Journal of Informetrics 4 (2010) 55–63

Contents lists available at ScienceDirect

Journal of Informetrics

journal homepage: www.elsevier.com/locate/joi

The difference between popularity and prestige in the sciences and in the social sciences: A bibliometric analysis

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ARTICLE INFO

Article history:
Received 23 June 2009
Received in revised form 3 August 2009
Accepted 5 August 2009

Keywords:
Journal influence
Impact factor
Eigenfactor

ABSTRACT

The status of a journal is commonly determined by two factors: popularity and prestige. While the former *counts* citations, the latter recursively *weights* them with the prestige of the citing journals. We make a thorough comparison of the bibliometric concepts of popularity and prestige for journals in the sciences and in the social sciences. We find that the two notions diverge more for the hard sciences, including physics, engineering, material sciences, and computer sciences, than they do for the geosciences, for biology-medical disciplines, and for the social sciences. Moreover, we identify the science and social science journals with the highest diverging ranks in popularity and prestige compilations.

1. Introduction

The status of an actor in a social context is determined by two factors: the total number of endorsements the actor receives from other actors and the prestige of the endorsing actors (Hubbell, 1965). We cite from Bollen, Rodriguez, and de Sompel (2006a) the following example: *An author of pulp detectives may sell many books, but may not have earned the respect of literary critics. Conversely, a Nobel Prize in Literature winner may be highly valued among literary experts, yet never make the New York Times bestseller list*. Similarly, the status of a journal in the academic setting is defined in terms of the number of citations received from other journals as well as in terms of the prestige of the citing journals. Following Bollen et al. (2006a), we refer to the former as *popularity* and to the latter as *prestige*.

The popularity of a journal is traditionally measured by the journal impact factor, which is the mean number of citations in a given year to papers published in the journal during a previous target period. Typical target periods are 2 and 5 years long. In this paper, we use the 5-year impact factor, since its longer target window allows a more fair evaluation of the more theoretical disciplines, like mathematics, in which results need to be well digested before they are cited.

The impact factor equally weights all citations: citations from highly reputed journals, like Nature, Science, and Proceedings of the National Academy of Sciences of USA, are treated as citations from obscure journals. In other words, the impact factor is a measure of popularity, but does not account for prestige. Pinski and Narin (1976) developed a recursive method, later reinterpreted by Geller (1978), that measures the *prestige* of a journal in terms of the prestige of the citing journals. The method has been recently implemented in two similar bibliometric indicators to evaluate journal status: journal PageRank (Bollen et al., 2006a; Bollen, Rodriguez, & de Sompel, 2006b) and Eigenfactor ™ (Bergstrom, 2007; Bergstrom, West, & Wiseman, 2008). The main advantage of the latter with respect to the former is that Eigenfactor scores are freely accessible at the Eigenfactor web site (West, Althouse, Bergstrom, Rosvall, & Bergstrom, 2009) and, from 2007, they have been incorpo-

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1751-1577/$ – see front matter
doi:10.1016/j.joi.2009.08.001

rated into Thomson-Reuters Journal Citation Reports (JCR) for both science and social science journals.[1] Interestingly, Brin and Page used a similar notion of weighted citations to design the popular PageRank algorithm that is currently used by Google search engine to rank web pages resulting from a user query: the importance of a web page is determined by the number of hyperlinks it receives from other pages as well as by the importance of the linking pages (Brin & Page, 1998; Brin, Page, Motwani, & Winograd, 1999).

The contribution of this paper is a detailed comparison of the bibliometric notions of popularity, as measured by the 5-year impact factor, and prestige, as captured by the Eigenfactor metric, at the journal level (Section 2). We study the overlaps and discrepancies of the two notions over both science and social science journals recorded in JCR. For the selection of significant and well-distributed journal samples, we use the map of science based on the clustering of JCR subject categories into macro-disciplines that was recently computed by Leydesdorff and Rafols (2009) using factor analysis on the category–category citation matrix. We also survey previous attempts to compare popularity-oriented and prestige-oriented metrics (Section 3). Section 4 concludes the paper.

