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Cooperation, scale-invariance and complex innovation systems: a generalization

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Abstract

The focus of this paper is the question "Can scale-invariant properties of collaborative research activities of a complex innovation system be quantified, modeled and used to inform decision makers about the effect that cooperation has on the impact of published peer-reviewed research?" Over the past few decades cooperative research activities have been extensively studied. Presently, encouragement and support for collaborative research and training is a cornerstone of many innovation policies and programs. Concurrently, the study of complex systems has produced tools and techniques that can be applied to the study of innovation systems. They have been shown to be complex systems with scale-invariant properties that can be measured and modeled providing novel insights to decision makers. An important factor contributing to the emergence of scale-invariant properties is the inseparable tension between competitive and cooperative activities among actors within a complex system. Peer-reviewed papers index in the 1990–2010 Web of Science and citations to these papers are used as a partial measure of size and impact, respectively. Documents are classified into 14 natural, health and applied sciences fields. Numbers of authors and country information from each paper are used to classify documents into various types of cooperation. Scale-invariant correlations between impact and sizes where prepared to provide measures and models used to explore the effects of cooperation types. It is shown that collaborative research tends to have greater impact and for a longer period of time that non-collaborative research. Cooperation in the more applied fields show higher growth of impact when compared to the growth of their sizes than cooperation in fields closer to the basic or 'blue sky' end of the R&D spectrum. Cooperation in a complex innovation system can have significant effects on the relative growth of impact with respect to growth of size and it enhances the sustainability of the Matthew Effect over time. Cooperative activities appear to sustain self-organization in a complex innovation system.

Keywords Allometric · Cooperation · Collaboration · Complex system · Innovation · Power-law · Scale-invariant · Self-similar · Scale independent

JEL Classification M0

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Introduction

Over the past few decades studies of cooperative activities among scientists, organizations and nations has produced an extensive body of peer-reviewed literature. Encouragement and support for cooperative research and training has become a foundation property of many research and innovation programs and policies. In fact, the recent rapid increase in trans- and multi-disciplinary investigations, particularly in the health sciences, with shared data, research infrastructures and personnel has become so prevalent that a new research area—the 'science of team science'—has emerged (Stokols et al. 2008).

Significant effort has been devoted to understanding the structure of cooperation networks and its impact on innovation and research from the complexity point of view (Barabási et al. 2002; Barabasi and Reka 1999; Kuhn et al. 2014; Newman 2001b; Perc et al. 2017). Concurrent with these studies methodologies and techniques used in the study of complex systems have been used to detect and study scale-invariant emergent properties of complex innovation systems (Katz 2006, 2016b). Scale-invariance is a useful property because it is recursive. Any smaller system contained within the larger complex system will have scale-invariant emergent properties too.

Scale-invariant emergent properties are one of the most often observed real world phenomena in a complex system. Scale-invariant properties cannot be measured using conventional measures but they can be quantified using scale-independent or scale-adjusted measures. These properties have self-similar patterns and regularities seen at many levels of observation. They frequently arise through interactions among smaller or simpler entities in a system that themselves do not exhibit such properties.

The question addressed in this paper is "Can scale-invariant properties of collaborative research activities of a complex innovation system be quantified, modeled and used to inform decision makers about the effect that cooperation can have on the impact of published peer-reviewed research?"

Background

The background section is divided into three general discussions. First the reader is provided with a general overview of what scale-invariant emergent properties are and how they can be identified. Next, a discussion of what is currently known about the scale-invariant properties of cooperative activities is presented. Finally, it will be shown how a scale-invariant relationship can arise from a simple relationship between any pair of coupled exponentially growing parameters. This principle will be used later to build scale-invariant measures and models of the affect that different types of cooperation can have on the impact of published research.

Scale-invariance and innovation systems

Scale-invariant emergent properties occur throughout nature and society. Scale-invariance may be perfect, as in the case of a deterministic fractal, or it can be statistical, as in the case of the jaggedness of an island shoreline or billowiness of clouds. An easy to visualize example of a scale-invariant emergent property that can be seen in a Romanesque broccoli.[1] It's a complex biological system that produces an edible flower constructed of elegant spiral swirls. The flower is composed of smaller florets that mimic the shape of the main flower. Each of the smaller florets is composed of even smaller florets with similar spiral swirls. This process repeats itself until near the cellular level. The spiral swirls are natural fractals that emerge during the growth of the flower. They are described by a series of arcs that follow the well-known recursive Fibonacci series (Rus 2008). These fractal arcs are not found at the level of individual cells and molecules. They are an emergent property of the collective dynamic activity of these entities.

Other terms synonymous for scale-invariance are *cumulative advantage*, *Matthew Effect*, *Yule process* and *preferential attachment* (Kuhn et al. 2014; Newman 2005; Perc 2013, 2014). They have their roots in Gibrat's law of proportionate effect (Gibrat 1931). Merton called this a 'success-breeds-success' phenomenon by which the rich get richer while the poor get comparatively poorer the "Matthew Effect," after a well-known verse in the Gospel according Matthew (Merton 1968, 1988).

Preferential attachment has been shown to occur in the formation and evolution of cooperative research networks (Barabási 2014; Barabási and Albert 1999; Barabási et al. 2002; Hébert-Dufresne et al. 2015; Ronda-Pupo and Katz 2016b). Preferential attachment belongs to a unique kind of *stochastic urn process* proven to generate scale-invariant distributions (He and Liu 2009; Newman 2005). The degree distributions of these networks are usually scale-invariant.

It is important to note that preferential attachment found in data sets does not imply that preferential attachment is the active mechanism. It simply implies that past activity is correlated with whatever scale-invariant growth mechanism is actually at play. Preferential attachment is an effective mechanism but not the only one that reproduces the statistical properties of scale-invariant growth (Hébert-Dufresne et al. 2016).

Scale-invariance is mathematically defined as $p(bx) = g(b)p(x)$ for any b (Newman 2005). That is, if we increase the scale or units by which we measure x by a factor of b, the shape of the distribution $p(x)$ is unchanged, except for an overall multiplicative constant. Only power law functions which have the general mathematical form shown in equations one and two (power law probability distributions and correlations) are scale-invariant. No other mathematical function has this characteristic.

