Differences in Impact Factor Across Fields and Over Time

Benjamin M. Althouse, Jevin D. West, and Carl T. Bergstrom
Department of Biology, University of Washington, Seattle, WA 98105. E-mail: bma85@u.washington.edu

Theodore Bergstrom
Department of Economics, University of California Santa Barbara, Santa Barbara, CA 93106.

The bibliometric measure *impact factor* is a leading indicator of journal influence, and impact factors are routinely used in making decisions ranging from selecting journal subscriptions to allocating research funding to deciding tenure cases. Yet journal impact factors have increased gradually over time, and moreover impact factors vary widely across academic disciplines. Here we quantify inflation over time and differences across fields in impact factor scores and determine the sources of these differences. We find that the average number of citations in reference lists has increased gradually, and this is the predominant factor responsible for the inflation of impact factor scores over time. Field-specific variation in the fraction of citations to literature indexed by Thomson Scientific's Journal Citation Reports is the single greatest contributor to differences among the impact factors of journals in different fields. The growth rate of the scientific literature as a whole, and cross-field differences in net size and growth rate of individual fields, have had very little influence on impact factor inflation or on cross-field differences in impact factor.

Introduction

When Eugene Garfield published his 1972 paper in *Science* describing the role of the impact factor in bibliometric studies, he provided a table of the highest impact journals in science based on 1969 data. At that time, only 7 journals had impact factors of 10 or higher, and *Science* itself had an impact factor of 3.0 (Garfield, 1972). Thirty-five years later, in 2006, 109 journals had impact factors of 10 or higher, and *Science* registered an impact factor of 30.0 (Thomson Scientific, 2006). Over the period from 1994 to 2005, the average impact factor of all journals indexed by Thomson Scientific's Science Citation Index and Social Science Citation Index increased by about 2.6% per year.

Received April 22, 2008; revised July 7, 2008; accepted July 8, 2008

 • Published online 21 August 2008 in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/asi.20936

Average impact factors differ not only over time, but across fields. For example, in 2006 the highest impact factor in the field of economics was 4.7, held by the review journal *Journal of Economic Literature*. The top impact factor in molecular and cell biology was 47.4, held by *Annual Reviews of Immunology*. The average impact factors in these fields differ sixfold: The average impact factor in economics is 0.8 whereas the average in molecular and cell biology is 4.8.

This article explores the sources of the increase in impact factor over the past 11 years, and the reasons for impact factor differences across fields. Citation and article counts were obtained from the CD-ROM version of the Thomson Scientific Journal Citation Reports (JCR) Science and Social Science editions, for the years 1994–2005. The 2005 edition of this database provides citation information for the more than 7,500 journals indexed in Thomson's Science Citation Index and Social Science Citation Index.

Changes in Impact Factor Over Time

A journal's impact factor is a measure of the number of times that articles published in a census period cite articles published during an earlier target window. The impact factor as reported by Thomson Scientific has a one year census period and uses the two previous years for the target window. Stated more formally, let n_t^i be the number of times in year t that the year $t-1$ and $t-2$ volumes of journal i are cited by all journals listed in the JCR. Let A_t^i be the number of articles that appear in journal i in year t. The impact factor IF_t^i of journal i in year t is

$$\mathrm{IF}_t^i = \frac{n_t^i}{A_{t-1}^i + A_{t-2}^i}. \tag{1}$$

Impact Factors of Individual Journals

The JCR database includes 4,300 journals that were indexed continually from 1994 to 2005. For these journals,

