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Indicators for complex innovation systems

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Abstract

Performance indicators such as national wealth (GDP per capita), R&D intensity (GERD/GDP) and scientific impact (citations/paper) are used to compare innovation systems. These indicators are derived from the ratio of primary measures such as population, GDP, GERD and papers. Frequently they are used to rank members of an innovation system and to inform decision makers. This is illustrated by the European Research Area S&T indicators scoreboard used to compare the performance of member states.

A formal study of complex systems has evolved over the past few decades from common observations made by researchers from many fields. Complex systems are dynamic and many of their properties emerge from the interactions among the entities in them. They also have a propensity to exhibit power law or scaling correlations between primary measures used to characterize them.

Katz [Katz, J.S., 2000. Scale independent indicators and research assessment. Science and Public Policy 27, 23–36] showed that scientific impact (citations/paper) scales with the size of the group (papers). In this paper it will be shown that two other common measures, R&D intensity and national wealth, scale with the sizes of European countries and Canadian provinces. Some of these scaling correlations are predictable. These findings illustrate that a performance indicator derived from the ratio of two measures may not be properly normalized for size.

This paper argues that innovation systems are complex systems. Hence scaling correlations are expected to exist between the primary measures used to characterize them. These scaling correlations can be used to construct scale-independent (scale-adjusted) indicators and models that are truly normalized for size. Scale-independent indicators can more accurately inform decision makers how groups of different sizes contribute to an innovation system. The ranks of member groups of an innovation system by scale-independent indicators can be subtly and profoundly different than the ranks given by conventional indicators. The differences can result in a shift in perspective about the performance of members of an innovation system that has public policy implications.

Keywords: Complex system; Emergent; Indicator; Power law; Innovation system

1. Introduction

Broadly speaking, an innovation system is composed of individuals and organizations that directly and indirectly invest time and energy in the production of scientific and technical knowledge. This knowledge flows and recombines in complex ways (Kline and Rosenberg, 1986).

Observers of innovation systems, for example, national systems of innovation, frequently make comparisons (Freeman, 1987; Lundvall, 1992; Stoneman, 1995). Invariably they aggregate individuals into groups or collective entities such as countries, institutions,

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departments and firms. They use quantitative and qualitative measures of the inputs, outputs and processes of these groups to construct performance indicators that are used to inform decision makers.

It will be argued that innovation systems are *complex* where the word *complex* will be defined using concepts from *complex systems research* (Baranger, 2001). Among other things, current complex systems research shows that a complex system is dynamic and it has a propensity to exhibit scaling properties (Amaral and Ottino, 2004; Newman, 2003; West, 2006).

The signature of a scaling property is a *power law correlation* between variables of the system or *power law probability distribution* of a property of the system.[1] Formally a power law is defined by $F(x) \propto x^{\alpha}$ where the variable of interest $x \in [x_0, x_n]$ and $n > 0$ (Newman, 2005). The exponent, α, of the power law relationship is called the *scaling factor*. It can be used as an indicator of a scaling property of the system. The complex systems research literature will be reviewed in the next section along with a detailed discussion of scaling properties and the processes that generate them.

There is plenty of evidence in the literature to show that innovation systems exhibit scaling properties. For example, notable observers such as Pareto (1897), Lotka (1926), Zipf (1949) and de Price (1963) found that innovative human processes like the use of language, the distribution of wealth and the productivity of innovators exhibit power law correlations and distributions. In the last century thousands, perhaps even tens of thousands, of research papers have been published illustrating scaling properties in data describing a wide variety of innovative human activities. Managers and decision makers use the notion of scaling when they apply the '80–20 rule', a rule that is based on Pareto's power law probability distribution (Juran, 1950). Curiously despite the prevalence of scaling relationships in human innovative activities almost no one has used them to inform public policy.

Many of our perceptions about innovation systems are informed by quantitative indicators. For example, agencies such as the OECD, Eurostat and the National Science Board collect measures of such things as population, GDP, GERD and numbers of scientific papers and citations. The ratios between these measures are used as performance indicators of such thing as national wealth (GDP per capita), R&D intensity (GERD/GDP) and scientific impact (citations/paper). Decision makers use many types of performance indicators derived from ratios to inform policies that impact innovation systems.

The use of performance indicators is exemplified by the ERA scoreboard. It was developed in response to a request from the Lisbon Summit of March 2000 for the Commission to draw up a methodology for benchmarking national research policies using indicators covering four themes (European Commission, 2003). The stated aim of these indicators is "to provide a broad overview of the performances of Member States in relation to the four themes, using currently available and internationally harmonised statistics". The scoreboard consists of 20 performance indicators. All of these indicators are derived from ratios. It is available at the CORDIS science and technology indicators web site.[2]

Frequently it is assumed that the resultant proportion derived from the ratio of two primary measures is *normalized* by the denominator. In other words, if the denominator is a measure of size (e.g., GDP, population and papers) then the ratio is assumed to be normalized for size. However, despite warnings from the OECD and others (Godin, 2005; Holbrook, 1991; Katz, 2005) measures like GERD/GDP, GDP/population and citations/paper are assumed to be useful for comparing regions and countries of different sizes. Although it may be thought that by dividing by size the indicator is normalized and valid comparisons can be made, this is not the case.

Recently it was shown that the amount of recognition received by scientific groups measured using citations scales with the number of papers they publish (Katz, 2000, 2005). Between 1981 and 1994 every time a group doubled the number of scientific papers they published that were indexed by ISI the amount of recognition they received by other publications in the ISI database increased about 2.4 ($2^{1.27}$) times. That is, there is a power law relationship between citations, c, and the number of papers, p, where $c \propto p^{1.27}$.

A power law correlation exists between the numerator and the denominator of this performance indicator thus the rules of power laws apply. Applying the rule $y = kx^n$ and therefore $y/x = kx^{n-1}$ we find that the ratio between the numerator and denominator also scales with the denominator. Therefore, citations/paper scales with the number of papers. In other words, using the previous finding it can be said that every time a group doubled its published output the amount of recognition received per paper increased about 1.2 ($2^{1.27-1.0} = 2^{0.27}$) times.

[1] It must be noted that by definition exponential functions do not scale.

[2] http://www.cordis.lu/indicators/home.html.

The amount of scientific impact received by a group measured using citations/paper scales with the size of the group measured using papers. The conventional scientific impact performance indicator is not normalized for size.

Throughout this paper it will argued that as a matter of accuracy a performance indicator derived from a ratio that exhibits a scaling correlation between the numerator and denominator must be scale-adjusted before it is used in comparisons. A scale-adjusted indicator is called a *scale-independent indicator* (Katz, 2000) and it can be used to compare groups of vastly different sizes.

van Raan (2005, 2006) argues that the scaling relationship between citations and papers when used as a measure of impact does not have to be adjusted for scale. He says, "one could also argue that a larger impact as measured on the basis of citations cannot be simply waved aside as purely a scale-dependent effect. In this way groups are 'punished' [for] growing because the number of citations received by them should be corrected for size". It is not a question of punishment but a question of accuracy and a better understanding of the nature of indicators. It may be that some (possibly the large) are being over rewarded and it is the small that are being punished.

In Section 3 it will be revealed that two other common performance indicators – R&D intensity and national wealth – scale with size. These findings will be illustrated using OECD and Statistics Canada data of the European and Canadian innovation systems. The scaling relationships GERD & GDP and GDP & population will be used to construct a variety of scale-independent indicators and two simple scale-independent models. It will be shown that scale-independent indicators and models provide policy relevant insights into innovation system activities that are not available using conventional indicators. The policy relevance of the findings will be summarized in the final section.