There are two general types of scale-invariant relationships—power law probability distributions, defined in equation one, and power correlations, defined in equation two, where k is a constant and α is a constant called the *scaling factor* (Katz 2016b). The scale-invariant region of a power law distribution is limited to the tail region for $x \geq x_{\min}$ where $x_{\min}$ is the point at which scale-invariance begins.

$$p(x) = kx^{-\alpha} \tag{1}$$

$$f(x) = cx^{\alpha} \tag{2}$$

There is a degenerate form of a power law distribution called a power law with exponential cutoff described by equation three. In this case some entities in the far-right hand tail of the distribution do not occur with as high a probability as would be expected of a pure power law distribution. However, the scale-invariant region of the tail of the distribution can be several orders of magnitude in size. Scale-invariance is a property that can be measured and used to provide useful information to policy makers.

[1] Available from https://cargocollective.com/annabelking/Fractal-1-Romanesco-Broccoli.

$$f(x) = kx^{-\alpha}e^{-\lambda x} \quad (3)$$

A scale-invariant probability distribution indicates that a cumulative advantage process is involved in its evolution. The magnitude of the scaling factor of a distribution provides useful information. It tells us when the mean and the variance can be used to characterize it and when it cannot. Power law distributions with exponents $\alpha > 3.0$ can be characterize by their mean and variance. However, most real-world distributions line in the range $2 < \alpha \leq 3$ and where the variance is infinite (Newman 2005). Unlike power law distributions with $\alpha < 3.0$ they don't reside in the domain of attraction of Gaussian distributions; hence, the Central Limit Theorem no longer applies and population averages cannot be used to characterize them (Newman 2011). Also, when $\alpha \leq 2$ both the mean and the variance are infinite.

The population average is only useful for characterizing a distribution when its variance is finite. Many conventional indicators used to inform decision makers about properties of an innovation system such as research impact (citations/paper) or R&D intensity (GERD/GDP) are based on population averages. They are not particularly useful for comparative purposes when the scaling exponent of the underlying distribution is ≤ 3. For example, the evolution of citation distributions to peer-reviewed papers indexed in the Web of Science or Scopus tend to be scale-invariant (Katz 2016b). The exponents of these distributions became < 3.0 as they evolved over time. However, for small population sizes such as scientific subfields the scaling exponents tended to become < 3.0 very early in their evolution.

Scale-invariant properties are self-similar. That is, they are recursively similar at many levels of disaggregation. In other words, when a population with a scale-invariant distribution is disaggregated into natural groups such as countries, regions, institutions or fields then these smaller populations are expected to be scale-invariant too. A natural population is one that preserves the clustering, 'community' or small world structure of the overall population (Girvan and Newman 2002; Palla et al. 2005).

Scale-invariance has important consequence for decision makers (Bettencourt et al. 2010; Katz 2016b). It cannot be characterized by conventional measures such as population averages. *Scale-independent* or *scale-adjusted* measures derived from scale-invariant properties are dimensionless and independent of size. They can be used to overcome size bias that tends to occur in with conventional measures. Examples will be provided later.

Scale-invariance and cooperation

An important factor contributing to the emergence of scale-invariant properties is the inseparable tension between competitive and cooperative activities among actors within a complex system (Bar-Yam 2001; Baranger 2001). This factor is the primary focus of this paper. Typically, competition at one scale is nourished by cooperation on the scale below it. This is readily observable in insect colonies and a glaring example is war between nations and the underlying patriotism that supports it. Understanding the interplay between cooperation and competition provides useful insights into evolutionary processes that now supersede the notion of 'the survival of the fittest' (Baranger 2001).

Members of an innovation system invariably compete for finite resources. This competition fosters the formation of cooperative networks, even among competitors, possessing the skills and tools needed to design, develop and disseminate innovative ideas, products and processes within given resource constraints (Wang et al. 2013). Numbers of co-authored peer-reviewed papers are frequently used as a partial measure of research cooperation between individuals and groups (Katz and Martin 1997). While other sources of data have been used they can be difficult to obtain, time consuming to produce and tend to be incomplete. Publication data are relatively easy to obtain, they are mostly noise free and their properties are well understood. Furthermore, the journals in which papers are published can be assigned to such things as domains, fields and subfields allowing for analysis at different levels of observation. The citation counts to these papers can be used as a partial measure of the impact a group's published research has on the rest of community. Moreover, the distributions of citations to peer-reviewed papers have been shown to be scale-invariant at many levels of observation ranging from the global innovation system to domains, fields and subfields (Katz 2016b; van Raan 1990).

In this article publication counts of peer-reviewed papers index in the Web of Science and citations to these papers are used as measures of group size and impact, respectively. Authors and countries listed on these papers are used to classify papers into various types of cooperative research.

Scaling correlations have been previously reported. A scaling correlation between group impact and group sizes was reported when peer-reviewed papers when disaggregated into fields. The exponent of the scale-invariant correlation can be used as a measure of the Matthew Effect. For example, consider a population of peer-reviewed papers published in a given year. At any point in time the evolution of distribution of citations to these papers is expected to be scale-invariant indicative of a Matthew Effect. These papers can be disaggregated into natural groups such as fields and the correlation between field sizes and impact determined across the fields.

If the scaling exponent $\alpha > 1.0$ then the correlation is super linear and its magnitude is a measure of the Matthew Effect or cumulative advantage (Katz 2006; van Raan 2013). For example, if $\alpha = 1.36$ then a doubling in the number of peer-reviewed publications by a group would be expected to increase the group's impact by $2^{1.36}$ or 2.57 times. When $\alpha < 1.0$ the correlation is sublinear and its magnitude is a measure of the inverse Matthew Effect or cumulative disadvantage (Katz and Cothey 2006). A doubling of group size would be expected to produce less than a doubling in group impact. Finally, when $\alpha = 1.0$ linear effects are at play, indicative of random organization rather than self-organization.

Now let's turn our attention to examine the scale-invariant nature of cooperative research activities in a complex innovation system. Cooperation is a key aspect of research that facilitates the transfer and improvement of knowledge (Archambault et al. 2014b). It has been extensively study over the past few decades. Among the most prominent papers on the topic are Katz and Martin (1997), Katz (1994), Persson et al. (2004), Beaver (2001), Luukkonen et al. (1993) and Hara et al. (2003). These papers account for 42% of the overall impact of this line of research in the last 25 years (Ronda-Pupo and Katz 2016b).