2. A bibliometric analysis of popularity and prestige

In this section, we first describe how we have defined the bibliometric notions of journal popularity and journal prestige and where we have tested the corresponding bibliometric indexes. Then, we make an exhaustive comparison of the defined bibliometric notions of popularity and prestige for science and social science journals.

. *The bibliometric notions of popularity and prestige*

We adopt as a metric of journal popularity the 5-year impact factor, that is, the mean number of citations in a given year to papers published in the journal during the previous 5 years. This measure is available at Thomson-Reuters JCR for science and social science journals. On the other hand, we use the Eigenfactor metric (Bergstrom, 2007; Bergstrom et al., 2008) as a measure of journal prestige. Unlike traditional journal metrics, like the impact factor, the Eigenfactor method weights journal citations by the prestige of the citing journals. As a result, a journal is prestigious if it is cited by other prestigious journals. The definition is clearly *recursive* in terms of prestige and the computation of the Eigenfactor scores involves the search of a *stationary* distribution, which corresponds to the leading eigenvector of a perturbed citation matrix (West et al., 2009). It is worth stressing that the Eigenfactor method uses a target window of 5 years as done by the 5-year impact factor.

We illustrate the Eigenfactor method as described at the Eigenfactor web site (West et al., 2009). The Eigenfactor computation uses a census citation window of 1 year and an earlier target publication window of 5 years. Let us fix a census year and let $C = (c_{i,j})$ be a journal–journal citation matrix such that $c_{i,j}$ is the number of citations from articles published in journal i in the census year to articles published in journal j during the target window consisting of the 5 previous years. Journal self-citations are ignored, hence $c_{i,i} = 0$ for all i. Moreover, let a be an article vector such that a_i is the number of articles published by journal i over the 5-year target window divided by the total number of articles published by all journals over the same period. Notice that a is normalized to sum to 1.

A dangling node is a journal i that does not cite any other journals; hence, if i is dangling, the i th row of the citation matrix has all 0 entries. The citation matrix C is transformed into a normalized matrix $H = (h_{i,j})$ such that all rows that are not dangling nodes are normalized by the row sum, that is

$$h_{i,j} = \frac{c_{i,j}}{\sum_j c_{i,j}} \tag{1}$$

for all non-dangling i and all j. Furthermore, H is mapped to a matrix $\hat{H}$ in which all rows corresponding to dangling nodes are replaced with the article vector a. Notice that $\hat{H}$ is row-stochastic, that is all rows are non-negative and sum to 1.

A new row-stochastic matrix P is defined as follows:

$$P = \alpha\hat{H} + (1 - \alpha)A \tag{2}$$

where A is the matrix with identical rows each equal to the article vector a, and α is a free parameter of the algorithm, usually set to 0.85. Let π be the left eigenvector of P associated with the unity eigenvalue, that is, the vector π such that $\pi = \pi P$. It is possible to prove that this vector exists and is unique. The vector π, called the *influence vector*, contains the scores used to weight citations allocated in matrix H. Finally, the Eigenfactor vector r is computed as

$$r = 100 \cdot \frac{\pi H}{\sum_i [\pi H]_i} \tag{3}$$

[1] Eigenfactor scores from 2007 are added to the Eigenfactor web site 6 months after they are published in JCR.

That is, the Eigenfactor score of a journal is the sum of normalized citations received from other journals weighted by the Eigenfactor scores of the citing journals. The Eigenfactor scores are normalized such that they sum to 100.

The idea underlying the Eigenfactor method originates from the work of Pinski and Narin (1976) and Geller (1978) in the field of bibliometrics and from the contribution of Hubbell (1965) in the context of sociometry, which, in turn, generalizes Leontief's input–output model for the economic system (Leontief, 1941). Notably, Brin and Page use a similar intuition to design the popular PageRank algorithm that is part of their Google search engine (Brin & Page, 1998; Brin et al., 1999). Eigenfactor scores are accessible at Thomson-Reuters JCR for science and social science journals and, freely, at the Eigenfactor web site (West et al., 2009) for journals listed in JCR and also for those journals that do not belong to JCR but are cited by other JCR journals.