2. Complex systems

It is difficult to precisely define a complex system; however, it is recognizable by its identifiable characteristics (Amaral and Ottino, 2004; Baranger, 2001). Amongst other things a complex system

- has a dynamic structure with interdependent constituents that interact in complex and non-linear ways
- is open in the sense that information flows across its boundaries which in turn are difficult to clearly identify
- possesses structures that span many scales
- exhibits emergent behaviours and patterns that are not caused by a single entity in the system but may arise from simple rules. Flocking of birds, swarming of bees, schooling of fish and swirling of hurricanes are emergent properties found in nature (Parrish et al., 2002; Peterson, 2000). The value of a good is an emergent property of an economic system (Stahel, 2005). And the stock market is a complex system that has emergent properties determined by the collective actions of investors (Blok, 2000).
- can self-organize, i.e., its emergent properties may change its structure or create new structures
- is composed of complex subsystems

A special of kind of complex systems was created to accommodate living beings (Baranger, 2001). They are *complex adaptive systems* (CAS) capable of changing themselves to adapt to a changing environment and changing the environment to suit themselves. Among other strategies they use the interplay between competition and co-operation to survive and evolve.

Frequently a complex system is represented as a complex network with nodes representing the units and edges representing the interactions between them (Albert and Barabasi, 2002; Strogatz, 2001). Researchers have developed a variety of models to simulate complex systems. Indicators commonly used to compare innovation systems have been used to confirm that many important properties exhibited by these models can be seen in empirical data (Albert and Barabasi, 2002; Amaral et al., 2001; Havemann et al., 2005). Examples of these will be discussed later.

2.1. Scaling and power laws

Most, if not all, complex systems have at least one common feature. They have a propensity to exhibit scaling properties (Carlson and Doyle, 2002; Newman, 2000). The identifying signature of a scaling property is a power law correlation or distribution. They are common to physical systems (Christensen et al., 2002; Warhaft, 2002), natural systems (Goldberger et al., 2002; Katz and Katz, 1999; West et al., 2002) and social systems (Newman et al., 2002). As mentioned earlier, they describe well-known statistical regularities[3] such as Pareto, Lotka, and Zipf's laws.

[3] Observers of social systems sometimes refer to these statistical regularities as social laws.

Recall that the formally a power law relationship is defined by $F(x) \propto x^{\alpha}$ were the variable of interest $x \in [x_0, x_n]$ and $n > 0$. In real world systems the range of a power law distribution may be finite since the tail of the distribution asymptotically approaches a power law as x gets large (Stanley and Plerou, 2001). In other words, in real systems the range of an ideal power law relationship maybe constrained. Power laws are readily identifiable when they are plotted on a log–log scale because they appear linear.

The exponent, α, of a power law is called its *scaling factor* and it is given by the slope of the linear regression line drawn through the log values. It is a useful indicator. For example, consider the trivial example of circle and sphere. The area and volume increase as the square and cube of the radius, respectively. The scaling factor for a circle is 2.0 and for a sphere it is 3.0. It tells us that if the radius doubles then the area of the circle increases fourfold (2^2) and the area of the sphere increases by eightfold (2^3). However, these scaling factors are unusual because they are integers. For most real world complex systems, the scaling factors are non-integer. For example, the scaling factor of objects like clouds, plants and the World Wide Web is between 1.0 and 3.0 (Strogatz, 2005).

2.2. Power law generators

Power laws are generated by a variety of mechanisms (Mitzenmacher, 2003) ranging from completely deterministic processes (strictly rule based) to completely non-deterministic processes (stochastic or random). In fact, Mitzenmacher says, "Power law distributions and lognormal distributions are quite natural models and can be generated from simple and intuitive generative processes." Examples of three types of generative models will be discussed: (1) deterministic generators; (2) non-deterministic generators; and (3) mixed deterministic and non-deterministic generators.

2.2.1. Deterministic generators

Ideal exponential growth is deterministic since all past and future values are predictable. It can be shown that a pair of exponential processes that are coupled through a common variable such as time will exhibit a power law correlation where the scaling factor is given by the ratio of the exponents of the exponential processes.[4] This relationship was used to demonstrate scaling correlations between the growth of citations[5] and papers in the ISI database (Katz, 2005). Deterministic power law generators have been identified that generate scale free networks (Barabási et al., 2001; Dorogovtsev et al., 2001).

2.2.2. Non-deterministic generators

Brownian motion, the random motion of liquid and gas molecules, is an example of a non-deterministic generator of power law distributions. Stock market processes and gains and losses from gambling activities generate brown noise, which is an allusion to Brownian motion because both have a $1/f^2$ power spectrum distribution. Brownian motion contains several power laws distributions (Blok, 2000; Schroeder, 1991).

A number of models have been proposed to generate the power laws commonly seen in word frequency distributions of language. All but one of these models is based on a mixed generator (a random process plus one or more rules). This type of generator will be discussed in the next section. In 1957, a researcher proposed a model based on a monkey typing randomly on a keyboard. The characters were struck with equal probabilities. It has been mathematically proven that this model generates a rank word frequency power law distribution (Mitzenmacher, 2003).

2.2.3. Mixed generators

Mixed deterministic and non-deterministic processes can be generators of power law distributions. A random multiplicative process is known to generate a lognormal or Gibrat distribution (Gibrat, 1931). This process is defined by $X_t = F_t X_{t-1}$ where X_0 and F_0 are the starting size and the initial growth factor. The growth factor can be positive or negative representing growth and shrinkage (negative growth). However, if a random multiplicative process is bounded by a minimum then it will yield a power law distribution instead of a lognormal distribution (Mitzenmacher, 2003; Solomon and Agay, 1997). There is a wide variety of mixed power law generators with dynamics that are governed by random processes and one or more rules.

The chaos game (Barnsley, 1988) is a simple example. It involves a random number generator and a simple rule. A player starts playing by placing three points on a piece of paper and selecting an arbitrary starting point.

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[4] Assume we are given any two exponential processes $x = ae^{pt}$ and $y = be^{qt}$. Using these two relationships, $e = (x/a)^{1/p} = (y/b)^{1/qt}$ and thus $(x/a)^p = (y/b)^{1/q}$ therefore it can be seen that $y = (b/a)^{q/p} x^{q/p}$ which has the form of $F(x) \propto x^{\alpha}$. In other words, any pair of coupled exponential processes will exhibit a power law correlation with exponent, $\alpha = q/p$, and intercept, $s = (b/a)^{q/p}$, that are predictable from the exponents and intercepts of the individual exponential processes. This relationship holds even if the two processes are delayed in time with respect to each other or if they have different starting values at $t = 0$.

[5] were counted using a 3-year window.

Randomly one of the three points is chosen and a rule is applied. The rule is 'go half way from the current point to the randomly selected point and make a point at that position'. After thousands of steps the well-known features of the Sierpinski triangle or gasket fractal will be visible in the structure of the dots. The probability distribution of the sizes of the triangles in the Sierpinski triangle follows a power law (Schroeder, 1991).

Recent research has demonstrated that the standard deviation of the growth rate of firms has a scaling correlation with the size of the firms measured using sales (Amaral et al., 2001, 1998). Furthermore, the scaling relationship remained whether size was measured using the number of employees, assets, costs of goods sold and plants, property or equipment. A power law correlation has also been found between the standard deviation of growth rates and the sizes of countries measured using GDP and between the standard deviation of growth rates of universities and their sizes measured using papers, patents and R&D expenditure (Plerou et al., 1999).

The web has spawned a variety of research activities some of which focus on constructing models to explain the evolution of its structure (Katz and Cothey, 2006). A *cumulative advantage* (de Price, 1976) or *preferential attachment* (Barabási, 2003) model has gained considerable favor because it appears to explain frequently observed scaling characteristics. Many investigators have reported that the probability distribution of in-links and out-links to web pages follow power law distributions (Albert and Barabasi, 2002; Barabási and Albert, 1999; Faloutsos et al., 1999). The preferential model assumes that the web grows by continuously adding new nodes. The links between nodes are added in a preferential manner. The preference is determined by the popularity of web pages measured by the number of in-links. In other words, pages that are linked to more frequently are preferred over other pages. At each step in the model a new page is created and then an existing page is randomly selected. The probability that the new page will link to the existing page is determined by the number of in-links to the existing page. Over time the in-link probability distribution of the web that is generated by the model will be a power law.

