define papers per GDP as 'paper intensity'. A relative 'paper intensity' (RPI) is calculated by taking the ratio between the actual papers and the papers predicted by the papers–GDP scaling correlations, shown in Table 5. Of the 22 nations, the United States leads the table, followed by the United Kingdom and Sweden. India and China are ranked at the bottom of the list, at 21st and 22nd position, respectively. This observation means that although the GDPs of China and India place them on the top position in the world, each has low relative paper intensity. In other words, their scientific outputs are not commensurable with their GDP.

3.3. Scaling from technology systems

Due to the unobservable "true" rate of technological innovation, patents are but an imperfect proxy for the level of new-to-the-world innovation (Furman, Porter, & Stern, 2002). Despite of the pitfalls associated with equating patenting with the level of innovation activity (Griliches, 1990; Trajtenberg, 1990), the rate of patent applications is widely recognized as one of the clearest indications of technological innovation performance. The number of patent applications filed in USPTO, EPO, and TPF, are extensively used to measure inventive performance, knowledge diffusion, and the internationalisation of innovative activities. Generally, patents from the above three datasets seem to protect inventions with a relative higher economic and technological value (Criscuolo, 2006; Furman et al., 2002; Hu & Mathews, 2005). For the purpose of international comparison, we only consider these three types of patent applications. Increase of innovation activity is usually accompanied by an increase in economic activity. For example, a striking increase in patenting rate often results from an increase in R&D expenditure. So, in this section we will explore the scaling correlations between patent applications and the economic indicators.

We next explore the patent-concerned scaling relationships of China, as compared with the G7 countries and another East Asian country, namely Korea. For this part we replace India by Korea for the following reasons. On the one hand, Korea is an innovation-type country in Asia and the total annual number of patent applications for Korea is very high. On the other hand, the three types of patent data for India are incomplete. The patent data used here cover the period 1991–2005, and the lag time between patents and economic data is also considered to be two years.

As shown by Table 6(a), the values of USPTO–GDP scaling factors for France, Italy and the UK are all close to 1.0 while others countries' scaling factors are larger than 1.0. This means that patents filing in the USPTO for France, Italy and the UK grew almost linearly with country size measured by GDP, while that of other nations tended to increase non-linearly. Particularly for China and Korea, the non-linear effect is very strong. In other words, the Chinese patents at the USPTO tended to grow about 4 ($2^{2.007}$) times with a doubling of GDP, while about 6 ($2^{2.551}$) times for Korea. In terms of the EPO–GDP and TPF–GDP scaling factors, the non-linear effects for China and Korea are also strong: the respective patents at the EPO and in the TPF tended to increase about 7 ($2^{2.796}$) times and 5.5 ($2^{2.472}$) times for China, and about 11 ($2^{3.454}$) times and 12 ($2^{3.607}$) times for Korea, when GDP doubled. For Japan, the three types of patents are growing faster than GDP over the observed period, but these non-linear effects are relatively weaker when compared to China or Korea.

Considering the USPTO–GERD scaling factors as shown Table 6(b), the number of patents at the USPTO grows faster than GERD except for Canada. For China, a doubling of the GERD is expected to increase the number of patents at the USPTO

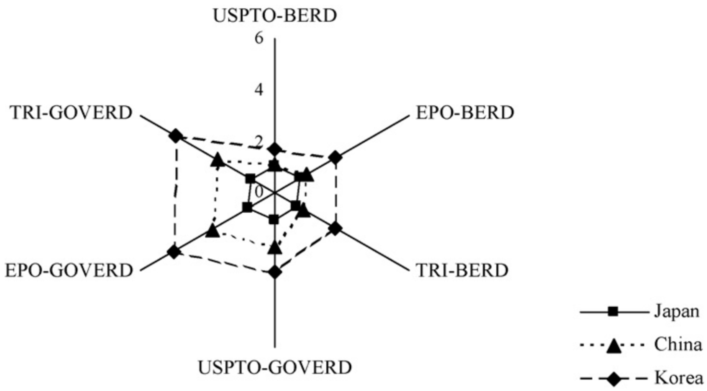

Fig. 3. Various patent scaling factors for the three Asian nations: China, Japan and Korea.

by nearly 2.4 ($2^{1.269}$) times. Korea's increase is about 3.8 ($2^{1.917}$) times. Moreover, China's EPO–GERD scaling factor is 1.712, meaning that the number of patents at the EPO tends to increase over 3 ($2^{1.712}$) times when GERD is doubled. Furthermore, among the G7 countries, the values of the TPF–GERD for Canada and Japan are above 1.0 while those of the others are all less than 1.0. China and Korea perform well on this indicator with scores of 1.525 and 2.680, respectively. These findings show that the non-linear effects of GERD on the three types of patents are all stronger for China and Korea than for the other countries.

Table 6(a) and (b) further shows that the reliability of the patents–GDP and patents–GERD scaling factors for some nations are questionable. For example, the TPF–GDP and TPF–GERD scaling factors for Italy all have low R^2 values. This occurred because, while the GDP and GERD for Italy exhibited exponential growth, the patents in the TPF had both positive and negative growth periods.