There are two minor differences between the journal PageRank method (Bollen et al., 2006a) and the Eigenfactor method (West et al., 2009). Journal PageRank includes journal self-citations,[2] while the Eigenfactor method does not. The exclusion of journal self-citations in the Eigenfactor method is meant to avoid over-inflated journals that engage in the practice of opportunistic self-citations. Moreover, to enforce irreducibility of the citation matrix, and hence convergence of the method, in both approaches the original citation matrix is perturbed by adding artificial transitions, with low probability, among journals (this perturbation is called *teleportation*). In the Eigenfactor method the weight of each teleporting transition is proportional to the number of article published by the target journal, that is, the teleportation is represented by the article matrix A, multiplied by $1 - \alpha$, in the method described above, whereas in the journal PageRank approach teleporting transitions are uniformly distributed over all journals.

We apply the bibliometric indicators of popularity and prestige to a sample of journals included in Thomson Reuters Science Citation Index as well as to a sample of journals contained in Thomson Reuters Social Science Citation Index. To select journals to include in the science sample, we take advantage of the map of science based on JCR subject categories that was recently computed by Leydesdorff and Rafols (2009). Using data from JCR 2006, the authors build a category–category citation matrix and use exploratory factor analysis to cluster the 175 JCR subject categories into 14 factors corresponding to macro-disciplines in science, e.g., biomedical sciences, engineering, geosciences. These 14 macro-disciplines have been further aggregated into 3 discipline poles according to the inter-discipline citation flow: biology–medicine, physics–materials–engineering–computing, and environment–ecology–agriculture–geosciences. Interestingly, chemistry plays a brokerage role between these three major poles. For each macro-discipline, we selected the five subject categories with the highest factor loadings on the cluster identified by the macro-discipline; they correspond to the most representative categories of the macro-discipline. Finally, we included in the science sample all journals belonging to the selected subject categories that have a defined value for both indicators of popularity and prestige. The resulting sample comprises 3499 science journals, classified into 71 subject categories, clustered into 14 macro-disciplines, corresponding to 3 major poles as follows:

- Hard sciences
  - engineering: mechanics; engineering, mechanical; mathematics, interdisciplinary applications; thermodynamics; engineering, multidisciplinary;
  - material sciences: materials science, multidisciplinary; nanoscience & nanotechnology; coatings & films; physics, applied; ceramics;
  - computer sciences: hardware & architecture; information systems; artificial intelligence; engineering, electrical & electronic; theory & methods;
  - physics: physics, multidisciplinary; physics, mathematical; physics, nuclear; physics, particles & fields; physics, fluids & plasmas.
- Geosciences
  - geosciences: geosciences, multidisciplinary; geology; geochemistry & geophysics; geography, physical; paleontology;
  - ecology: ecology; biodiversity conservation; zoology; marine & freshwater biology; ornithology;
  - environmental sciences: engineering, environmental; environmental sciences; water resources; engineering, civil; limnology;
  - agriculture: horticulture; agronomy; agriculture, multidisciplinary; plant sciences; food science & technology.
- Biology-medical disciplines
  - biomedical sciences: cell biology; biochemistry & molecular biology; biophysics; developmental biology; multidisciplinary sciences;
  - clinical medicine: surgery; critical care medicine; emergency medicine; transplantation; respiratory system;
  - neurosciences: neurosciences; psychology; behavioral sciences; neuroimaging; psychiatry;
  - infectious diseases: infectious diseases; immunology; microbiology; allergy; virology;
  - general medicine & health: health care sciences & services; medical ethics; public, environmental & occupational health; medicine, general & internal; medical informatics.
- Chemistry

[2] In fact, the original proposal (Bollen et al., 2006b) did not consider self-citations.

Table 1
Rankings of top 10 science journals according to popularity and prestige.