In summary, a variety of processes generate power law correlations and distributions. Unlike some physical processes social activities are never completely deterministic nor are they completely random. Human activity is complex ranging from the free will of individuals to the laws of society. It is likely that most, if not all, of the power law distributions and correlations observed in complex social systems are generated by mixed processes. In the next section it will be shown that regional and national innovation systems exhibit scaling behaviors that emerge with time and exist at points in time.

3. Complex innovation systems

An innovation system is a social construct. Its character emerges from the interactions between its members and the members of other systems. Some of the interactions are more "rule-like" than others because they are governed by laws, regulations, treaties, etc. Other interactions are more random because they are governed by complex social, political and economic forces. Intuitively we know that innovation processes and the systems in which they are embedded must be complex and adaptive. If we assume they are complex then we expect them to exhibit scaling properties. Furthermore, these properties should be evident in measures commonly used to construct performance indicators of these systems.

3.1. Scaling and innovation systems

The following examples explore scaling correlations between GERD & GDP and GDP & population for the European (EU15) and Canadian innovation systems (1) over time and (2) at points in time. Scale-independent indicators derived from these relationships are used to examine characteristics of the two systems.

A *scale-independent indicator* is *an indicator derived from a power law distribution or correlation.* The phrase *scale-independent* is used because indicators that have been derived from a power law are normalized by the scaling relationship so they can be comparable over a wide range of sizes. This paper focuses on only two types of scale-independent indicators: scaling factor indicators and relative magnitude indicators. Examples of both of these indicators will be given later.

There are other scale-independent indicators. For example, the distribution pattern of the data points about an ideal power law can provide indicators to underlying dynamics (Katz and Katz, 1994, 1999).[6] Sometimes the intercept of a power law is used as an indicator, particularly in physical systems. Also, some power law distributions have exponential cut-off points (Mossa et al., 2002; Newman, 2001) that may be a useful indicator.

The European and Canadian innovation systems are used in this paper for two reasons. First, there is a large difference between the scales of the systems; by almost any measure the European system is about an order of

[6] For example, the common patterns seen in European and Canadian data presented in Fig. 7 might be indicative of a common dynamic.

magnitude larger than the Canadian system. Second, the structures of the two systems are considerably different. The European innovation system is a collection of 15 national systems that has been evolving into a supranational system for about 50 years through a variety of democratic and legal processes (Schuch, 1998). All fifteen countries did not join at once. The European Economic Community was formed in 1958 and it consisted of six countries (Germany, France, Italy, the Netherlands, Luxembourg, and Belgium). The UK, Ireland and Denmark joined in 1973, Greece in 1981, Spain and Portugal in 1986 and Austria, Finland and Sweden in 1995. In contrast, the Canadian innovation system is composed of 10 provincial and two territorial systems that has evolved for nearly 135 years into a federal innovation system (Bührer and Ludewig, 2004). Most of the provinces had joined the Canadian Federation by 1873. The last provinces to join were Saskatchewan and Alberta in 1905 and Newfoundland in 1949.

Monies for publicly funded research in the Canadian system come primarily from the federal government with smaller contributions from the provincial and territorial governments. In contrast, publicly funded research in the European system is funded primarily by national governments with smaller contributions from the European Commission. EC programmes, such as European Framework Programmes have a strong focus on activities that encourage more cohesion in the European research area. Similarly, in Canada a variety of government programs encourages federal cohesion.

The data in the following examples were obtained from the OECD and Statistics Canada. The Canadian data are more complete than OECD data. For example, GERD data are available for every Canadian province for every year in the time interval while the OECD data are missing certain values for many European nations. For analysis purposes, missing European data were interpolated.[7] The economic data for the Canadian system are in a common currency and the OECD data have been converted to purchasing power parity at current prices in US dollars (PPP $US). The conversion introduces errors into the OECD data (Neary, 2005) that are not found in the Canadian data. This can affect the quality of the indicators built from OECD data.

3.1.1. Scaling over time

Fig. 1 plots the growth of GDP and GERD from 1981 to 2000 for the European Union and Canada. Fig. 1a shows that the European GDP tended to grow exponentially with an exponent of 0.051 ± 0.001. Over the same period the GERD also tended to grow exponentially with an exponent of 0.052 ± 0.002. Fig. 1b shows exponential growth trends in Canada too.

It is apparent from the graphs that neither the GDP nor GERD exhibited perfect exponential growth. In fact, we would not expect the growth to be perfectly exponential since the magnitude of the national and provincial GERDs and GDPs are determined by the interplay of many factors. On the other hand, the exponential growth trend suggests there are some rule-like tendencies such as interest rates that exist in these systems.

The mathematical relationship given in the footnote of Section 2.2.1 shows that two coupled exponential processes will exhibit a scaling correlation. GERD and GDP are coupled in time, therefore, they should exhibit a predictable scaling correlation. Using the values for the exponential growths from Fig. 1 it is predicted that the scaling factor for the power law correlation between GERD and GDP for the European innovation system should be $0.052/0.051 = 1.027$. Fig. 2a shows that the measured value was 1.034 ± 0.028, which is within 1% of the predicted value. The predicted value for the Canadian innovation system was $0.076/0.053 = 1.418$ and the measured value was 1.418 ± 0.028 (Fig. 2b).

If two measures exhibit a scaling relationship then the ratio between those measures also exhibits a scaling relationship with the divisor. Consider a power law relationship given by $y = kx^{\alpha}$ then $y/x = kx^{\alpha-1}$. If a scaling relationship exists between GERD and GDP then GERD/GDP should exhibit a scaling relationship with GDP. Using this relationship the R&D intensity indicator for the European innovation system is predicted to scale with GDP with a scaling factor of 0.027 and the Canadian innovation system with a scaling factor of 0.418. The measured values were 0.034 ± 0.028 and 0.418 ± 0.028, respectively. Since the European GERD scaled nearly linearly with GDP its R&D intensity remained almost constant over the time interval illustrated by the fact that its scaling factor was close to zero.[8] On the other hand, the R&D intensity for the Canadian innovation system exhibited a tendency to increase 1.33 times ($2^{0.418}$) when the GDP doubled. This is a strong non-linear tendency.

What do the scaling factors tell us about these two innovation systems? The GERD–GDP scaling factor tells us two things. The size of the scaling factor indi-

[7] The exponential growth trend over the time period was used to interpolate missing GERD values.

[8] Only in the special case where $\alpha = 1$, that is the relationship is linear, does $y/x = k$.