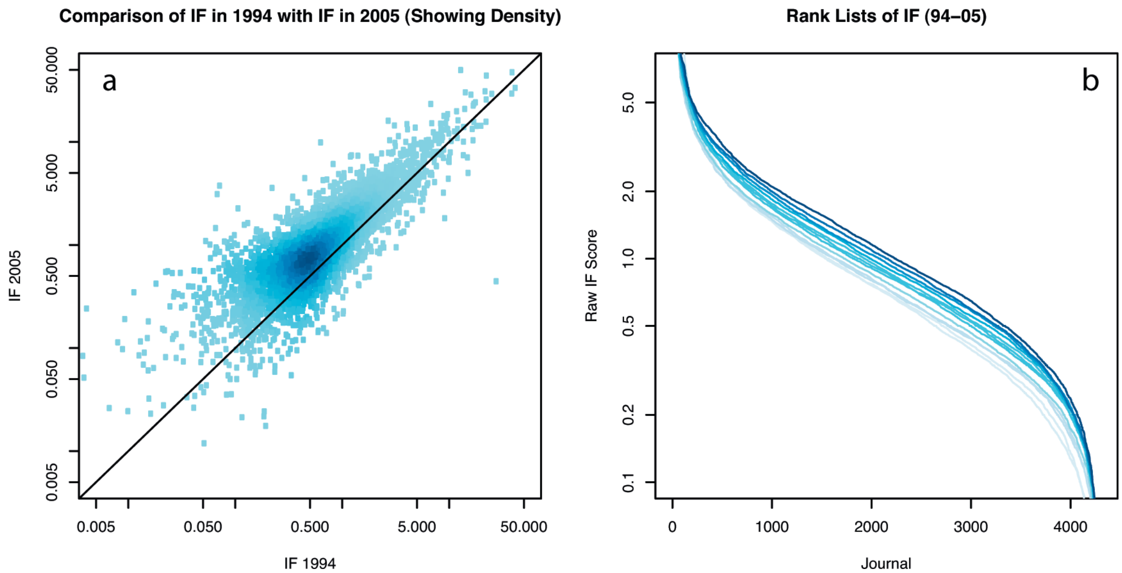

FIG. 1. Changes in impact factor from 1994 to 2005. Panel (a) is a log-log plot of 1994 impact factor against 2005 impact factor for the 4,300 journals that were listed in every year from 1994 to 2005 in the JCR dataset. Shading indicates density of points, with darker tones representing higher density. Panel (b) plots the rank-order distribution of impact factors for these 4,300 journals from 1994 to 2005. The progression of darkening shade indicates years, with the lightest shade representing 1994 and the darkest 2005. Note that the highest and lowest-scoring journals do not fall within the scales of the plot.

Figure 1(a) plots 1994 impact factor scores against 2005 scores. Points above the diagonal represent journals with impact factors that have risen, and points below represent journals with impact factors that have fallen. About 80% of the journals have increased in impact factor over the eleven years.

Figure 1(b) shows the rank-order distribution of impact factors for years 1994 (lighter blue) through 2005 (darker blue). Impact factor scores increase annually, predominantly through the midrange of the distribution. From these figures, it is apparent that impact factors have increased steadily for most journals, irrespective of their initial impact factors in 1994.

Weighted Average Impact Factor

To measure average rate of change, it is appropriate to assign larger weights to journals that publish more articles (see also Egghe & Rousseau, 1996). The most convenient formulation assigns weights proportional to the number of articles that a journal published during the target years. Let A_t^i be the number of articles published by journal i in year t and let A_t be the sum of the articles published over the set S_t of all journals indexed in year t. We define the weight for journal i in year t as

$$w_t^i = \frac{A_{t-1}^i + A_{t-2}^i}{A_{t-1} + A_{t-2}}. \tag{2}$$

Notice that $\sum_{i \in S_t} w_t^i = 1$. Define the weighted average impact factor as

$$\overline{\mathrm{IF}}_t = \sum_{i \in S_t} w_t^i \mathrm{IF}_t^i. \tag{3}$$

The weighted average impact factor for all journals listed in the JCR increased by an average rate of 2.6% per year from 1994 to 2005. For the journals that appeared in the index throughout the entire period from 1994 through 2005, the average annual increase was 1.6%.

Decomposing Changes in Average Impact Factor

To identify the source(s) of the increase in impact factors, we have found it useful to decompose the average impact factor into the product of four components and to measure the growth rate of each component. These components are

1. The ratio of the number of articles published in the census period (year t) to the number of articles published in the target window (years $t-1$ and $t-2$).
2. The fraction of all citations from articles written in the census period that are directed to articles published within the target window.
3. The fraction of cited articles published within the target window that appear in journals indexed by the JCR.
4. The average number of citations in the reference list of each published article.

To construct this decomposition, we use the following definitions. Let A_t be the number of articles published in year t in JCR-indexed journals. Then $\alpha_t = A_t/(A_{t-1} + A_{t-2})$ is the ratio of articles published in year t to articles that appeared in the target window. Let p_t be the fraction of citations in indexed articles in year t that are directed to articles published in the target window. Let v_t be the fraction of articles in the target window cited in year t that appear in journals indexed by the JCR. (This excludes unpublished working papers, conference proceedings, books, and journals not indexed by the JCR.)

DOI: 10.1002/asi

Let c_t be the average number of references cited per article appearing in year t in JCR-indexed journals.

Recall that n_t^i is the number of citations to articles published in journal i during the target window from articles published in JCR-indexed journals in year t. The total number of citations from indexed journals in year t to articles that appeared in issues of indexed journals published during the target window is

$$\sum_{i \in S_t} n_t^i = A_t p_t v_t c_t. \tag{4}$$

The weighted average impact factor in year t is

$$\begin{aligned}\overline{\mathrm{IF}}_t &= \sum_{i \in S_t} w_t^i \mathrm{IF}_t^i \\ &= \sum_{i \in S_t} \frac{A_{t-1}^i + A_{t-2}^i}{A_{t-1} + A_{t-2}} \cdot \frac{n_t^i}{A_{t-1}^i + A_{t-2}^i} \\ &= \frac{\sum_{i \in S_t} n_t^i}{A_{t-1} + A_{t-2}} \\ &= \frac{A_t c_t p_t v_t}{A_{t-1} + A_{t-2}}.\end{aligned} \tag{5}$$

From Equation 5, it follows that the weighted average impact factor at time t can be written as the product

$$\overline{\mathrm{IF}}_t = \alpha_t p_t v_t c_t. \tag{6}$$

The growth rate of a variable is approximated by the change in the logarithm of that variable. The multiplicative form of Equation 6 makes it easy to decompose the growth rate of the average impact factor into the sum of growth rates of the variables α, c, p, and v. It follows from Equation 6 that

$$\rho_t(\overline{\mathrm{IF}}) = \rho_t(\alpha) + \rho_t(p) + \rho_t(v) + \rho_t(c), \tag{7}$$

where for any variable x, we define $\rho_t(x) = \ln x_t - \ln x_{t-1}$. From the JCR data we are able to determine α_t, p_t, v_t, and c_t, and hence $\rho_t(\alpha)$, $\rho_t(p)$, $\rho_t(v)$, and $\rho_t(c)$. Our methods for doing so are described in the Appendix. The results are reported in Tables 1 and 2.