According to the OECD Science and Technology Indicators, R&D expenditure is subdivided into five sources of funds: funds from business enterprises, from the government, from higher education, from private non-profit institutions and from abroad. BERD and GOVERD are the main driving forces for patent applications. Hence, we next look closely at the scaling correlations between the three types of patents and the two types of R&D expenditure, and this in particular for the three East Asian countries, namely China, Japan and Korea. Fig. 3 compares the footprints of the various scaling factors for the three

Table 6
Scaling factors of patents for China, Korea and the G7 group.

(a)

Country	USPTO–GDP SF			EPO–GDP SF			TPF–GDP SF		
	α	SE[a]	R^2	α	SE[a]	R^2	α	SE[a]	R^2
Canada	1.284	0.045	0.98	1.912	0.126	0.95	1.576	0.123	0.93
France	0.929	0.110	0.85	1.056	0.081	0.93	0.705	0.074	0.88
Germany	1.594	0.192	0.84	1.626	0.213	0.82	1.161	0.175	0.77
Italy	1.013	0.141	0.80	1.770	0.091	0.97	0.305	0.088	0.48
Japan	1.627	0.142	0.91	1.86	0.17	0.90	1.631	0.149	0.90
UK	0.997	0.113	0.86	0.687	0.136	0.66	0.325	0.073	0.61
US	1.233	0.067	0.96	0.950	0.076	0.92	0.747	0.067	0.91
China	2.007	0.273	0.81	2.796	0.179	0.95	2.472	0.197	0.92
Korea	2.551	0.124	0.97	3.454	0.168	0.97	3.607	0.12	0.99

(b)

Country	USPTO–GERD SF			EPO–GERD SF			TPF–GERD SF		
	α	SE[a]	R^2	α	SE[a]	R^2	α	SE[a]	R^2
Canada	0.916	0.023	0.99	1.354	0.096	0.94	1.106	0.101	0.90
France	1.166	0.150	0.82	1.282	0.151	0.85	0.85	0.122	0.79
Germany	1.430	0.131	0.90	1.393	0.914	0.80	0.951	0.177	0.69
Italy	1.114	0.093	0.92	1.733	0.178	0.88	0.311	0.091	0.47
Japan	1.241	0.097	0.93	1.365	0.159	0.85	1.2	0.137	0.86
UK	1.333	0.161	0.84	0.854	0.208	0.56	0.408	0.108	0.53
US	1.233	0.067	0.96	0.953	0.073	0.93	0.752	0.062	0.92
China	1.269	0.119	0.90	1.712	0.045	0.99	1.525	0.061	0.98
Korea	1.917	0.137	0.94	2.548	0.23	0.90	2.68	0.201	0.93

[a] SE is the standard error for α; TPF: triadic patent families; SF: scaling factor.

nations, revealing some marked asymmetries. For China and Korea, the footprints of GOVERD are bigger than the footprints of BERD. This indicates that when GOVERD doubles, the number of patent applications tends to grow more than BERD. In other words, for the two countries, the GOVERDs have a stronger impact on the patent productivity than BERD. A comparison of China and Korea shows that Korea has bigger footprints than China. This means that the non-linear impacts of GOVERD and BERD on patents for Korea are stronger than for China. The Japanese footprints are symmetric and form roughly a regular hexagon. Moreover, the values of the scaling factors are all close to 1.0. These findings indicate that while the Japanese BERD and GOVERD are growing at similar rates, the numbers of the three types of patent applications are also growing at the same rate. In other words, patent applications tend to grow almost linearly with BERD and GOVERD. These non-linear effects are weaker for Japan than for China and Korea.

3.4. Summary

Using scale-independent indicators, we have provided a thorough investigation of many aspects of the Chinese innovation system, including economic, scientific and technological aspects. In comparison with the selected countries, the following conclusions can be drawn.

First, the GERD–GDP scaling factor tells us that over the observed period the Chinese GERD is growing faster than GDP. In other words, the GERD grew quite non-linearly with GDP. Also, the R&D intensity exhibits a relatively strong non-linear tendency to increase with GDP. However, among the countries chosen for comparison, China ranks on the bottom of the list by relative GERD. Further, it is shown that the relative GERD for China has a larger increase over the studied 15-year time interval. According to the GDP–POP scaling factor, the growth rate of the Chinese GDP far exceeds the rate of the population, and this non-linear effect is extremely strong.

Next, the recognition–size scaling factor indicates that the Chinese science system experiences a non-linear increase in the amount of recognition it receives as its size increases. This non-linear effect is, however, weaker than Japan's and India's. The indicator of ARCI further shows that China's total number of publications and citations has been increasing over the recent years, but on average, its output impact is still the lowest among the 22 nations. However, its ARCI growth rate is the highest among these countries (comparing the periods 1995–1999 and 2001–2005). Moreover, when GDP, GERD or HERD double the amount of recognition tends to increase faster than that of pure size. Furthermore, China takes the last position on the list ranked by the relative 'paper intensity'. This means that although the number of Chinese papers has been increasing rapidly over the recent years, it is still not commensurable with its GDP.