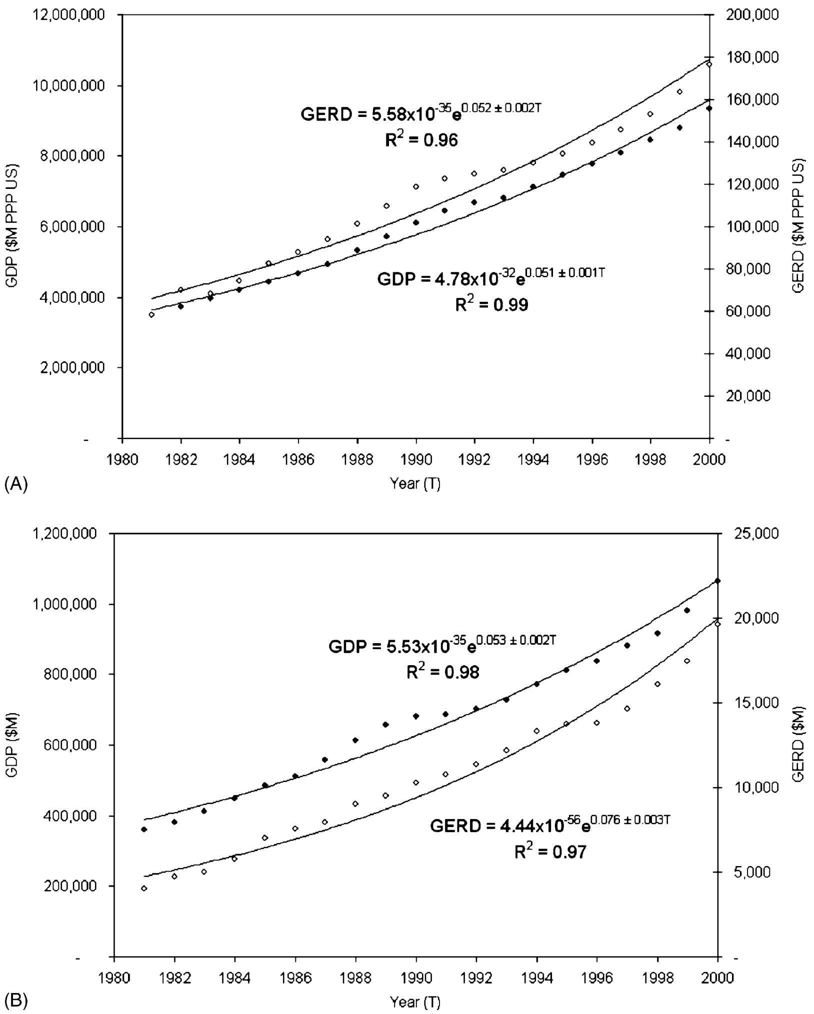

Fig. 1. Growth of GERD and GDP for (A) European innovation system and (B) Canadian innovation system from 1981 to 2000.

cates whether the GERD is growing faster or slower than GDP. The magnitude of the scaling factor indicates how much the GERD would be expected to grow as GDP increases. For example, over the 20-year period the European GERD tended to grow 2.05 ($2^{1.034}$) times and the Canadian GERD tended to grow 2.67 ($2^{1.418}$) times every time the GDP doubled ($2^{1.0}$). In other words, the European GERD grew almost linearly with GDP and the Canadian GERD grew quite nonlinearly with GDP. This is evident from the fact that the OECD reported that the R&D intensity for the European innovation system grew from 1.67% in 1981 to 1.89% in 2000 for a difference of 0.22%. On the other hand, the Canadian system grew from 1.24% in 1981 to 1.92% in 2000 for a larger difference of 0.68%.

In summary, the scaling factor, α, can be used as a scale-independent indicator. In the earlier example it was used as a measure of the relative growths of two coupled exponential processes. When $\alpha = 1$ then the relative growth rates are the same; when $\alpha > 1$ then GERD is growing faster than GDP; and when $\alpha < 1$ then GERD is growing slower than GDP.

A naming notation will be used from now on to uniquely identify the scaling factor between the two variables, X and Y where variable $\log Y$ is regressed on variable $\log X$. The name given is the *Y–X scaling factor*. For example, in the previous case the indicator was called the GERD–GDP scaling factor because it compared the growth rate of GERD to GDP.

Intersystem scale-independent indicators can also be produced. For example, since the European and Canadian systems exhibited exponential GDP growth trends and they are coupled in time they exhibit a scaling correlation. The scaling relationship between the Canadian

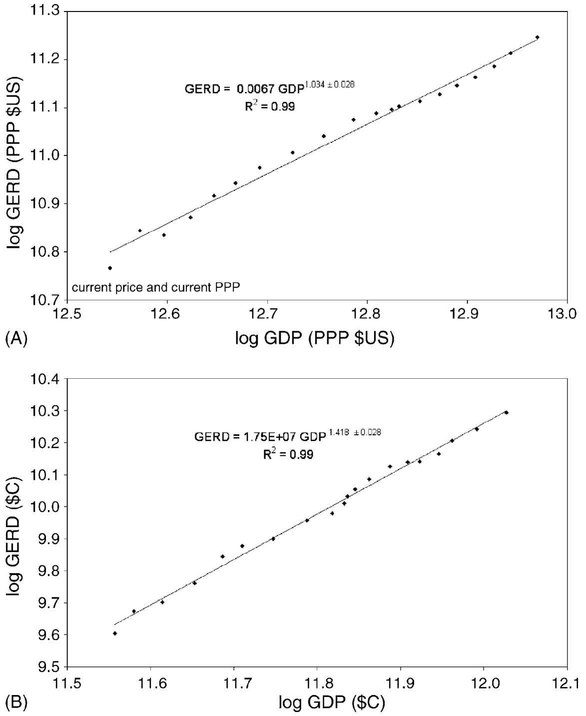

Fig. 2. Scaling correlation between GERD and GDP for (A) European innovation system and (B) Canadian innovation system from 1981 to 2000.

GDP (GDP_C) and the European GDP (GDP_E) had a scaling factor equal to 1.05 ± 0.03. The $GERD_C$–$GERD_E$ scaling factor had a value of 1.43 ± 0.03. These indicators show that the Canadian GDP and GERD grew faster than the European GDP and GERD between 1981 and 2000. According to these scaling relationships, if the European GDP and GERD doubled the Canadian GDP and GERD would be expected to increase 2.07 ($2^{1.05}$) and 2.7 ($2^{1.43}$) times, respectively.

Tables 1 and 2 give the GERD–GDP scaling factors sorted in descending order of magnitude for the nations and provinces in the European and Canadian innovation systems. Also, the population in the year 2000 is given for each nation and province to give the reader a sense of their sizes.

The standard errors and the R^2 values indicate that the power law correlations have statistical significance. The GERDs for two of the largest nations in the European system, UK and Germany, did not grow as fast their respective GDPs. On the other hand, the GERDs of all Canadian provinces grew faster than their respective GDPs. There appears to be a tendency for the significance to decrease slightly with the size of the nation or province measured using population. The tables will be referred to again in later analysis.

Table 1
European GERD–GDP scaling factors (1981–2000)

Country	Population ('000)	α	SE[a]	R^2
Greece	10917	2.58	±0.06	0.99
Finland	5176	2.05	±0.05	0.99
Portugal	10225	1.84	±0.05	0.99
Denmark	5338	1.82	±0.02	1.00
Spain	39927	1.75	±0.06	0.98
Sweden	8872	1.57	±0.05	0.98
Austria	8012	1.50	±0.03	0.99
Ireland	3799	1.49	±0.05	0.98
Belgium	10246	1.26	±0.03	0.99
France	60594	1.11	±0.04	0.98
Italy	57762	1.11	±0.09	0.91
Netherlands	15922	1.03	±0.04	0.98
Germany	82188	0.87	±0.05	0.95
United Kingdom	58643	0.73	±0.02	0.99

[a] SE is the standard error for α.

3.1.2. Scaling at points in time

Fig. 3a is a log–log plot of 1990 GERD and GDP values for nations in the European innovation system. The year 1990 was chosen because it was halfway through the time interval under consideration. Fig. 3b is a similar plot for the provinces in the Canadian innovation system. The following question is being asked of these data. In 1990, did the members of the European and Canadian innovation systems exhibit a scaling correlation between GERD and GDP?