TABLE 1. Summary of time behavior of α_t, c_t, p_t, v_t and $\overline{\mathrm{IF}}$ for the years 1994 to 2004. See text for details.

Year (t)	# of articles	α_t	c_t	p_t	v_t	$\overline{\mathrm{IF}}$
1994	689,876	0.544	22.121	0.176	0.835	1.764
1995	709,504	0.533	22.810	0.175	0.839	1.786
1996	734,565	0.530	24.390	0.171	0.835	1.846
1997	739,890	0.517	25.040	0.167	0.833	1.796
1998	753,919	0.513	27.936	0.163	0.788	1.846
1999	767,825	0.516	28.527	0.163	0.812	1.948
2000	785,583	0.518	28.913	0.162	0.820	1.988
2001	788,323	0.510	29.835	0.161	0.839	2.055
2002	808,241	0.514	30.542	0.159	0.849	2.119
2003	847,705	0.535	30.666	0.157	0.857	2.206
2004	885,043	0.537	31.593	0.159	0.843	2.266

TABLE 2. Summary of time behavior of $\rho_t(\alpha)$, $\rho_t(c)$, $\rho_t(p)$, $\rho_t(v)$ and $\rho_t(\overline{\mathrm{IF}})$ for the years 1995 to 2004. The ρ values approximate the fractional annual increase in each component, α, c, p, v, and $\overline{\mathrm{IF}}$. The final row shows the average annual increase of each component over the period 1995–2004.

Year (t)	$\rho_t(\alpha)$	$\rho_t(c)$	$\rho_t(p)$	$\rho_t(v)$	$\rho_t(\overline{\mathrm{IF}})$
1995	−0.019	0.031	−0.004	0.005	0.012
1996	−0.007	0.067	−0.022	−0.005	0.033
1997	−0.025	0.026	−0.027	−0.001	−0.027
1998	−0.007	0.109	−0.019	−0.056	0.027
1999	0.005	0.021	−0.002	0.030	0.054
2000	0.004	0.013	−0.007	0.010	0.020
2001	−0.015	0.031	−0.006	0.023	0.033
2002	0.008	0.023	−0.013	0.012	0.031
2003	0.040	0.004	−0.012	0.009	0.040
2004	0.004	0.03	0.009	−0.016	0.027
Mean	−0.001	0.036	−0.010	0.001	0.025

The average increase in weighted impact factor is 2.6% per year over the period 1994–2005. This growth rate must be the sum of the growth rates of the four factors, α, c, p, and v. Table 2 displays the growth rate ρ for each factor in each year.

We see from the table that the effect of changes in α, the ratio of the number of articles published in the census period to the number published in the target window, and that of changes in p, the fraction of citations in the census period that are directed to articles in the target window, has been to slightly reduce, rather than increase, the average impact factor. Changes in v, the fraction of citations that go to JCR-indexed articles, have had only a negligible effect on the average impact factor. Essentially all of the increase in average impact factors is a result of an increase in c, the average number of reference items cited per article. Over this period, the average number of citations in the reference section of each article has increased by approximately 3.6% per year. One can imagine a number of potential causes for this increase. These include the following:

1. As the size of a field increases, the number of published papers that are relevant to any given manuscript might be expected to increase. Thus we might expect reference lists to grow longer as fields get bigger.
2. Internet search engines, online citation databases, and electronic access to the literature itself have considerably reduced the time-cost to authors of finding and obtaining relevant articles. This may have resulted in a concomitant increase in the number of cited items.
3. As researchers become increasingly aware of the value of citations to their own work, referees may demand that authors add numerous citations to their work, and authors may preemptively cite any number of potential editors and referees in their manuscript.

Preliminary regression analysis provided no evidence that increasing numbers of citable articles lead to increases in the length of reference lists. While it would be interesting to seek out data that would allow us to distinguish among the other

DOI: 10.1002/asi

sources of the change in the average number of references per paper, we do not do so here.