Finally, we have shown that each of the three patent applications for China tends to increase non-linearly with the doubling of GDP or GERD, and that these non-linear effects are relatively strong. Further analysis indicates that for China and Korea the GOVERD has stronger positive non-linear impact on patent productivity than BERD, while for Japan the two non-linear impacts seem to be comparative. Finally, these non-linear effects are weaker for Japan than for China and Korea.

4. Policy implications

An innovation system is complex. Scale-independent indicators may shift our perceptions about innovation systems from the conventional linear view to a more appropriate non-linear view. They also provide policy makers with better tools to interpret past performance and predict future outcomes.

Next let us see what our analysis using scale-independent indicators learns about China's future. In the Essentials of National Medium and Long-term Science and Technology Plan of China (2006–2020)[1], the Chinese government set a target to increase R&D expenditure to above 2.5% of GDP by 2020. According to the scaling correlation between GERD and GDP, we find that the Chinese R&D intensity exhibits a relatively strong non-linear increase with its GDP. Further calculations[2] show that the goal to increase R&D intensity to above 2.5% will be realized by 2020 as long as the annual growth rate of GDP is kept on the level of about 6.7% over the 15-year period 2006–2020. Since its reform (1978) China has sustained a fast economic growth and on average, the annual growth rate of the GDP has been 9.88% (over the whole 30-years period 1978–2007). Therefore, it can be said with confidence that increasing the R&D intensity to above 2.5% by 2020 is a feasible target. Moreover, we observed a strong non-linear relationship between GDP and population. The GDP–POP scaling factor tells us that the Chinese GDP is growing more than 2200 times as fast as the population. Stated otherwise, although the population of China has been growing for years, the GDP per capita would still be expected to increase remarkably more.

Scientific outputs and impacts of China have been increasing, particularly over the recent years. But they have not yet had a chance to catch up with its fast economic growth. There is still a large gap in scientific outputs and impact between China and some advanced countries. Fortunately, such pairs as citations & papers, papers & GDP, citations & GDP, and paper & GERD all exhibit 'Matthew effects'. Consequently scientific outputs and impacts are growing faster than the economy and than

[1] www.gov.cn.

[2] The scaling correlation between the Chinese R&D intensity (GERD/GDP) and its GDP is $GERD/GDP = 0.0767GDP^{0.646}$. Assuming we are given $1.34\% = GERD_{2005}/GDP_{2005}$, $= 0.0767GDP_{2005}{}^{0.646}$ (1) and $2.50\% = GERD_{2020}/GDP_{2020} = 0.0767GDP_{2020}{}^{0.646}$ (2), where $GERD_i$ and GDP_i denote GERD and GDP in the year i, respectively. Assume moreover that the GDP is increasing at an annual growth rate of x over the 15 period 2006–2020, then $GDP_{2020} = GDP_{2005}(1+x)^{15}$ (3). Using (1), (2) and (3), we have $2.50/1.34 = (GDP_{2020}/GDP_{2005})^{0.646} = [GDP_{2005}(1+x)^{15}/GDP_{2005}]^{0.646}$, $x = 0.067$.

research investments. We interpret this to mean that China's scientific outputs and impacts will catch up with the country's economic growth. These good prospects may be due to the effective policies of scientific research that have been taken by the Chinese government. For example, with improved investment in research infrastructure and funding, China is attracting Chinese scientists who have been trained, and in some cases worked, in other countries, particularly in the United States (Jonkers & Tijssen, 2008; King, 2004).

In the case of the ranking provided by King (2004), China and India are listed at the bottom of the rankings by citation-based indicators, such as number of citations, citation intensity, re-based impact (RBI) and so on. However, simple citation rankings can hide important developments, as admitted by King (2004), especially in countries such as China and India. These developments may be brought to the fore by using scale-independent indicators. For example: citations–papers and citations–GDP scaling factors of China and India all exhibit strong 'Matthew effects'. This means that the Chinese and Indian science systems experience a non-linear increase in the amount of recognition (citations) they receive as their sizes (papers or GDP) increase. Further, scaling properties such as the Matthew effect indicate that China and India have the potential to catch up with advanced nations.

Similarly, there are strong 'Matthew effects' between the outputs of technology (patents) and economic growth and research investment. This means that the Chinese 'efficiency in technological productivity', measured by the value of the scaling factor, is high, and the outputs of technology are expected to increase considerably with an increase of GDP and R&D expenditure. Moreover, GOVERD has a stronger positive non-linear impact on patent productivity than BERD. This agrees with the report by the *China Science and Technology Statistics* that research institutions financed by the government play a more important role in China's innovation system than enterprises. So, on one hand, with further economic growth the leading role of government-financed research institutions in Chinese technological innovation activities will be further strengthened. On the other hand, it must be stressed that over the longer term the role of enterprises must change, and they must become leaders in technological innovation activities.

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