To help answer the question three regression lines have been drawn through the data points. There are two dotted lines and a solid line. The upper dotted line is a linear regression constrained to pass through the origin. This case is a special power law where the scaling factor is equal to 1.0. The lower dotted line is a linear regression that was not constrained to pass through the origin. The solid line is the power law

Table 2
Canadian GERD–GDP scaling factors (1981–2000)

Province	Population ('000)	α	SE[a]	R^2
Quebec	7382	1.84	±0.05	0.99
British Columbia	4060	1.40	±0.06	0.97
New Brunswick	756	1.38	±0.14	0.85
Saskatchewan	1022	1.35	±0.12	0.88
Ontario	11698	1.33	±0.04	0.98
Newfoundland and Labrador	538	1.21	±0.09	0.90
Nova Scotia	942	1.14	±0.07	0.94
Alberta	3010	1.09	±0.08	0.91
Prince Edward Island	138	1.09	±0.07	0.94
Manitoba	1146	1.06	±0.08	0.92

[a] SE is the standard error for α.

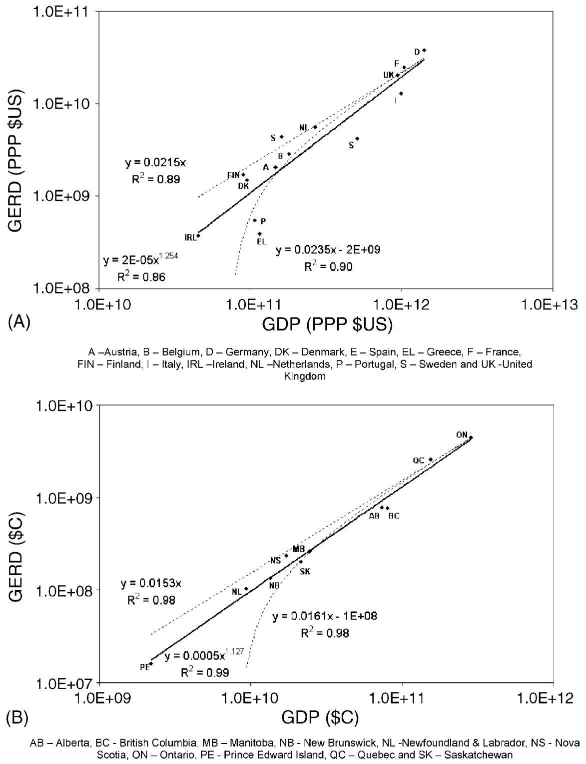

Fig. 3. Systemic scaling correlation between GERD and GDP in 1990 for (A) European innovation system and (B) Canadian innovation system.

regression line. The R^2 statistics suggests that both linear regressions fit the data better than the power law. However, a visual inspection[9] reveals that neither linear regression fits the data very well. The variances of the actual GERD values from the values predicted by the linear regressions vary with the size of the GDP. In other words, the data are heteroscedastic[10] and therefore the R^2 value has little statistical significance. On the other hand, the power law regression is close to homoscedastic and it has a good R^2 value. The same observations are true for the Canadian innovation system (Fig. 3b).

The GERD–GDP scaling factor will be called a *systemic scaling factor* because it quantifies the relationship between GERD and GDP across members of the system at a point in time. The system scaling factor is not determined by any individual entity in the system. It evolves from the complex interaction between its members and between itself and other systems. It is an emergent property of the system.

The systemic GERD–GDP scaling factor tells us how the expenditures on R&D by members of an innovation system tended to scale at a point in time with the size of the member economies. For example, the systemic GERD–GDP scaling factor for the European system was 1.25 telling us that when the size of the national economy doubled the systemic tendency was for GERD to increase by 2.4 times ($2^{1.25}$). In the Canadian system, GERD tended to increase by 2.2 times ($2^{1.13}$).

As shown in the previous section, the R&D intensity is also expected to show a tendency to scale with GDP. The measured value of the scaling factor for the scaling relationship between R&D intensity and GDP for the European innovation system in 1990 was 0.25 ± 0.15 and for the Canadian innovation system it was 0.13 ± 0.04. In other words, in the European innovation system the R&D intensity showed a systemic tendency to increase 1.19 times ($2^{0.127}$) with a doubling in country size measured by GDP. In the Canadian system, R&D intensity tended to increase 1.09 times ($2^{0.127}$) as the province size doubled. In other words, the R&D intensity indicator is not normalized for size. Before it can be used to compare countries and provinces of different size it has to be adjusted for scaling relationship between GERD and GDP. For instance, Austria and Saskatchewan are 1/10 the size of Germany and Ontario, respectively. The systemic scaling relationships between GERD and GDP for the European and Canadian innovation systems indicate that the R&D intensity for Germany was expected to be about 75% higher than for Austria and the R&D intensity for Ontario should be approximately 35% higher than for Saskatchewan.[11] A relative GERD indicator that has been scale-adjusted will be introduced shortly that can be used instead of the R&D intensity for comparisons.

Some might argue that when the scaling factor is close to 1.0 the non-linear effects can simply be ignored. Assume the scaling factor is 1.05 and we wish to compare two innovation systems where one system has a GDP ten times larger than the other system. Given a scaling factor of 1.05, we would expect the larger system to have a GERD 11.2 times ($10^{1.05}$) larger than the smaller one. In other words, the larger system would be expected to have a 12% larger GERD than if we assumed the scaling factor was 1.0 or linear. A small scaling factor can have a large effect.

[9] The residuals were plotted against the estimated y values and it confirmed that the data were heteroscedastic.

[10] Data are heteroscedastic when the errors in the actual y values from the predicted values are related to the size of x values.

[11] The percentages were determined by using the fact that $10^{0.25} = 1.78$ and $10^{0.127} = 1.34$.

Table 3
Comparison of ERA R&D intensity (1990)

Country	GERD/GDP (%)	Country	GERD′/GERD
Sweden	2.74	Sweden	2.25
Germany	2.67	Finland	1.79
France	2.37	Netherlands	1.49
UK	2.15	Denmark	1.47
Netherlands	2.07	Belgium	1.27
Finland	1.88	Germany	1.26
Belgium	1.59	France	1.21
Denmark	1.57	Austria	1.17
Austria	1.39	UK	1.13
Italy	1.29	Ireland	0.94
Ireland	0.83	Italy	0.67
Spain	0.82	Spain	0.50
Portugal	0.51	Portugal	0.46
Greece	0.34	Greece	0.30

Fig. 3a and b shows a striking difference between the European and Canadian innovation systems. The national GERDs in the European system exhibit a larger range of variances from the GERDs predicted by the systemic scaling correlation than the range of variances displayed by the provincial GERDs from the Canadian systemic scaling correlation. This difference probably occurs because the European innovation system is more loosely coupled than federal Canadian system. Later it will be shown that the variances of the two systems evolve differently over time.

Tables 3 and 4 give the conventional R&D intensity indictors and the relative GERD indicators for the members of each innovation system in 1990. Countries and provinces are listed in decreasing rank order by each indicator. The relative GERD indicator is calculated by taking the ratio between the actual GERD and the GERD predicted by the measured systemic scaling correlation. For example, Table 3 shows that the UK had a R&D intensity of 2.15% and a relative GERD of 1.13. The UK is ranked 4th by the R&D intensity indicator and 9th by size-adjusted relative GERD indicator. There is a subtle and profound difference in the ranking of European countries and Canadian provinces once GERD has been adjusted for the size of the country and province.

Table 4
Comparison of Canadian R&D intensity (1990)

Province	GERD/GDP (%)	Province	GERD′/GERD
Quebec	1.69	Nova Scotia	1.33
Ontario	1.57	Quebec	1.22
Nova Scotia	1.39	NFL	1.15
NFL	1.12	Ontario	1.05
Manitoba	1.09	Manitoba	0.99
Alberta	1.07	New Brunswick	0.98
New Brunswick	1.00	PEI	0.91
British Columbia	0.97	Saskatchewan	0.88
Saskatchewan	0.95	Alberta	0.85
PEI	0.74	British Columbia	0.76

NFL: Newfoundland and Labrador; PEI: Prince Edward Island.