Recently the debate about research on scientific collaboration has changed its focus into a discussion about the effect that scientific cooperation has on the impact of published research. A body of research exists on the study of the influence that collaboration has on impact (Katz and Hicks 1997; Katz and Martin 1997; Kliegl and Bates 2010; Tang and Shapira 2010; Zhai et al. 2014). Recently, Avkiran (1997), Elena Luna-Morales (2012), Glänzel (2002), González-Teruel et al. (2015), Rousseau (2000), Rousseau and Ding (2015) and van Raan (1998) published research about the existence or absence of a relationship between collaboration and the impact of articles.

Relatively few studies of cooperative research activity have investigated their scale-invariant characteristics. Newman (2001a, 2004) published a detailed examination of cooperative research networks and the scale-invariant character of cooperative networks. Generally speaking, he found that the distribution of the number of authors on co-authored papers was a power law with an exponential cut-off. He speculated that the cut-off might be due to the small window of time over which the observations were made.

Internationally co-authored peer-reviewed papers have been reported to have a scale-invariant distribution (Wagner and Leydesdorff 2005). The probability distribution of number of links between cities for co-authored papers was shown to be scale-invariant (Pan et al. 2012). These authors reported that the probability of a link was a scale-invariant function of the distance between cities for cooperative and citation networks. Recently, the probability distribution of the number of authors per paper (i.e., coauthor team sizes) in three nanoscience subfields were reported to be scale-invariant (Milojević 2010). Also, the topology of the cooperative R&D European aerospace research network was shown to be scale-invariant too (Biggiero and Angelini 2015).

Frame and Carpenter (1979) were the first researchers to report a scaling correlation in published international cooperative research activity. They reported a scale-invariant correlation between numbers of multi-author international papers and the scientific sizes of countries measured using number of published papers. The exponent reported had a value of 0.67 indicative of an inverse Matthew Effect. A doubling of country size would be expected to increase the number of multi-author papers 1.6 times ($2^{0.67}$). More recently the exponent of the scaling correlation between the numbers of internationally co-authored papers and country size was reported to be 0.90 (Archambault et al. 2011). They confirmed the inverse Matthew Effect reported by Frame & Carpenter. In addition, the authors showed that collaboration affinity maps derived from scale-adjusted measures were intuitively easier to understand than maps derived from conventional measures such as the *co-authorship preference index*.

In 2000 a scaling correlation was reported between the number of UK papers involving various types of cooperation and institutional sizes (Katz 2000). The exponent was >1.0 for international and institutional cooperation indicative of a Matthew Effect and it was <1.0 for industrial and domestic cooperation indicative of an inverse Matthew.

Ronda-Pupo and Katz (2016a, b) recently explored the scaling correlations between impact and size for various types of collaboration. A scaling correlation was found between citations to Management Sciences journals and their sizes that differed between single and multi-authored papers. The impact of multi-author papers was expected to increases $2^{1.89}$ or 3.70 times while single author papers were only expected to increase $2^{1.35}$ or 2.55 times when the number of collaborative articles published in a journal doubled. The Matthew Effect for co-authored papers was stronger for collaborative than for single author papers. In addition, the authors reported a scaling correlation between impact and size across 33 natural science subfields that differed by cooperation type. They found that the impact of multi-author papers was expected to increase $2^{1.20}$ or 2.30 times while the impact of single author papers was only expected to increase $2^{0.85}$ or 1.89 times for a doubling of subfield size. The Matthew Effect was strong for multi-author papers but single author papers exhibited an inverse Matthew Effect.

Scale-invariance and exponential growth

The simplest form of scaling correlation is one that takes place between any pair of coupled exponentially or logistically growing parameters (Katz 2005; Sahal 1981). The mathematical proof for the logistic function uses a simplification that reduces its form to exponential growth by ignoring small x and y values. Both proofs show that the scaling exponent for a power law correlation between exponentially growing functions is given by the ratio of the exponential exponents in the form:

$$x = am^{pt} \tag{4}$$

$$y = bm^{qt} \tag{5}$$

where m is the base, t is time and a and b are constants.

Let

$$y = sx^{\alpha} \tag{6}$$

where s is a constant. We can rewrite the Eq. 6 as:

$$bm^{qt} = s\left(am^{pt}\right)^{\alpha} \tag{7}$$

or

$$b/s(a)^{\alpha} = m^{(pa-q)t} \tag{8}$$

because,

$$m^{(p\alpha-q)t} \tag{9}$$

is a time-dependent variable, and it cannot be equal to

$$b/s(a)^{\alpha} \tag{10}$$

a constant, unless

$$p\alpha - q = 0 \tag{11}$$

therefore,

$$a = q/p \tag{12}$$

and

$$s = b/a^{q/p} \tag{13}$$

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 $t = 0$. In other words, the exponent for the scaling correlation $\alpha = q/p$ where p and q are the exponents of the exponentially growing processes given by $x \approx e^{pt}$ and $y \approx e^{qt}$, respectively.

Recently a study of the relative growth of internationally co-authored papers and domestically co-authored papers in various fields was done using an allometric approach (Coccia and Bozeman 2016). Allometric studies are typically done in biological and ecological science investigations that explore the scaling relationship between size and its biological consequences (Smith 2009; Warton et al. 2006; West et al. 1997). The authors reported that the growth of international co-authored papers was faster than the growth of domestically co-authored papers with scaling exponents ranging from 1.40 in physics to 4.90 in the medical sciences indicative of increased growth rates ranging from 2.60 to 29.8 times, respectively.

Ordinary least square (OLS) on log transformed data are usually used to determine the scaling parameter for scaling correlations. OLS is used particularly if the parameters are being used for predictive reasons, there is little error in the measure of the independent variable and the slope differs depending upon which variable is x and which is y (Warton et al. 2006). However, other methods such as Major Axis (MA) or Standardized Major Axis (SMA), Also known as Reduced Major Axis (RMA) maybe better suited for allometric studies when the correlation is not being used for predictive purposes but to simply summarize the relationship between two, perhaps unrelated, variables having the general relationship $y \approx x^{\alpha}$.