Growth of Science and Impact Factor Inflation

It seems appealing to attribute the inflation of impact factors to growth of the scientific enterprise and in particular to the growth in the number of articles indexed by the JCR. The raw numbers lend a superficial plausibility to this view. From 1994 to 2005, the number of articles in JCR-indexed journals increased by 28% and the weighted impact factor increased by 29%. But the link from the growth of science to rising impact factors is not so simple. For any given article, an increase in the number of related articles is a source of additional chances to be cited, but it is also a source of additional competition for the attention of potential readers and citations.[1]

A simple formal model is useful here. Suppose that the number of articles published grows at a constant rate γ. Let $A_t = A_0(1+\gamma)^t$. The ratio $\alpha_t = A_t/(A_{t-1} + A_{t-2})$ of articles published in the census year to articles published in the target years is then

$$\alpha_t = \frac{(1+\gamma)^t}{(1+\gamma)^{t-1} + (1+\gamma)^{t-2}} = \frac{(1+\gamma)^2}{2+\gamma}. \tag{8}$$

Since α_t is constant, its growth rate, $\rho_t(\alpha)$ is zero for all t.

Thus a constant rate of growth, γ, in the number of articles indexed annually leads to a constant impact factor (no inflation). However, higher rates of growth will yield higher constant impact factors because the derivative of Equation 8 with respect to γ is positive. By contrast, accelerating growth in the number of articles published (increasing γ over time) generates impact factor inflation and decelerating growth generates impact factor deflation.

Natural Selection?

During the period 1994–2005, the JCR added 4,202 new journals that were not previously listed and removed 2,415 journals that were listed in 1994. What effect, if any, did this process of journal substitution have on average impact factors? If the average impact factors of entering journals exceeded the average impact factor of exiting journals by a sizable margin, this could pull up the entire distribution. We could view this effect as a form of natural selection: the most fit—those with the highest impact factor scores—would enter or stay in the data set, while the least fit—those with the lowest scores—would drop out of the data set.

At first glance this seems to be a plausible explanation. The journals that entered the JCR over the period 1995–2004 have significantly higher impact factor scores than those that exited over the same period (two sample Kolmogorov- Smirnov test, $D = 0.074, p = 5.6 \times 10^{-7}$). However, even the entering journals had average impact factors well below the average for the full JCR. Because nearly twice as many journals entered as exited, the net effect of flux into and out of the JCR was actually to decrease the average impact factor of the full set of JCR-listed journals.

We see this as follows. For a given year t, if we multiply the numbers of articles in years $t-1$ and $t-2$ by the overall weighted impact factor score for that year, we can calculate the expected number of citations the set of entering or exiting journals would have to accrue in order to leave the average impact factor of the full set unchanged. The difference between the expected and the actual number of citations brought in by the entering journals can be considered a "citation cost" of adding new journals (whether positive or negative), and similarly the difference between the actual and the expected number of citations by journals exiting can be considered a "citation gain" of removing these journals from the data set. We can calculate then, the total effect of the flux of journals into and out of the data set by summing these quantities. For the years 1995–2004, an average cost of 18,200 citations per year was incurred due to turnover in the journals listed. Thus natural selection has not contributed to impact factor inflation.

While the journals that entered the JCR did not on average contribute to impact factor inflation by virtue of entering, they did contribute in the sense that subsequent to entering, their impact factors grew more strongly than did the average for the JCR as a whole. The average annual growth rate for those journals entering in years 1995–2004 is 6%, more than twice the rate of the overall data set (see also Wilson, 2007). This suggests two possible (and not mutually exclusive) scenarios: Thomson may be successfully selecting journals that are rising stars for inclusion in the JCR, or the journals, once selected and included in the JCR, become more visible and are thus cited more often.

Differences in Impact Factor Across Fields

Impact factors are well known to vary widely across disciplines (Seglen, 1997; Vinkler, 1988). Sources of this variation include differences in citation practices (Moed, Burger, Frankfort, & Van Raan, 1985), differences in the lag time between publication and subsequent citation (what we call p; Moed et al.; Marton, 1985), and differences in the proportions of citations directed to JCR-indexed literature (what we call v; Hamilton, 1991; Vanclay, in press). Here we explore the source of these differences in detail. To delineate disciplinary boundaries, we use the field categories developed by Rosvall and Bergstrom (2008). These categories use citation patterns to partition the sciences and social sciences into 88 nonoverlapping fields.

Table 3 lists the 2004 weighted impact factors for the 50 largest fields. Indeed, we see wide variation. For example, the field of mathematics has a weighted impact factor of $\overline{\text{IF}} = 0.56$, whereas molecular and cell biology has a

[1]This point was observed by Garfield (2006) who noted that there was no a priori reason to expect journals serving large scientific communities to have higher impact factors than those serving small ones.

DOI: 10.1002/asi

TABLE 3. Table showing $\overline{\text{IF}}$, α, c, p, v and exponential growth rates for individual fields. All except growth rate were calculated using 2004 data. See text for details.