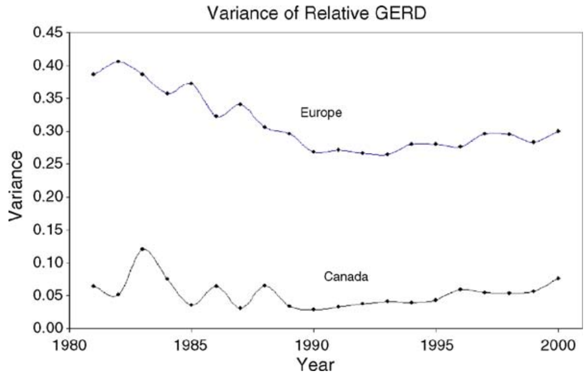

Fig. 4. Variance of the relative GERDs for the European and Canadian innovation systems.

The relative GERD indicators for the European innovation system ranged from about 0.30 to 2.25. In comparison the relative GERD indicators for the Canadian systems ranged from about 0.75 to 1.35. An analysis of the variances from the population mean was performed assuming that the nations and provinces listed in the tables represent the entire European and Canadian innovation systems. This assumption is not quite true because Luxembourg and two Canadian territories have not been included due to lack of GERD data. Also, Statistics Canada reports the Federal funding for the Nation Capital Region[12] (NCR) separate from the provincial funding. The NCR values accounted for approximately 3% of the total GERD in 2000 and they have not included.

The variance from the population mean of the relative GERDs for each innovation system was calculated for each year and the values are plotted in Fig. 4. It can be seen that the variance for the European innovation system decreased from above 0.40 to about 0.29 in the first half of the time period and levelled off for the second part of the time period. On the other hand, the variance from the population mean for the Canadian innovation system was about 1/10 as large as the variance for the European innovation system and it varied comparatively little over the time period.

The larger variances of the relative GERD in the European innovation system compared to the Canadian

[12] Canada's National Capital region is centred upon the cities of Ottawa in Ontario and Gatineau in Quebec.

innovation system can be partially explained by the time span over which the innovation systems have been evolving and the differences in their governance structures. Most Canadian provinces have been in the Canadian confederation for over 100 years but some European nations have only been in the European Union for a couple of decades. Also, Europe is a *union* based on treaties. Canada is a *confederation* with a central federal government. The governance of European innovation system is more decentralized than the Canadian system. It seems natural to assume that the characters of the two innovation systems will be different. For example, the European Union has less influence on national R&D expenditures than the Federal government has over the R&D expenditures by the provinces. Less variance from the systemic scaling trend could be indicative of a system whose members are more tightly integrated. Perhaps time-dependent variance from the systemic scaling trend can be used as an indicator of systemic integration.

3.2. A scale-independent model of an innovation system

The scaling relationships between GERD and GDP over time and at points in time can be combined to build a composite scale-independent model that show how they evolved together.

Fig. 5a and b contains log–log plots of GERD versus GDP for the European and Canadian innovation systems. The circles are the 1990 data points seen in Fig. 3a and b, respectively. The dotted lines are the 1990 regression lines seen in the same figures. The long solid dark lines are power law regressions at two other points in time across the national and provincial systems of innovation in 1981 (lower) and 2000 (upper). The systemic scaling factors and R^2 values for the three regression lines are given in the top left hand corner of the figures.

The short light lines in the figures are power regression lines representing the scaling correlation between the exponential growth rates of GERD and GDP for each nation and province. The scaling factors are the slopes of the power law regression lines and they were given in Tables 1 and 2. For example, in Fig. 5a the short line labelled UK for the United Kingdom gives the scaling correlation between the exponential growth rates of the GERD and GDP from 1981 to 2000. The scaling factor was 0.73 indicating that the UK GERD did not grow as fast as its GDP. On the other hand, the short line labelled FIN for Finland had a scaling factor of 2.05. Its GERD grew much faster than its GDP.

Fig. 6 is a plot of the values of the systemic GERD–GDP scaling factors for the European and Canadian innovation systems over the time period. The system scaling factor for the European innovation system had an obvious decline from 1.31 ± 0.19 in 1981 to 1.02 ± 0.15 in 2000. The Canadian systemic scaling factor was 1.09 ± 0.06 in 1981 and 1.14 ± 0.07 in 2000.

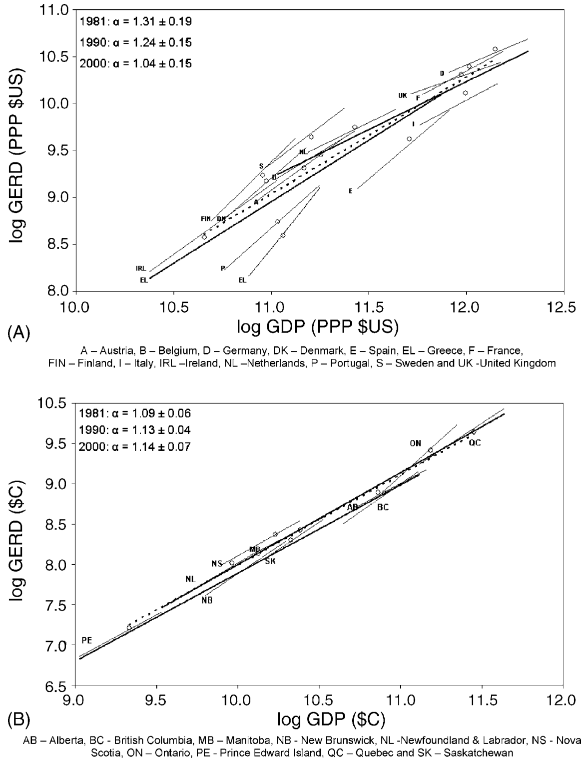

Fig. 5. Scale-independent GERD–GDP models of the (A) European innovation system and (B) Canadian innovation system from 1981 to 2000.

Table 1 and Fig. 5a give clues as to why the European systemic scaling factor decreased with time. The GERDs of the small and medium sized nations tended to grow significantly faster than their respective GDPs. In

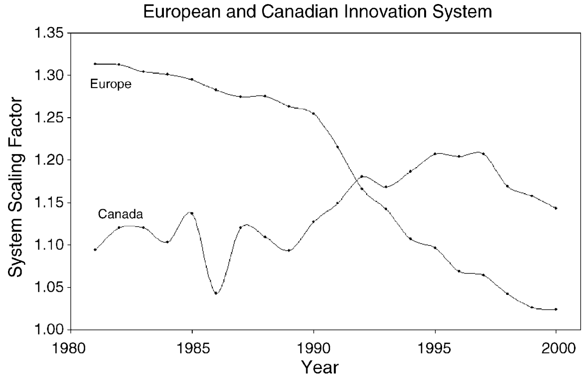

Fig. 6. Value of the GERD–GDP systemic scaling factor over time for European and Canadian innovation systems.

contrast the GERD of the larger nations like Italy, UK, France and Germany grew close to the same as or slower than their respective GDPs. The systemic tendency of the European innovation system was for the small and medium sized members to force the lower GDP end of the systemic scaling correlation up with time and the larger nations tended to move the upper end down or at least maintain a level close to status quo. Overall, the systemic GERD–GDP scaling factor for the European innovation system changed from being quite non-linear (1.31) to being more linear (1.02). If the trend continues it will become non-linear again as GERD will be growing at a slower rate than GDP. In fact, recently the European Commission released a statement on July 2005 saying that stagnation of R&D intensity is a major threat to the European knowledge-based economy.[13]

In comparison, the GERDs of every Canadian province grew close to or faster than their respective GDPs. The larger provinces, particularly Quebec, grew their GERDs at rates similar in magnitude to the rates of the small- and medium-sized European nations. It is unclear if the tendency of the systemic GERD–GDP scaling factor for the Canada innovation system is increasing or perhaps fluctuating around 1.1 or thereabout. This issue will be explored in the next section.