Table 1 Total paper and citation counts for fields

Science	Field	Abbrev.	Papers	Citation
Applied	Agriculture, Fisheries & Forestry	AGR	438,583	2,559,718
	Built Environment & Design	BED	46,613	234,670
	Enabling & Strategic Technologies	EST	710,065	7,147,570
	Engineering	ENG	559,976	3,629,590
	Information & Communication Technologies	ICT	283,897	1,993,200
Health	Biomedical Research	BMR	1,117,429	18,681,299
	Clinical Medicine	CLM	2,789,904	34,167,809
	Psychology & Cognitive Sciences	PCS	263,405	2,470,163
	Public Health & Health Services	PHS	244,282	2,052,170
Natural	Biology	BIO	581,683	4,857,148
	Chemistry	CHM	1,065,398	11,224,042
	Earth & Environmental Sciences	EES	392,805	3,522,265
	Mathematics & Statistics	M&S	312,792	1,316,683
	Physics & Astronomy	P&A	1,166,985	11,338,189

Scale-invariant models of the evolution of scientific impact, R&D intensity and national wealth have been constructed using scaling correlations (Katz 2006, 2012, 2016a). This approach will be used to illustrate how scale-invariant measures and models can inform decision makers how the impact of published research in the natural, health and applied science domains evolved depending on the type of cooperation involved.

Methodology

9.9 million peer-reviewed documents (article, note, review and conference articles published in journals) indexed in the Web of Science between 1990 and 2010, inclusive and 105.2 million citations to these documents were used as a partial measure of size and impact, respectively. Documents were classified into 14 natural, health and applied sciences fields (see Table 1) using the Science Metrix journal classification scheme[2] (Archambault et al. 2014a).

This paper focuses solely on the effect of various cooperation types on the scaling correlations between field impact and size. Citations to papers were counted using a fixed 5-year time window which included the year of publication plus four additional years. This window size ensures the cohort of documents for each field will have accumulated the majority of their cited half-life citations and it is short enough to build models useful for informing decision makers. Papers were classified into five cooperation types using information from the country and institutional address fields given in the Web of Science. The definition of each cooperation type is given in Table 2.

The Web of Science data are relatively noise free and there is little error in the measurement of the number of papers or citations and given that relationship between papers and citations is asymmetrical OLS was used. MA or SMA methods can be used if one was

[2] Available from http://science-metrix.com/files/science-metrix/sm_journal_classification_106_1.xls.

Table 2 Cooperation type definitions

Cooperative type	Definition
Mixed	Single author and multi-author (co-op and no co-op)
No cooperation	Single author
Cooperation	Two or more authors
Domestic cooperation	Two or more author from a country
International cooperation	Authors from more than one country
Domestic and international cooperation	Two or more authors from a country and more than one country

interested in constructing allometric models. A comparison of OLS and SMA for these data gave the same results.

Scale-invariant models of the evolution of impact with size

Scale-invariant models will be constructed for the different types of cooperative activities defined in Table 2. The models will be built in two steps. First, the scaling correlation over time between the growth of impact and size will be used to build part 1. Next the scaling correlations across fields at a point time called, the *systemic scaling correlation,* will be used to complete the model.

Scale-invariance over time

The scaling correlations between the growth of overall impact and size for peer-reviewed papers in 14 natural, health and applied science fields published between 1990 and 2010 were examine. The total impact and the total size for all fields grew exponentially given by citations $\approx e^{0.108t}$ and papers $\approx e^{0.0845t}$, respectively. The mathematics shows that the ratio of $\frac{0.108}{0.085} = 1.27$ should be the value of the exponent for the scaling correlation between this pair of growth processes. The calculated value seen in Fig. 1 is within the error range of the measured scaling exponent 1.26 ± 0.02 determined using OLS on log transformed data. The exponent tells us that the impact of the sciences is growing faster than their sizes and the impact is expected on average to increase $2^{1.26}$ or 2.4 times for a doubling in size.

The same approach was used to examine the relative growth of impact and size for each of the 14 science fields and for each type of cooperation. The table in Appendix 1 gives the scaling exponent of the relative growths, the standard errors (se), R^2 and an indication if $R^2 \geq 0.90$ and $p < 0.005$. Confidence in the values for the scaling exponents is excellent for all types of cooperation except for the 'None' group. The magnitudes of R^2 were less than 0.90 for 13 of the 14 fields in the 'None' group and 10 of the 14 fields had p values greater than 0.025. There is good support for mathematics and statistics (M&S) scaling exponent and weak support for Built Environment & Design (BED), Enabling & Strategic Technologies (EST) and Information and Communication Technologies (ICT). There was a tendency for the scaling exponents in 8 fields in the 'None' group to be negative. An inspection of the data shows that these cases the growth of impact and size were not exponential and, in some instances, it was flat or slightly declining.

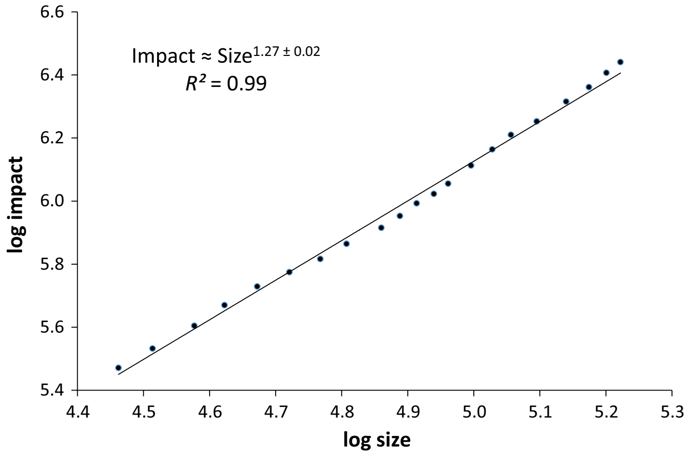

Fig. 1 Scaling correlation for the relative growth of impact and size for 14 natural, health, and applied science fields between 1990 and 2010, inclusive. The scaling exponent was determined using Ordinary Least Squares on log-transformed data. The exponent 1.27 indicates the presence of the Matthew Effect. A doubling of the size returned more than a doubling of its impact. The interpretation is, when the size of a field doubled, its impact was expected to increase $2^{1.27}$ or 2.41 times

The fields in Table 3 were ranked by their scaling exponents in decreasing order of magnitude for each cooperation type except for 'None'. The 'Mixed' group was included for the reader's reference. Scaling exponents with the same value were given the same rank. Ranks with values ≥ 5 are in bold.