Field (Size)	$\overline{\text{IF}}$	α	c	p	v	Growth rate
Molecular and Cell Biology (511)	4.763	0.515	45.81	0.205	0.803	0.006
Astronomy and Astrophysics (25)	4.295	0.53	38.249	0.215	0.813	0.074
Gastroenterology (40)	3.475	0.494	39.669	0.193	0.849	0.03
Rheumatology (20)	3.348	0.519	37.818	0.184	0.826	0.079
Neuroscience (224)	3.252	0.515	43.768	0.159	0.81	0.017
Medicine (766)	2.896	0.515	33.92	0.183	0.76	0.036
Chemistry (145)	2.61	0.539	33.103	0.17	0.821	0.026
Pharmacology (28)	2.331	0.575	32.947	0.149	0.737	0.098
Psychiatry (178)	2.294	0.522	43.025	0.131	0.67	0.039
Urology (23)	2.132	0.513	25.501	0.176	0.806	0.032
Medical Imaging (84)	2.043	0.502	28.727	0.161	0.784	0.034
Pathology (28)	1.991	0.516	29.523	0.166	0.803	0.02
Physics (503)	1.912	0.543	23.963	0.167	0.783	0.018
Ophthalmology (36)	1.905	0.536	29.105	0.144	0.823	0.029
Environmental Health (73)	1.871	0.533	37.234	0.14	0.691	0.048
Analytic Chemistry (129)	1.789	0.538	26.702	0.158	0.762	0.022
Geosciences (224)	1.768	0.526	40.529	0.113	0.647	0.021
Law (71)	1.657	0.485	76.826	0.199	0.231	0.01
Ecology and Evolution (349)	1.555	0.523	42.172	0.1	0.64	0.051
Parasitology (38)	1.527	0.505	32.076	0.134	0.711	0.036
Environmental Chemistry and Microbiology (181)	1.505	0.518	31.648	0.117	0.679	0.039
Computer Imaging (31)	1.446	0.514	26.47	0.133	0.332	0.067
Dermatology (38)	1.427	0.48	28.442	0.128	0.734	0.05
Psychology (210)	1.387	0.513	45.139	0.091	0.538	0.033
Chemical Engineering (75)	1.29	0.587	23.66	0.124	0.711	0.041
Dentistry (43)	1.284	0.529	32.046	0.102	0.717	0.029
Orthopedics (72)	1.226	0.531	30.033	0.103	0.683	0.066
Telecommunication (37)	1.192	0.55	19.518	0.163	0.334	0.054
Applied Acoustics (36)	1.171	0.526	25.942	0.115	0.575	0.031
Crop Science (61)	1.04	0.523	29.467	0.104	0.631	0.025
Business and Marketing (101)	1.035	0.538	46.865	0.091	0.376	0.032
Geography (56)	0.986	0.526	46.055	0.148	0.254	0.029
Information Science (23)	0.918	0.539	28.402	0.22	0.217	0.078
Agriculture (56)	0.882	0.53	27.503	0.093	0.67	0.024
Anthropology (62)	0.872	0.496	52.104	0.098	0.275	0.02
Material Engineering (107)	0.826	0.537	22.038	0.1	0.578	0.063
Economics (159)	0.823	0.511	30.423	0.121	0.299	0.021
Fluid Mechanics (107)	0.804	0.52	22.096	0.107	0.516	0.041
Probability and Statistics (57)	0.796	0.528	21.974	0.089	0.496	0.023
Veterinary (77)	0.767	0.48	26.512	0.115	0.62	0.041
Sociology (96)	0.715	0.51	50.84	0.11	0.189	0.001
Media and Communication (24)	0.69	0.479	46.932	0.133	0.19	0.024
Control Theory (64)	0.681	0.474	21.394	0.102	0.407	0.061
Political Science (99)	0.68	0.5	45.014	0.176	0.131	0.012
Computer Science (124)	0.631	0.717	17.215	0.193	0.266	0.034
Education (86)	0.59	0.509	39.89	0.119	0.213	0.015
Mathematics (149)	0.556	0.512	18.477	0.085	0.552	0.033
Operations Research (62)	0.542	0.521	21.714	0.086	0.408	0.043
History and Philosophy of Science (32)	0.456	0.507	51.316	0.068	0.159	−0.003
History (23)	0.416	0.466	81.775	0.101	0.059	−0.028

weighted impact factor of 4.76—an eight-fold difference. There are several possible sources of this difference, including but not limited to differences in growth rates, differences in the time course of citations, and differences in the fraction of citations that go to nonindexed literature. By extending the model developed in the previous section to partition the weighted impact factor into four separate contributing components, we can quantify the influence of each upon the cross-field differences.

To begin the analysis we recall Equation 7:

$$\rho_t(\overline{\text{IF}}) = \rho_t(\alpha) + \rho_t(c) + \rho_t(p) + \rho_t(v).$$

If journals received citations only from other journals in the same field, the following equation would hold exactly for each field F.

$$\rho_t(\overline{\text{IF}}_F) = \rho_t(\alpha_F) + \rho_t(c_F) + \rho_t(p_F) + \rho_t(v_F) \qquad (9)$$

In practice, not all citations come from within the same field, so the equation above is only approximate—though it will be a very good approximation if most cross-disciplinary citations go between fields with similar α_F, c_F, p_F, and v_F values.