Popularity		Prestige	
IF5	Journal	Journal	EF
49.642	Annu Rev Immunol	Nature	1.83870
45.941	New Engl J Med	P Natl Acad Sci USA	1.74485
42.292	Rev Mod Phys	Science	1.69272
33.811	Annu Rev Biochem	J Biol Chem	1.53982
32.422	Nat Rev Mol Cell Bio	Phys Rev Lett	1.26804
31.499	Nat Rev Immunol	J Am Chem Soc	0.95019
30.631	Science	Appl Phys Lett	0.71774
30.616	Nature	New Engl J Med	0.69405
30.495	Annu Rev Neurosci	Cell	0.67067
29.567	Nat Med	J Immunol	0.49206

◦ chemistry: chemistry, multidisciplinary; chemistry, organic; chemistry, inorganic & nuclear; chemistry, physical; chemistry, applied; crystallography.

Leydesdorff and Rafols chose to exclude the social sciences from their map. In order to populate the social science sample, we selected the JCR subject categories in the social sciences with the highest number of journals and aggregated them into 6 macro-disciplines using domain knowledge. The resulting sample contains 1018 journals, classified into 18 subject categories, factored into 6 macro-disciplines forming the discipline pole of social science as follows:

- psychology: psychology, applied; psychology, biological; psychology, clinical; psychology, developmental; psychology, educational; psychology, experimental; psychology, mathematical; psychology, multidisciplinary; psychology, psychoanalysis; psychology, social;
- economics: economics; management; business; business, finance;
- education: education & educational research;
- law: law;
- political science: political science;
- sociology: sociology.

2.2. A comparison between popularity and prestige

In this section we perform the analysis of the association between the bibliometric notions of popularity, as measured by the 5-year impact factor (IF5, for short) and prestige, as captured by the Eigenfactor metric (EF, for short) in science and social science. Table 1 compares the top 10 popularity and prestige compilations in science: only 3 journals are represented in both lists, namely The New England Journal of Medicine, Science, and Nature. As found by Bollen et al. (2006a), the most popular journals belong to the medical pole. Moreover, review journals are heavily represented in the top 10 IF5 listing, confirming the characterization of IF5 as a popularity-oriented metric. On the other hand, many of the top-ranked journals with respect to EF are generally considered highly prestigious. We found that the overlap between the top 10 rankings according to EF and journal PageRank metric as defined in Bollen et al. (2006b) (which excludes journal self-citations) is of 10 over 10 journals, while the overlap with the listing according to journal PageRank metric as defined in Bollen et al. (2006a) (which includes journal self-citations) is of 8 over 10 journals.

Furthermore, Fig. 1 is a rank plot and Fig. 2 is a rank change histogram comparing popularity and prestige compilations. In the 3499 science journals we have analyzed, the median change of rank between the two compilations amounts at 371 positions (10.6% of the compilation length), the mean rank change is 495 positions, and the maximum rank shift is 3280 positions. We have that 75 journals (2.1%) show an impressive rank shift greater than one half of the compilation length, while 590 journals (16.9%) have a rank change greater than one quarter of the compilation length. The Spearman rank-based correlation between the two bibliometric measures is 0.78, while Kendall rank-based correlation is 0.59; the p-value is less than 0.001 in both cases.

We analyzed journals having strongly diverging ranks for popularity and prestige. Two kinds of discrepancies were investigated:

- journals with high popularity and low prestige; these journals have a high citation rate, but they receive their endorsements by journals with low prestige;
- journals with high prestige and low popularity; these journals receive relatively few citations compared to the number of articles they publish, but their citations come from highly prestigious journals.

Table 2 shows the most significative examples of journals with diverging ranks for the two metrics. For instance, Advances in Nuclear Physics is 97th in the popularity ranking and only 3377th in the prestige compilation. On the other hand, Journal