These data tell us that the growth of impact relative to the growth in size was greatest in the applied sciences. These fields had the majority of the highest ranks for all cooperation types. Two health science fields, Psychology & Cognitive Sciences (PCS) and Public Health & Health Services (PHS), rank 2nd in the relative growth of the impact of domestic cooperation. In the natural sciences Mathematics & Statistics (M&S), Biology (BIO) and Chemistry (CHM) had relative impact growths with ranks > 5. M&S exhibited a high rank for international, domestics and international and domestic cooperation types perhaps indicative of the universal nature of mathematics. Interestingly, Biomedical Research (BMR), Physics & Astronomy (P&A), Clinical Medicine (CLM) and Earth & Environmental Sciences showed some of the lowest ranked relative growths of impact irrespective of the type of cooperation.

Figure 2 illustrates the first part of a scale-invariant model of the evolution of impact with field size for 'Mixed' cooperation. Similar models can be constructed for other cooperation types. The figure is a log–log plot of impact versus size for each of the 14 fields. The exponents found in the table in Appendix 2 give the magnitudes of the upward slopes of each line's trajectory from 1990 to 2010. Collectively, these lines are defined by 14 scale-invariant functions that model the evolution of the impact of each field as its size grew from 1990 to 2010.

Scale-invariance at points in time

A scaling correlation called the *systemic scaling correlation* can occur across members of a complex innovation system at a point in time (Katz 2006). For example, consider

Table 3 Rank of the relative growth exponents

Cooperation type	Field rank													
	Applied					Health				Natural				
	AGR	BED	EST	ENG	ICT	BMR	CLM	PCS	PHS	BIO	CHM	EES	M&S	P&A
Mixed	1	5	7	2	10	*13*	9	4	4	3	8	11	6	12
Coop	**1**	**3**	**5**	**2**	9	*13*	8	7	7	**4**	6	11	10	12
Intl	7	**4**	**2**	**1**	**3**	*12*	11	8	8	6	**5**	9	**4**	10
Dom	6	**4**	**2**	**1**	**3**	*12*	7	**2**	**2**	8	7	9	**5**	*11*
Dom + Intl	**5**	**1**	**2**	**2**	**3**	10	8	7	7	7	6	6	**4**	9

Mixed cooperation and no cooperation; *None* no cooperation (single author); *Coop* cooperation (multi-authors); *Intl* international cooperation; *Dom* domestic cooperation; *AGR* Agriculture, Fisheries & Forestry; *BED* Built Environment & Design; *EST* Enabling & Strategic Technologies; *ENG* Engineering; *ICT* Information & Communication Technologies; *BMR* Biomedical Research; *CLM* Clinical Medicine; *PCS* Psychology & Cognitive Sciences; *PHS* Public Health & Health Services; *BIO* Biology; *CHM* Chemistry; *EES* Earth & Environmental Sciences; *M&S* Mathematics & Statistics; *P&A* Physics & Astronomy. Italics $R^2 \geq 0.90$, bold $p < 0.005$

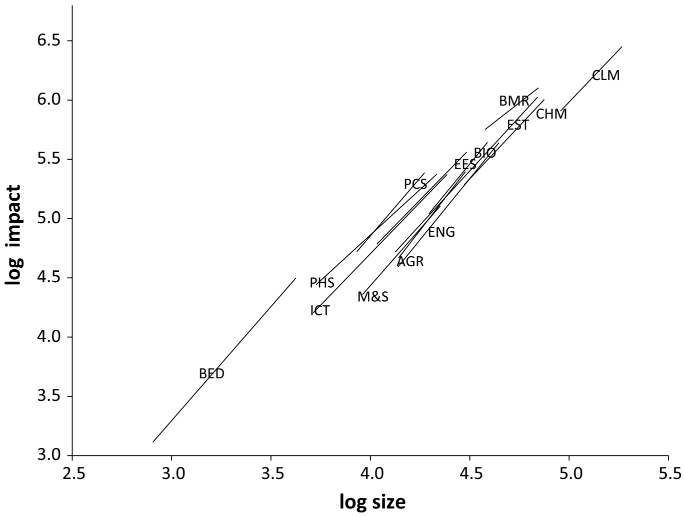

Fig. 2 Scale-invariant model Part I for mixed cooperation. A log–log plot of impact versus size for each of the 14 fields. The values of exponents of each field and for all types of cooperation are given in the table in Appendix 1. AGR = Agriculture, Fisheries & Forestry, BED = Built Environment & Design, EST = Enabling & Strategic Technologies, ENG = Engineering, ICT = Information & Communication Technologies, BMR = Biomedical Research, CLM = Clinical Medicine, PCS = Psychology & Cognitive Sciences, PHS = Public Health & Health Services, BIO = Biology, CHM = Chemistry, EES = Earth & Environmental Sciences, M&S = Mathematics & Statistics, P&A = Physics & Astronomy

Fig. 3 which is a log–log plot of the scaling correlation between field impact and sizes across the 14 science fields under consideration. The size of each field is the sum of the number of papers published in the field between 1990 and 2010. The impact is the sum of the 5-year citations to each year's publications over the same time interval. The systemic scaling correlation was found to have a value of 1.26 ± 0.08 indicating that on average when the size of a field doubles its impact was expected to increase $2^{1.26}$ or 2.39 times.

The systemic scaling correlation is a measure of the *average citedness* of peer-reviewed papers published in all fields. It can be used to calculate an expected impact, I_e, against which the observed impact, I_o, can be compared. The ratio $\frac{I_o}{I_e}$ is a scale-independent relative impact measure. When it is > 1 the observed impact is higher than expect, when it is < 1 the impact is less than expected and when it is $= 1$ observed and expected impact are equal.