3.3. Using a scale-independent model

It was demonstrated in the previous sections that scaling correlations exist between GERD and GDP across European nations and Canadian provinces at points in time. Also, it was shown that the value of the systemic scaling factor can change over time. The systemic scaling factors are not mathematically predictable from the underlying exponential growth rates; however, they can be measured. The exponential growth trends can be used to predict future values of GERD and GDP and then these values can be used to measure the systemic scaling factor at a point in the future.

Consider the following. If GERD and GDP had exhibited perfect exponential growth then their future values would be exactly predictable and the future values of the systemic scaling factor could be accurately measured. In fact, if the exponential growth was prefect then all past and future values could be predicted from any two consecutive years of data. However, GERD and GDP do not exhibit exactly exponential growth rates; they only exhibit a tendency to grow exponentially. It takes more than two consecutive years of data to identify the trend.

[13] ftp://ftp.cordis.lu/pub/indicators/docs/kf2005_pressrelease.doc.

Table 5
European innovation system (1996–2000)

Country	α	SE[a]	R^2
Greece	2.38	±0.44	0.91
Finland	2.16	±0.20	0.97
Austria	2.06	±0.20	0.97
Denmark	1.94	±0.15	0.98
Portugal	1.92	±0.24	0.95
Germany	1.84	±0.13	0.98
Belgium	1.70	±0.05	1.00
Spain	1.53	±0.13	0.98
Sweden	1.38	±0.19	0.95
Italy	1.28	±0.16	0.96
United Kingdom	0.98	±0.14	0.94
Netherlands	0.75	±0.15	0.89
France	0.74	±0.11	0.94
Ireland	0.66	±0.04	0.99

[a] SE is the standard error for α.

The longer the time window over which the observations are made the more accurately the trend can be predicted. For example, the scale-independent models in the previous section were constructed using a 20-year time window. It could have been built using a different size of time-window. A smaller observation window would capture more recent trends but at the cost of losing longer term accuracy in the model. Scale-independent models were constructed using 20- and 5-year observation time windows and then they were used to predict the size of national and provincial GERDs and GDPs in the year 2005.

Tables 5 and 6 give the scaling factor for the power law correlation between GERD and GDP measured using the 5-year observation window from 1996 to 2000. As expected, the R^2 values for these scaling factors tended to be lower that those seen in Tables 1 and 2 where a 20-year observation window was used.

The two models were used to predict the 2005 GERD and GDP values which were then used to calculate the

Table 6
Canadian innovation system (1996–2000)

Province	α	SE[a]	R^2
Prince Edward Island	4.24	±0.36	0.98
British Columbia	2.52	±0.31	0.96
Saskatchewan	2.45	±0.80	0.76
Manitoba	2.34	±0.61	0.83
Nova Scotia	1.74	±0.28	0.93
Ontario	1.55	±0.14	0.97
Quebec	1.53	±0.12	0.98
Newfoundland Labrador	1.00	±0.18	0.91
New Brunswick	0.70	±0.58	0.33
Alberta	0.58	±0.19	0.76

[a] SE is the standard error for α.

2005 systemic scaling factors. The European systemic scaling factor was predicted to be 0.93 ± 0.12 using a 20-year observation window and 0.92 ± 0.15 using a 5-year observation window. The values of the system scaling factor for the Canadian innovation system were projected to be 1.22 ± 0.06 and 1.08 ± 0.09, respectively. These findings suggest that the systemic scaling factor for the European innovation system will tend to decrease and in fact the GERD is anticipated to grow slower than GDP. However, it is still not clear what will happen to the systemic scaling factor for the Canadian innovation system other than it will likely stay well above 1.0.

3.4. Another scale-independent view

Population is an important measure of the size of an economic system. It is used to calculate such things as GDP per capita, an indicator that is frequently used to compare the income of nations. We know from the preceding discussion that the growth of GDP can be approximated by an exponential growth trend. An examination of the growth trends of the European and Canadian populations showed that they tended to growth exponentially too. Over the 20-year time interval the European population tended to grow by 0.31% per annum and the Canadian population grew by 1.16% per annum.

Fig. 7 is a log–log plot of GDP versus population for Europe and Canada. A predictable scaling correlation exists between these two measures. The predicted value of the scaling factor for the European innovation system was $0.051/0.003 = 16.30$. The measured value was 15.96. The predicted value of the scaling factor for the Canadian innovation system was $0.053/0.012 = 4.56$. The measured value was 4.54 ± 0.18.

In both systems the actual data exhibit similar patterns of distribution about the predicted scaling trend lines. This pattern might be indicative of other underlying trends in such things as migration and economic factors. This requires further investigation.

It can be said with confidence that the scaling relationship between GDP and population in Europe and Canada observed from 1981 to 2000 is reasonably predictable. It tells us that a doubling of the population would be expected to increase GDP by nearly 638,000 times ($2^{15.96}$) in Europe but only 23.6 ($2^{4.56}$) times in Canada. The large difference in the scaling factors can be explained by the fact that the GDP_C–GDP_E scaling factor was 1.03 and the POP_C–POP_E scaling factor was measured to be 3.69. This indicates that while the European and Canadian GDPs are growing at similar rates the Canada's population was growing nearly four times as fast as the European population. It will take Europe a much longer to double its size that it will take Canada. The GDP–POP scaling factors also indicate that GDP per capita would expected to increase 32,000 ($2^{14.96}$) and 12 ($2^{3.56}$) fold, respectively, each time the GDP doubles.

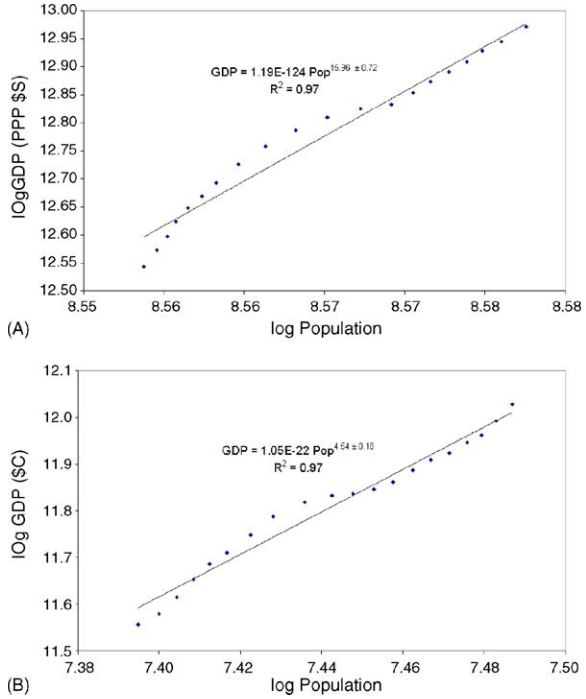

Fig. 7. Scaling correlation between GDP and population for (A) Europe and (B) Canada from 1981 to 2000.

Figs. 8 and 9 and Tables 7 and 8 give the highlights of scale-independent models for Europe and Canada based on the exponential growth of population and GDP between 1981 and 2000. Fig. 8a contains the log–log plots of GDP versus population for Europe. As shown in Fig. 5a, the circles are the 1990 data points and there are three power law regression lines. The dotted line is the regression line through the 1990 data. The lower line is the regression line through the 1981 data and the upper line is through the 2000 data. The scaling factors of the regression lines are given in the upper right hand corner of the graph. The shorter lines give the scaling correlation between GDP and population for each European country. Fig. 8b contains a similar plot for Canada. Fig. 9 is a plot of the value of the systemic scaling factor over time.