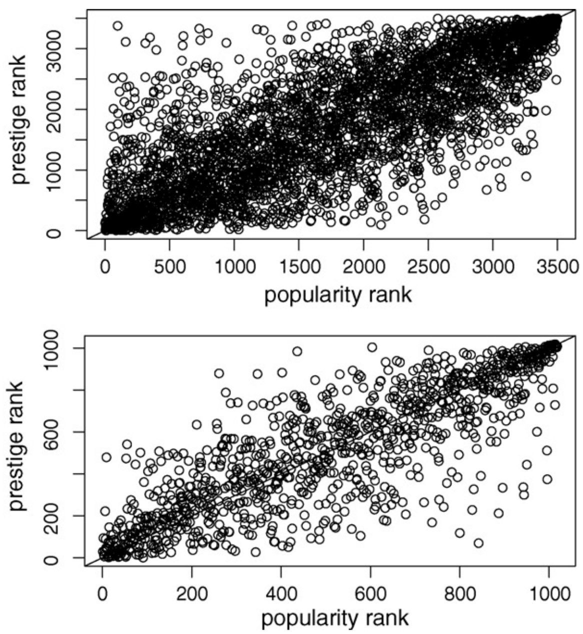

Fig. 1. Popularity vs. prestige rank plot for science journals (top) and social science journals (bottom). Journals are sorted in decreasing order with respect to popularity and prestige and the rank of journals in the popularity compilation is plotted against the rank of journals in the prestige compilation. The straight line is the bisector. The top-left part of the plot contains journals of high popularity and low prestige, whereas the bottom-right zone allocates journals of high reputation and low popularity.

De Physique IV is 3259th in the popularity ranking but ranks 893rd in the prestige compilation. However, we noticed that popular journals contained in the table are characterized by a low number of items published in the 5-year publication window: on average, these journals published 3.36 articles per year during the publication window. On the other hand, prestigious journals shown in the table, which are well represented by physics journals, published a significant number of

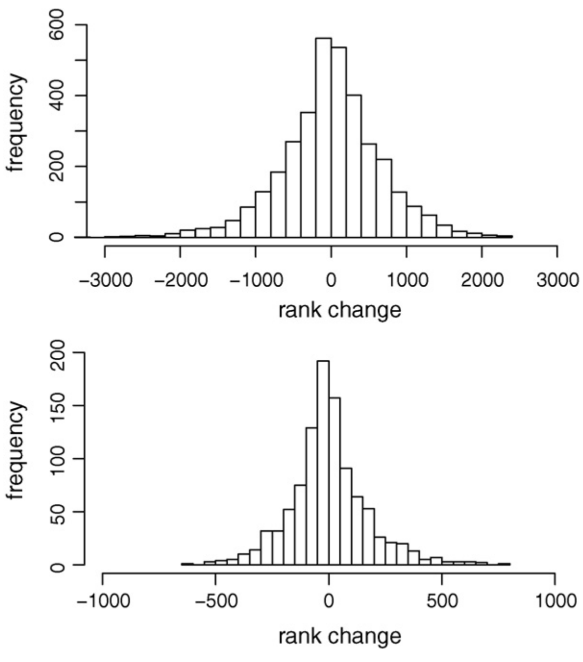

Fig. 2. Popularity vs. prestige change of rank histogram for science journals (top) and social science journals (bottom). The rank change is the rank in popularity minus the rank in prestige. Both histograms resemble a normal curve centered in 0. The curve for science has a longer left tail (skewness is −0.25); 49% of the rank changes are negative and 51% of them are positive (only two journals do not change their ranks). On the other hand, the curve for social science shows a longer right tail (skewness is 0.46); 54% of the rank changes are negative and 46% of them are positive (all journals change their ranks).

Table 2
Science journals with the highest diverging ranks between popularity and prestige. Popular journals have low ranks in the popularity compilation (that is, high popularity) and high ranks in the prestige compilation (that is, low prestige), and vice versa for prestigious journals; Δ is the journal rank shift between popularity and prestige compilations.

Popular journals		Prestigious journals	
Journal	Δ	Journal	Δ
Adv Nucl Phys	−3280	J Phys IV	2366
Nano Today	−2951	Acta Crystallogr E	2343
Prog Histochem Cyto	−2838	Electron Lett	2286
Adv Appl Mech	−2779	Microw Opt Techn Let	2280
Systems Biol	−2602	Int J Mod Phys B	2193
Adv Geophys	−2602	Transpl P	2134
Wildlife Monogr	−2583	Physica C	2106
Plasmonics	−2459	Physica E	2065
J Environ Sci Heal C	−2452	Jpn J Appl Phys	2038
Adv Catal	−2450	Theor Comput Sci	2028

Table 3
Science journals with the highest diverging ranks between popularity and prestige, where prestige is measured as the mean Eigenfactor score per published article.