Scientific impact or average number of citations per paper is a traditional measure used for such comparison. However it is biased by size while the relative impact measure is not size-biased (Katz 2000). For example, from Fig. 3 we see that relationship between impact, C, and size, p, is given by $C \approx P^{1.26}$. Therefore, scientific impact, $C/P \approx P^{0.26}$ showing that its magnitude is a function of field size. 8 of the 14 fields changed ranks by two or more positions using the relative impact measured compared to the conventional measure. The size effect of conventional measures can distort a policy

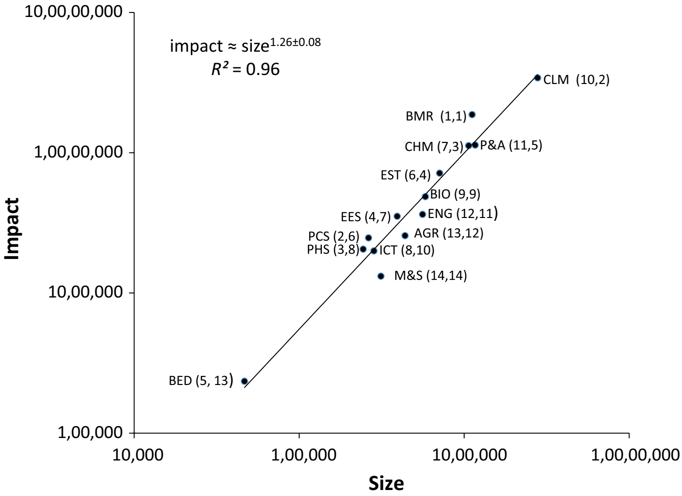

Fig. 3 Systemic scaling correlation—mixed cooperation. The systemic scaling correlation is a measure of the average citedness of peer-reviewed papers published in all fields. It can be used to calculate an expected impact. The numbers in brackets after the field abbreviations are the field rank determined using (a) relative impact measure, $\frac{I_o}{I_e}$ and (b) scientific impact, citations per paper

maker's understanding of the relative performance of groups in a complex innovation system. This problem can be alleviated through the use of scale-independent measures. For example, the scale-adjusted measures affect field ranks when compared with conventional indicators. 79% of cases scale adjusted measures show different ranks. Five fields improved their position; six areas lowered their level and, three remain the same place. This model suggests that scale adjusted indicators bring unbiased field rankings.

The table in Appendix 1 gives the annual systemic scaling correlations for each cooperation type, standard error, R^2 and an indication if $R^2 \geq 0.90$ and $p < 0.05$. R^2 was > 0.95 $p < 0.005$ for all exponents except those in the 'None' cooperation type. All but one exponent in the 'None' group has $0.70 < R^2 < 0.90$ with $p < 0.005$. The correlation for the 'None' type is indicative of a scale-invariant effect but it is not good enough to be useful for computing reliable expected impact values.

Figure 4 graphically depicts how the magnitude of the systemic scaling exponent for each cooperation type evolved between 1990 and 2010. In every instance it decreased with time. However, the scaling factor for the 'None' cooperation type decreased more rapidly than those publications with some type of cooperation. The Matthew Effect for the 'None' group approached linearity with increasing time while the other types of cooperation maintained a persistent strong Matthew Effect having exponents in the range of 1.18–1.23 at the end of the time period.

The trend lines show that at the beginning of the period, the scaling exponents for all types of cooperative and non-cooperative publications had exponents in the range of 1.28–1.38. The year 2000 marked a milestone, and the impact of solo papers dropped abruptly. Only

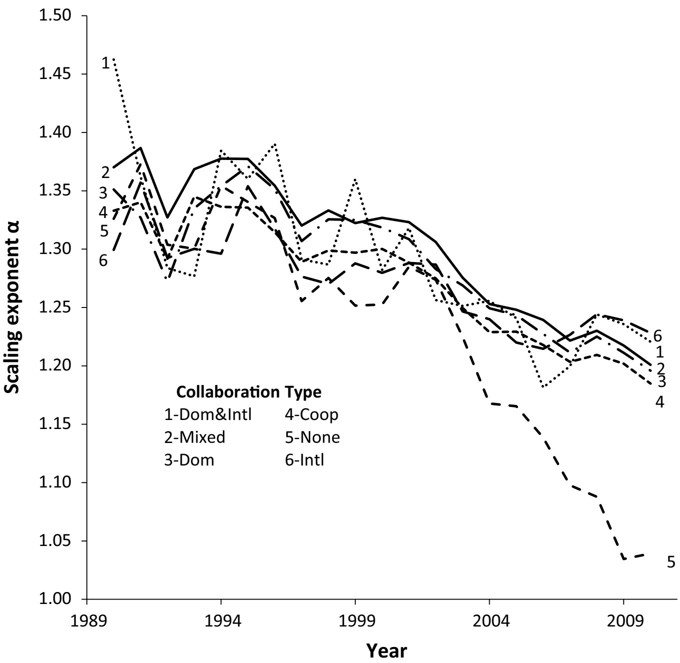

Fig. 4 Evolution of the systemic scaling exponent with time. A graphically depicts how the magnitude of the systemic scaling exponent for each cooperation type evolved between 1990 and 2010

cooperative documents sustained a strong Matthew Effect with exponents in the range 1.20–1.25 through 2010. Although the exponents show no stability over time, it remained above 1.20. Collaborative activities appear to represent a competitive advantage for enhancing the impact of complex innovation systems. The exponent for non-cooperative papers dropped to nearly 1.0 suggesting a disadvantage.

Figure 5 is the completed scale-invariant model of the evolution of field impact and size for the ‘Mixed’ cooperation type. Similar graphs could be constructed for the other types of cooperation.

The inset graph in the upper right-hand corner is a plot of the annual value of the system scaling exponent. It declined from 1.37 to 1.20 indicating that the expected increase in impact for a doubling in field size decreased from 2.59 ($2^{1.37}$) to 2.30 ($2^{2.30}$) times over the time period. The completed scale-invariant model illustrates how the impact and size of 14 science fields involving mixed cooperation evolved with time and at points in time. Similar models can be constructed for each cooperative activity.