This will let us examine the influence on $\overline{\text{IF}}$ of each component, α, c, p, and v, in each field F separately. How important is each component? A univariate linear regression of $\rho_t(\alpha)$, $\rho_t(c)$, $\rho_t(p)$, and $\rho_t(v)$ with $\rho_t(\overline{\text{IF}})$ yields the following coefficients of determination (r^2 values, indicating the proportion of total variability explained by each term):

$$\begin{aligned} r_\alpha^2 &= 0.045 \\ r_c^2 &= 0.172 \\ r_p^2 &= 0.083 \\ r_v^2 &= 0.456 \end{aligned} \tag{10}$$

These coefficients of determination tell us a number of things. Firstly, the low value of r_α^2 indicates that α_t, the total number of articles in year t over the total numbers of articles in years $t-1$ and $t-2$, explains very little of the variance across fields in weighted impact factor. In contrast, the high value of r_v^2 indicates that the fraction of citations that go into JCR-listed material, v_F, explains the greatest fraction of variation of any of the four components.

If we progress to a multiple regression among pairs of variables, we find

$$\begin{aligned} r_{\alpha,c}^2 &= 0.235 \\ r_{\alpha,p}^2 &= 0.118 \\ r_{\alpha,v}^2 &= 0.457 \\ r_{c,p}^2 &= 0.401 \\ r_{c,v}^2 &= 0.585 \\ r_{p,v}^2 &= 0.577 \end{aligned} \tag{11}$$

This further demonstrates the minimal explanatory power of α: $r_{\alpha,v}^2$ is approximately equal to r_v^2, and similarly for $r_{\alpha,c}^2$ and $r_{\alpha,p}^2$. It also confirms the considerable predictive power of v—any regression containing v has a relatively high r^2, and shows that c and p are also predictively useful in concert with v. Multiple regressions with three and four variables yield:

$$\begin{aligned} r_{\alpha,c,p}^2 &= 0.451 \\ r_{\alpha,c,v}^2 &= 0.591 \\ r_{\alpha,p,v}^2 &= 0.577 \\ r_{c,p,v}^2 &= 0.854 \\ r_{\alpha,c,p,v}^2 &= 0.855 \end{aligned} \tag{12}$$

The r^2 with all four variables is 0.855; the model is unable to perfectly predict the weighted impact factor because our assumption that all citations received come from the same field is not strictly true. Notice also that $r_{\alpha,c,p,v}^2 \cong r_{c,p,v}^2$, further indicating that α has little, if any, predictive power.

TABLE 4. Table showing the results of hierarchical partitioning.

Predictor	I (%)
α	2.858
c	26.624
p	20.178
v	50.340

The method of hierarchical partitioning (Chevan & Sutherland, 1991) provides a more formal method to estimate the relative contributions or "importance" of the various independent variables in explaining the total variance in a multivariate regression. The statistic I estimates the contribution of each independent variable. Using the hierarchical partitioning `hier.part` package by Chris Walsh in the statistical analysis program R, we find the I values for the year 2004 data listed in Table 4.

These results indicate that the predictor v (the fraction of citations to JCR-indexed literature) accounts for 50% of the explained variance in $\overline{\text{IF}}$. The predictor c (number of outgoing citations per article) accounts for an additional 27%. Those fields that cite heavily within the JCR data set, such as molecular biology or medicine, buoy their own scores. Those fields that do not cite heavily within the JCR data set, such as computer science or mathematics, have correspondingly lower scores.

Figure 2 summarizes the differences in weighted-average impact factor across fields (panel d) and the factors responsible for these differences (panels a–c).

Inflation Differences Across Fields

As we have shown in previous sections, the weighted impact factor is increasing every year and is different for each field. Naturally, the next several questions to be asked are, Is inflation ubiquitous across fields? Do some fields inflate more than others? Which fields inflate the most? Differences in inflation rates between fields will be important when evaluating citation data within a specific field over time. Knowing that, for instance, psychiatry is inflating twice as fast as neuroscience, would help one compare journals across these fields over time.

The results of the analysis are reported in Table 3. Fields vary substantially in their rates of impact factor inflation. Further analysis shows that inflation rate is not correlated to size of field ($r^2 = 0.001$), nor weighted impact factor scores of that field ($r^2 = 0.018$).

Summary

Impact factors vary across fields and over time. By decomposing average impact factors into four contributing