Popular journals		Prestigious journals	
Journal	Δ	Journal	Δ
Fluoride	−1307	Comb Probab Comput	1799
J Microbiol Biotechn	−1291	Brit J Math Stat Psy	1690
Chinese Phys	−1238	Design Code Cryptogr	1653
Z Psychosom Med Psyc	−1167	J Time Ser Anal	1599
Acta Phys Sin-ch Ed	−1155	J Math Econ	1556
Contact Dermatitis	−1124	Corros Rev	1510
Arch Bronconeumol	−1081	Math Financ	1445
J Dairy Sci	−1060	Psychometrika	1382
Anal Quant Cytol	−1058	Financ Stoch	1365
Cereal Res Commun	−1048	Discrete Comput Geom	1354

papers during the publication window (on average, 1050 papers per year). In order to correct for the factor represented by the number of published papers, we normalized the Eigenfactor scores by the number of items published in the 5-year publication windows, and then we identified journals having strongly diverging ranks for popularity and prestige (as defined by the average Eigenfactor per article). The resulting compilations are shown in Table 3. Interestingly, the updated prestige compilation is dominated by highly esteemed interdisciplinary mathematics and theoretical computer science journals.

As to social science journals, the top 10 popular journals and the top 10 prestigious ones are listed in Table 4. The popularity compilation is dominated by psychology journals (9 over 10), with review publication sources well represented. In the prestige listing we find a number of well respected journals in economics and finance. Only one journal, Trends in Cognitive Sciences, is present in both rankings.

The rank plot and the rank change histogram for the metrics of popularity and prestige are contained in Figs. 1 and 2, respectively. With respect to the 1018 journals we have analyzed, the median rank shift between the two compilations is 82.5 positions (8.1% of the compilation size), the average rank change is 123.6, and the maximum change amounts to 772 positions. We found 14 journals (1.4%) shifting greater than one half of the compilation length, and 145 journals (14.2%) show a rank change greater than one quarter of the compilation length. The Spearman rank-based correlation between the two bibliometric measures is 0.83, while Kendall rank-based correlation is 0.65; the p-value is less than

Table 4
Rankings of top 10 social science journals according to popularity and prestige.

Popularity		Prestige	
IF5	Journal	Journal	EF
17.263	Annu Rev Psychol	Am Econ Rev	0.09701
16.391	Behav Brain Sci	J Pers Soc Psychol	0.05924
15.230	Psychol Bull	J Financ	0.05899
12.421	Trends Cogn Sci	Econometrica	0.05413
10.607	Psychol Rev	Q J Econ	0.05227
10.129	Adv Exp Soc Psychol	Trends Cogn Sci	0.05120
9.257	MIS Quart	J Clin Psychiat	0.04909
8.978	Psychol Methods	J Polit Econ	0.04803
8.348	Monogr Soc Res Child	Psychol Sci	0.04545
8.338	Am Psychol	J Cognitive Neurosci	0.04457

Table 5
Social science journals with the highest diverging ranks between popularity and prestige. Popular journals have low ranks in the popularity compilation (that is, high popularity) and high ranks in the prestige compilation (that is, low prestige), and vice versa for prestigious journals; Δ is the journal rank shift between popularity and prestige compilations.

Popular journals		Prestigious journals	
Journal	Δ	Journal	Δ
NEBR Sym Motiv	−618	Econ Lett	772
Appl Prev Psychol	−548	Econ Theor	682
Q J Polit Sci	−530	Psychol Rep	675
Int J Manag Rev	−512	Nation	644
Annu Rev Clin Psycho	−486	Fortune	622
Z Psychosom Med Psyc	−481	Educ Leadership	605
Monogr Soc Res Child	−470	Percept Motor Skill	600
Supreme Court Rev	−450	Appl Econ	570
Learn Individ Differ	−438	Appl Econ Lett	562
J Nonverbal Behav	−424	Wash Quart	521

Table 6
Social science journals with the highest diverging ranks between popularity and prestige, where prestige is measured as the mean Eigenfactor score per published article.