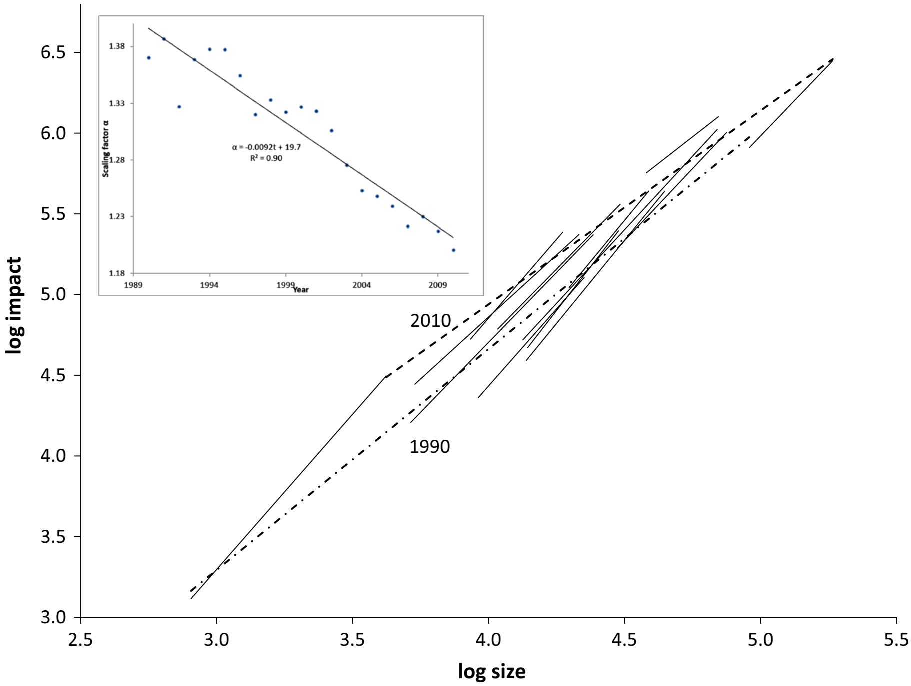

Fig. 5 Scale-invariant model for mixed cooperation. The graph contains the lines plotted in Fig. 3 overlaid with the 1990 and 2010 systemic scaling correlation shown as dotted lines. The inset graph in the upper left hand corner is a plot of the annual value of the system scaling exponent. The slopes represent the scaling exponent for each field overtime. The slopes above the general regression line indicates that the exponent of that field is above the exponent considering all fields together. Conversely if it appears below. When the field slope crosses the regression line the relative impact is about the same than expected

Discussion and summary

Contrary to previous studies that show no agreement to support the hypothesis that collaboration is a driver to foster citation impact, the results of the study confirmed that collaborative activities appear to represent a competitive advantage for enhancing the impact of complex innovation systems. In practical terms, it suggests that solo papers do not contribute to the growth of the citation impact of scientific fields as multi-authored papers do.

The rankings (see Table 3) show applied sciences had higher relative impact growth irrespective of cooperation type when compared to the fields closer to the basic end of the R&D spectrum. There were some notable exceptions. Domestic cooperation in Psychology & Cognitive Sciences and Public Health & Health Services as well as international and international + domestic cooperation in Mathematics & Statistics showed strong impact growth relative to their sizes. Even these exceptions are fields that tend to be closer to the applied than the blue-sky end of the R&D spectrum.

Specifically (see Appendix 1), the relative impact for cooperative research publication in 9 of 14 natural, health and applied science fields was greater than the relative impact for non-cooperative publications. Single author publications in Mathematics & Statistics tended to be higher than other fields perhaps reflecting the more solitary and theoretical nature of the field (Hicks and Katz 1996; Newman 2004). Single author papers in 4 applied science fields (BED, EST, ENG and ICT) had larger scaling exponents that cooperative papers however, statistical confidence in the values of these exponents is low.

The effect of cooperative activity on the persistence of the Matthew Effect was explored by examining the evolution of the magnitude of the systemic scaling correlation across fields at points in time. Figure 4 shows that at the beginning of the time period the scaling exponents for all types of cooperative and non-cooperative publications had scaling exponents in the range of 1.28–1.38. However, only cooperative papers sustained a strong Matthew Effect with exponents in the range 1.20–1.25 at the end of the period while the exponent for non-cooperative papers dropped to nearly 1.0. Cooperative activities appear to sustain self-organization in a complex innovation system.

The systemic scaling correlation across entities in a system at a point in time can be used as a reference trend against which the impact of individual fields can be compared. Figure 3 illustrates the effect that scale-adjusted measures can have on a field ranks when compared with conventional measures. For example, Clinical Medicine (CLM) drops from 2nd to 10th and Built Environment & Design (BED) increased from 13th to 5th rank when the effect of size on field impact was considered. 9 of the 14 fields experienced rank changes of 2 or more positions presenting decision makers with a much different view than one provides by a conventional measure. The effect of size matters when comparing entities of vastly different sizes in a complex innovation system.

Scale-invariant emergent properties are a common property of a complex innovation system. These properties can be qualified and quantified using the parameters of scale-invariant distributions and correlations. In turn these parameters can be used to prepare measures and models useful for informing public policy about scale-invariant emerging properties of a complex innovation system. This paper used a scale-invariant approach to show how cooperative activities can affect the evolution of relative growth of impact and the sustainability of the Matthew Effect with time. These measures and models give decision makers novel insights unobtainable using conventional measures.

"Appendix 1, 2" bring practitioners, research evaluation scholars, and policymakers the values of the exponents of growth for each type of collaboration and non-collaboration peer-reviewed papers for each field. These values can be used as a reference to compare the citation-based performance of countries, universities, or research groups in these fields.

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Appendix 1—Scaling exponents for relative growth of citations and papers