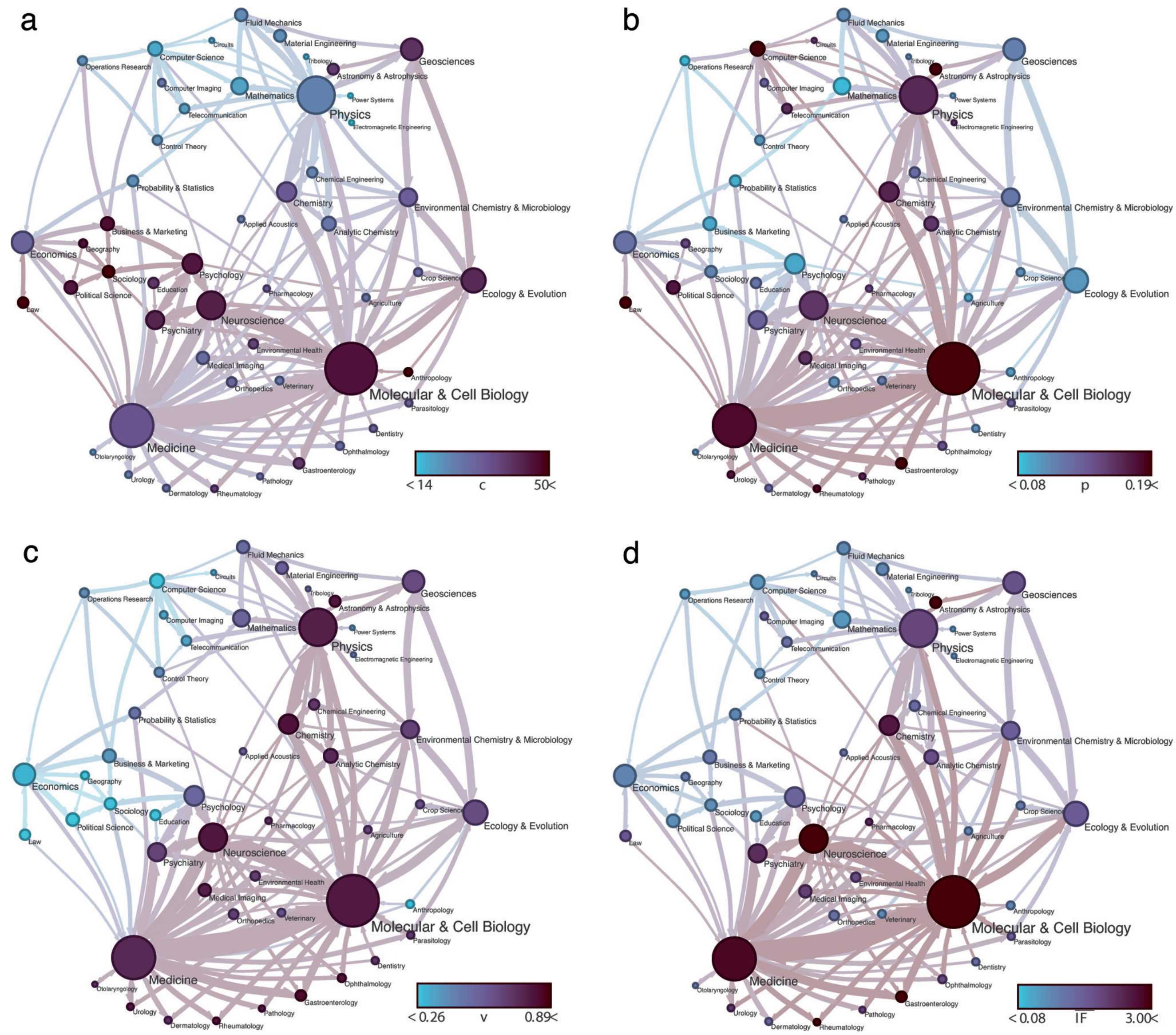

FIG. 2. Differences in citation patterns across fields. This figure illustrates the differences in c, p, v, and $\overline{\text{IF}}$ across fields. Panel (a) shows differences in c, the average number of items cited per paper. Panel (b) shows differences in p, the fraction of citations to papers published in the two previous calendar years. Panel (c) shows differences in v, the fraction of citations to papers published in JCR-listed journals, and panel (d) shows differences in $\overline{\text{IF}}$, the weighted impact factor. Fields are categorized and mapped as in Rosvall and Bergstrom (2008).

components—field growth, average number of cited items per paper, fraction of citations to papers published within two years, and fraction of citations to JCR-listed items—we are able to determine the sources of this variation. We find that an increasing number of citations in the reference lists of published papers is the greatest contributor to impact factor inflation over time. Differences in the fraction of citations to JCR-indexed literature is the greatest contributor to differences across fields, though cross-field differences in impact factor are also influenced by differences in the number of citations per paper and differences in the fraction of references that were published within two years. By contrast, the growth rate of the scientific literature and cross-field differences in net size and growth rate have very little influence on impact factor inflation or on cross-field differences in impact factor.

Competing Interests

The authors are the developers of Eigenfactor (http://www.eigenfactor.org), a method for ranking journal influence using citation-network data.

Acknowledgments

The authors would like to thank Martin Rosvall for generating the maps used in Figure 2, and also Alan Wilson for drawing our attention to impact factor inflation. This work was supported in part by a Mary Gates Research Scholarship and a Howard Hughes Medical Institute Integrative Research Internship to B.M.A.

References

Chevan, A., & Sutherland, M. (1991). Hierarchical partitioning. The American Statistician, 45, 90–96.

Egghe, L., & Rousseau, R. (1996). Average and global impact of a set of journals. Scientometrics, 36, 97–107.

Garfield, E. (1972). Citation analysis as a tool in journal evaluation. Science, 178, 471–79.

Garfield, E. (2006). The history and meaning of the journal impact factor. JAMA, 295, 90–93.