Tables 7 and 8 show that the reliability of the GDP–population scaling factors for some smaller nations and provinces are questionable. For example, the GDP–population scaling factor for Saskatchewan has a large standard error and a low R^2 value. This occurred because while the provincial GDP exhibited exponen-

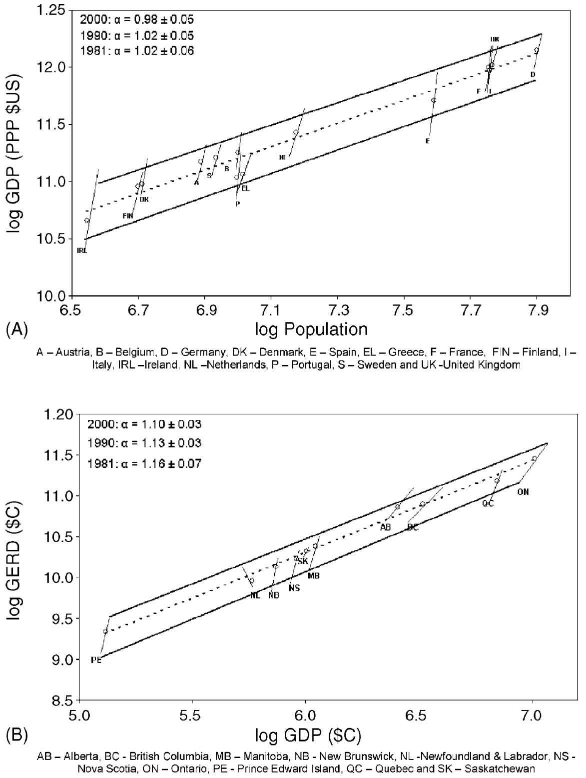

Fig. 8. Scale-independent GDP–population model of (A) Europe and (B) Canada from 1981 to 2000.

tial growth the population had both positive and negative growth periods. Also, the scaling factors in Europe tended to be larger and had less variation in their ranges than those for Canada. This is illustrated by the fact that the scaling factors in Europe ranged from 8.09 ± 0.20 for Greece to 33.40 ± 3.80 for Italy and had an average magnitude of 16.5. In Canada they ranged from -6.01 ± 1.58 for NL to 14.8 ± 0.08 for New Brunswick with an average magnitude of 6.4.

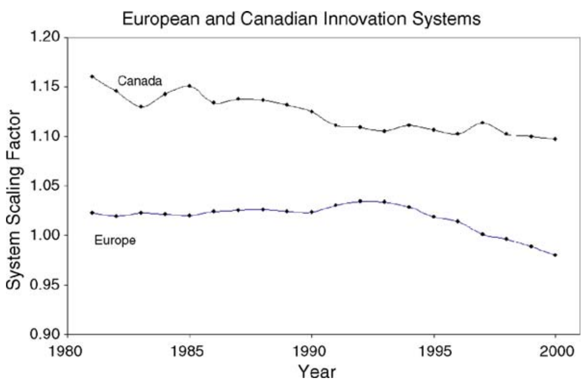

Fig. 9. GDP–population systemic scaling factor for the Europe and Canada from 1981 to 2000.

Table 7
European GDP–population scaling factors

Country	α	SE[a]	R^2
Italy	33.59	±3.80	0.81
Portugal	25.15	±6.47	0.46
United Kingdom	23.21	±1.00	0.97
Spain	22.55	±0.87	0.97
Belgium	19.01	±1.20	0.93
Denmark	17.39	±1.81	0.84
Ireland	16.70	±1.75	0.84
Germany	12.51	±1.19	0.86
Austria	11.86	±0.97	0.89
Finland	11.18	±0.67	0.94
France	10.42	±0.13	1.00
Sweden	10.06	±0.77	0.90
Netherlands	8.95	±0.21	0.99
Greece	8.09	±0.20	0.99

[a] SE is the standard error for α.

Fig. 9 suggests that the systemic GDP–population scaling factor is decreasing for Europe and Canada. It was quite constant in Europe staying around 1.02–1.04 until the mid 1990s and then declined dipping below 1.0 in 1998. Over the same interval the systemic GDP–population scaling factor for Canada decreased from 1.16 and then appeared to level off around 1.1.

Fig. 8b illustrates an interesting point. A scale-independent model can accommodate exponential decreases. Newfoundland and Labrador (NL) exhibited a decline in population and GDP over the 20 year time frame as seen by the negative slope of its power law regression line. Also, a scale-independent model can accommodate the case where one variable exhibits exponential growth and the other exponential decay.

3.5. Summary

Complex systems are expected to exhibit scaling relationships. If innovation systems are complex then we

Table 8
Canadian GDP–population scaling factors

Province	α	SE[a]	R^2
New Brunswick	14.78	±0.89	0.94
Prince Edward Island	10.71	±0.60	0.95
Nova Scotia	10.38	±0.43	0.97
Manitoba	9.20	±0.30	0.98
Quebec	7.27	±0.38	0.95
Saskatchewan	5.12	±4.17	0.08
Ontario	3.81	±0.18	0.96
Alberta	3.37	±0.16	0.96
British Columbia	2.77	±0.12	0.97
Newfoundland and Labrador	-6.01	±1.58	0.44

[a] SE is the standard error for α.

expect to find scaling correlations between measures commonly used to construct conventional performance indicators.

Scaling correlations between GERD & GDP and GDP & population have been shown for the European and Canadian innovation systems. The scaling correlations across time are predictable from the underlying exponential growths of GERD, GDP and population. The scaling correlations that exist across national and provincial innovation systems at points in time are not predictable but they are measurable.

The European and Canadian innovation systems exhibit emergent properties. For example, the systemic scaling relationship between GERD & GDP and GDP & population at points in time are not predictable and they are not solely determined by any national or provincial innovation system. The systemic scaling relationships are determined by the complex activities of the member systems within the European and Canadian innovation systems. Furthermore, the systemic scaling factor can change with time indicative of another emergent property.

Conventional and scale-adjusted performance indicators were constructed from common used statistical measures. The scaling correlation between the numerator and denominator were measured at points in time and across time. These correlations were then used to scale adjust the conventional indicator properly for size. It was then shown how these scale-independent indicators could used to construct scale-independent models that compared the evolution of the European supranational and Canadian federal innovation systems between 1981 and 2000.

4. Policy relevance

R&D intensity, GDP per capita and citations per paper[14] are performance indicators commonly used to compare innovation systems. Governments and agencies use them to set targets and inform public policy. For example, in 2002 the Lisbon Summit Strategy set a target to increase European R&D spending to 3% of GDP by 2010. This common goal can only be accomplished by individual European nations modifying their R&D spending targets so that the European innovation system quickly and efficiently moves toward its target. It has been shown that the conventional R&D intensity indicator might be not normalized for size. As a result, decision makers can be mislead about the role of different sized groups in the overall system.

The ERA scoreboard is composed of 20 performance indicators derived from ratios of primary measures. It is likely that some, if not many, of these indicators exhibit scaling relationships between primary measures and therefore these indicators are not normalized for size. Each indicator should be tested to see if it has to be scale-adjusted before it is used to inform national policy makers who set national and European goals.

An innovation system is complex. It is expected to display predictable and measurable scaling properties. Unfortunately, our perceptions about innovation systems are only informed by indicators based on linear assumptions even though our observations tell us that they behave differently. A renaissance occurred in the natural sciences when the study of chaotic processes[15] and fractal geometry taught us that power law correlations and distributions can be used to characterize the properties of complex systems. A similar renaissance could occur in the study of social systems if scale-independent indicators and models were be used to inform public policy.

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[14] Scaling correlations between citations and papers have been shown in my previous papers (Katz, 2005).

[15] A chaotic system is a nonlinear dynamical system sensitive to initial conditions. Its behavior can appear random even though the generating process is deterministic.

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