Cooperation type		Field scaling exponents													
		Applied					Health				Natural				
		AGR	BED	EST	ENG	ICT	BMR	CLM	PCS	PHS	BIO	CHM	EES	M&S	P&A
Mixed	α	2.17	1.92	1.82	2.06	1.73	1.31	1.76	1.95	1.95	2.04	1.79	1.72	1.91	1.49
	SE	0.04	0.07	0.05	0.07	0.07	0.03	0.05	0.07	0.07	0.04	0.05	0.02	0.04	0.04
	R^2	***0.99***	***0.98***	***0.99***	***0.98***	***0.97***	***0.99***	***0.98***	***0.97***	***0.97***	***0.99***	***0.99***	***1.00***	***0.99***	***0.98***
None	α	−0.64	2.19	3.47	2.41	3.62	−0.06	−1.11	−1.22	−1.22	−0.61	−0.66	−1.46	3.11	−0.97
	SE	0.12	0.20	0.43	1.65	0.64	0.18	0.47	0.26	0.26	0.11	1.19	0.34	0.23	0.57
	R^2	0.61	0.86	0.78	0.10	0.63	**0.01**	**0.23**	0.53	0.53	0.61	0.02	0.49	***0.90***	**0.13**
Coop	α	1.95	1.81	1.75	1.89	1.58	1.25	1.65	1.68	1.68	1.77	1.73	1.56	1.57	1.40
	SE	0.03	0.05	0.04	0.06	0.06	0.02	0.04	0.05	0.05	0.03	0.04	0.02	0.03	0.04
	R^2	***1.00***	***0.98***	***0.99***	***0.98***	***0.98***	***0.99***	***0.99***	***0.99***	***0.99***	***1.00***	***0.99***	***1.00***	***0.99***	***0.99***
Intl	α	1.40	1.49	1.53	1.55	1.51	1.10	1.29	1.35	1.35	1.42	1.44	1.33	1.49	1.30
	SE	0.03	0.04	0.04	0.03	0.04	0.02	0.01	0.02	0.02	0.02	0.05	0.02	0.05	0.04
	R^2	***0.99***	***0.98***	***0.99***	***0.99***	***0.99***	***1.00***	***1.00***	***0.99***	***0.99***	***0.99***	***0.98***	***0.99***	***0.98***	***0.99***
Dom	α	1.42	1.47	1.50	1.60	1.49	1.06	1.28	1.50	1.50	1.36	1.38	1.34	1.44	1.21
	SE	0.02	0.05	0.03	0.03	0.04	0.02	0.02	0.03	0.03	0.02	0.03	0.02	0.03	0.02
	R^2	***1.00***	***0.98***	***0.99***	***0.99***	***0.98***	***0.99***	***1.00***	***0.99***	***0.99***	***1.00***	***0.99***	***1.00***	***0.99***	***1.00***
Dom + Intl	α	1.29	1.50	1.41	1.41	1.40	1.04	1.20	1.26	1.26	1.26	1.27	1.27	1.32	1.18
	SE	0.02	0.05	0.03	0.02	0.04	0.02	0.01	0.02	0.02	0.02	0.04	0.02	0.03	0.02
	R^2	***1.00***	***0.98***	***0.99***	***1.00***	***0.98***	***0.99***	***1.00***	***1.00***	***1.00***	***0.99***	***0.99***	***1.00***	***0.99***	***0.99***

Mixed cooperation and no cooperation; *None* no cooperation (single author); *Coop* cooperation (multi-authors); *Intl* international cooperation; *Dom* domestic cooperation; α scaling exponent, *SE*-standard error of α, bold $p < 0.005$, italics $R^2 \geq 0.90$

Appendix 2—Annual systemic correlation scaling exponents

Cooperation type		Year 1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Mixed	α	1.37	1.39	1.33	1.37	1.38	1.38	1.35	1.32	1.33	1.32	1.33
	SE	0.08	0.09	0.09	0.10	0.09	0.09	0.09	0.09	0.09	0.09	0.09
	R^2	***0.96***	***0.95***	***0.95***	***0.94***	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***
None	α	1.33	1.37	1.30	1.30	1.35	1.34	1.33	1.26	1.28	1.25	1.25
	SE	0.16	0.18	0.17	0.17	0.18	0.20	0.19	0.20	0.18	0.18	0.19
	R^2	*0.84*	*0.84*	*0.83*	*0.82*	*0.83*	*0.79*	*0.81*	*0.78*	*0.81*	*0.80*	*0.78*
Coop	α	1.33	1.34	1.29	1.34	1.34	1.34	1.31	1.29	1.30	1.30	1.30
	SE	0.07	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.07
	R^2	***0.97***	***0.96***	***0.96***	***0.96***	***0.96***	***0.96***	***0.96***	***0.96***	***0.96***	***0.96***	***0.96***
Intl	α	1.30	1.36	1.29	1.30	1.30	1.35	1.32	1.28	1.27	1.29	1.28
	SE	0.08	0.09	0.08	0.09	0.09	0.09	0.09	0.09	0.08	0.09	0.09
	R^2	***0.96***	***0.95***	***0.95***	***0.94***	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***
Dom	α	1.35	1.33	1.27	1.33	1.35	1.37	1.35	1.31	1.33	1.33	1.32
	SE	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.07
	R^2	***0.98***	***0.97***	***0.96***	***0.96***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***
Dom + Intl	α	1.46	1.36	1.28	1.28	1.38	1.36	1.39	1.29	1.29	1.36	1.28
	SE	0.05	0.06	0.06	0.07	0.06	0.06	0.06	0.07	0.06	0.06	0.07
	R^2	***0.99***	***0.98***	***0.98***	***0.97***	***0.98***	***0.98***	***0.98***	***0.97***	***0.98***	***0.98***	***0.97***

Cooperation type		Year 2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Mixed	α	1.32	1.31	1.28	1.25	1.25	1.24	1.22	1.23	1.22	1.20
	SE	0.08	0.08	0.08	0.08	0.08	0.07	0.08	0.07	0.08	0.07
	R^2	***0.95***	***0.95***	***0.95***	***0.95***	***0.96***	***0.96***	***0.96***	***0.96***	***0.95***	***0.96***
None	α	1.28	1.27	1.22	1.17	1.17	1.14	1.10	1.09	1.03	1.04
	SE	0.21	0.20	0.20	0.19	0.19	0.18	0.18	0.22	0.19	0.17
	R^2	*0.76*	*0.77*	*0.75*	*0.76*	*0.76*	*0.76*	*0.75*	*0.67*	*0.71*	*0.76*
Coop	α	1.29	1.27	1.25	1.23	1.23	1.22	1.20	1.21	1.20	1.18
	SE	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.07	0.06
	R^2	***0.96***	***0.96***	***0.96***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***
Intl	α	1.29	1.29	1.25	1.24	1.22	1.21	1.23	1.24	1.24	1.23
	SE	0.08	0.08	0.08	0.08	0.08	0.07	0.08	0.08	0.07	0.07
	R^2	***0.95***	***0.95***	***0.95***	***0.95***	***0.95***	***0.96***	***0.95***	***0.96***	***0.96***	***0.96***
Dom	α	1.31	1.28	1.27	1.25	1.24	1.23	1.21	1.23	1.21	1.20
	SE	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
	R^2	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***
Dom + Intl	α	1.32	1.26	1.25	1.26	1.24	1.18	1.20	1.24	1.24	1.22
	SE	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.06
	R^2	***0.98***	***0.98***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.97***	***0.98***

Mixed cooperation and no cooperation; *None* no cooperation (single author); *Coop* cooperation (multi-authors); *Intl* international cooperation; *Dom* domestic cooperation; α scaling exponent, *SE* standard error of α, bold $p < 0.005$, italics $R^2 \geq 0.90$

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