Hamilton, D. (1991). Research papers: Who's uncited now? Science, 251, 25.

Journal Citation Reports. (2006). Philadelphia: Thomson Scientific.

Marton, J. (1985). Obsolescence or immediacy? Evidence supporting Price's hypothesis. Scientometrics, 7, 145–153.

Moed, H.F., Burger, W.J.M., Frankfort, J.G., & Van Raan, A.F.J. (1985). The application of bibliometric indicators: Important field and time-dependent factors to be considered. Scientometrics, 8, 177–203.

Rosvall, M., & Bergstrom, C.T. (2008). Maps of random walks on complex networks reveal community structure. Proceedings of the National Academy of Sciences USA, 105, 1118–1123.

Seglen, P. (1997). Why the impact factor of journals should not be used for evaluating research. British Medical Journal, 314, 497.

Vanclay, J. (in press). Bias in the journal impact factor. Scientometrics.

Vinkler, P. (1988). Bibliometric features of some scientific subfields and the scientometric consequences therefrom. Scientometrics, 14, 453–474.

Wilson, A. (2007). Journal impact factors are inflated. BioScience, 57, 550–551.

Appendix: Deriving α_t, c_t, p_t, and v_t from the JCR data

All citation data sets come from the JCR data sets for the years 1994–2005. The JCR does not list article counts for year t in the data set for year t; the year $t+1$ and year $t+2$ data sets typically do not agree exactly on the number of articles that were published in year t. Therefore, in order to compute the year t article count, A_t, we average the article count listed for year t in the $t+1$ data set and year t in the $t+2$ data set. We then calculate $\alpha_t = A_t/(A_{t-1} + A_{t-2})$ using the total article counts for years A_{t-1} and A_{t-2} as given in the data set for year t.

We calculate c_t by dividing the total outgoing citations for all journals in year t by the total articles for year t:

$$c_t = \frac{\text{total out-citations in year } t}{A_t}.$$

We calculate p_t by dividing the total outgoing citations for all journals to material published in the previous two years ($t-1$ and $t-2$) by the total outgoing citations for all journals in year t:

$$p_t = \frac{\text{2-year total out-citations from year } t}{\text{total out-citations in year } t}.$$

The calculation of v_t is slightly more complicated than the other calculations; Figure 3 provides a schematic representation. To calculate the percentage of citations into the JCR for the entire dataset we divide the total *incoming* citations for the previous two years (Figure 3, top panel, arrow A) by the total outgoing citations over that period (arrows A + C):

$$v_{(t,\text{Entire Dataset})} = \frac{\text{2-year total in-citations from year } t}{\text{2-year total out-citations from year } t}.$$

This is done because the incoming citations for the entire dataset are the outgoing citations from the JCR to itself. However, this is not true for the specific field calculations. To calculate $v_{t,F}$ for any field F, we divide the 2-year outgoing citations from that field to itself (Figure 3, bottom panel, arrow A) plus the 2-year outgoing citations from that field to the rest of the JCR (arrow B) by the total 2-year outgoing citations from that field (arrows A + B + C):

$$v_{(t,F)} = \frac{\left(\begin{array}{l}\text{2-year out-citations from } F \text{ to } F+ \\ \text{2-year out-citations into rest of JCR}\end{array}\right)}{\text{2-year total out-citations from year } t}.$$

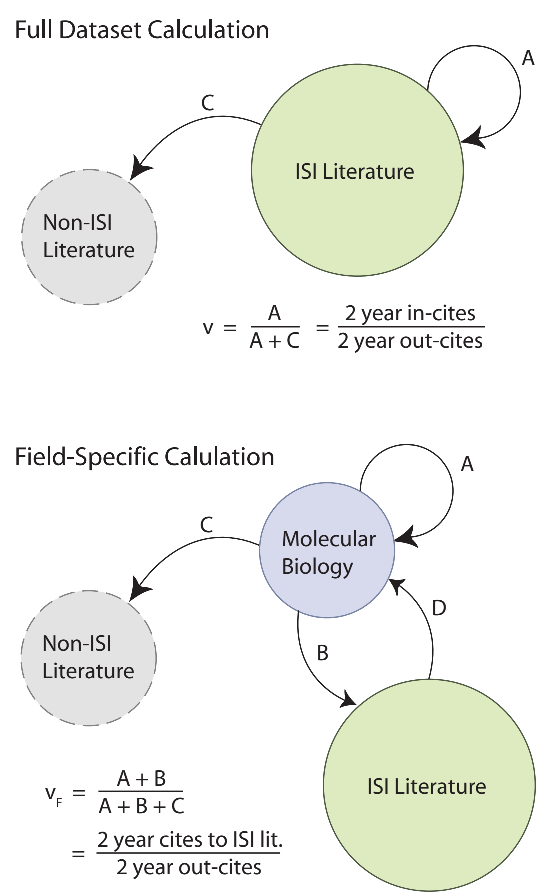

FIG. 3. Calculating v_t. The top panel gives the schematic for calculating v_t for the entire dataset, and the bottom panel gives the schematic for specific fields. Details are provided in the text.