Popular journals		Prestigious journals	
Journal	Δ	Journal	Δ
Z Psychosom Med Psyc	−458	Econ Theor	439
Z Psychiatr Psych Ps	−360	Rev Econ Dynam	420
Psychother Psych Med	−357	Wash Quart	399
Cyberpsychol Behav	−327	Survival	382
Appl Psychophys Biof	−324	J Polit Philos	380
Int J Clin Exp Hyp	−293	Brit J Math Stat Psy	378
Sport Psychol	−292	J Math Econ	375
J Appl Res Intellect	−276	Econ Inq	369
Z Arb Organ	−276	Comp Polit	367
Manage Learn	−273	Scand J Econ	365

0.001 in both cases. Hence, the association between popularity and prestige is slightly stronger in social science than it is in science.

Table 5 lists the most significant examples of journals with highly diverging ranks in popularity and prestige compilations. For instance, Nebraska Symposium on Motivation is 261st in popularity and only 879th in prestige. By contrast, Economics Letters ranks 70th in prestige and only 842nd in popularity. Again, popular journals published much less papers than prestigious ones during the publication window; as an example, Quarterly Journal of Political Science published only 11 papers (all in 2006), while Fortune published 1593 papers. Notice that journals in economics and business are well represented in the compilation of prestigious journals shown in the table (5 over 10). As done for science, we computed the highly diverging journals in popularity and prestige, where prestige has been re-defined as the mean Eigenfactor score per published article. The resulting listings are contained in Table 6. Economics journal are still well represented in the prestige ranking, but there are also two new entries represented by interdisciplinary mathematics journals.

Finally, we analyzed the intra-discipline association between popularity and prestige (Table 7). The association strength, as measured by the Spearman rank-based correlation, differs across disciplines and runs from a minimum of 0.597 for physics to a maximum of 0.860 for law. With respect to the discipline poles isolated by Leydesdorff and Rafols (2009), we have that popularity and prestige mostly differ in the hard science pole comprising physics, engineering, material sciences, and computer sciences (average correlation is 0.682). The two concepts are more intertwined in the geoscience pole, formed by geosciences, ecology, environmental sciences, and agriculture (average correlation is 0.796), as well as in the biology-medicine pole, containing biomedical sciences, general medicine and health, clinical medicine, infectious diseases, and neurosciences (average correlation is 0.776). The association strength of the two measures for chemistry (0.738) is between that of the three main poles in science. Finally, the social science pole, comprising economics, education, law, political science, psychology, and sociology, has an average correlation of 0.785, comparable to that of the biology-medicine and geoscience poles.

3. Related work

Bollen et al. (2006a) compare journal PageRank with 2-year impact factor on 2003 science edition JCR dataset. They find that the top 10 rankings in the two metrics diverge significantly, with only 3 journals, Nature, Science, and The New England Journal of Medicine, being represented in both lists. They note that journals that are likely to publish background material (like review journals) are among the sources with the highest impact factor, while journals typically appreciated by domain experts have high journal PageRank, confirming the characterization of the former indicator as a popularity-oriented metric

Table 7
The table lists, in increasing order, the Spearman rank-based correlation (ρ) between popularity and prestige compilations for journals inside disciplines.

Discipline	ρ
Physics	0.597
Computer sciences	0.684
Education & educational research	0.692
Material sciences	0.709
Economics management business	0.722
Engineering	0.737
Political science	0.738
Environmental sciences	0.738
Chemistry	0.740
General medicine & health	0.748
Geosciences	0.762
Biomedical sciences	0.778
Neurosciences	0.784
Infectious diseases	0.784
Clinical medicine	0.798
Ecology	0.831
Psychology	0.841
Agriculture	0.844
Sociology	0.855
Law	0.860

and of the latter as a prestige-oriented measure. The Spearman rank correlation between the whole rankings is 0.61, while that for physics, computer science, and medicine is 0.59, 0.63, and 0.77, respectively. These results are generally confirmed by our findings. Our contribution is inspired and is parallel to that of Bollen et al. (2006a) but has a broader scope in the following sense:

- we use popularity and prestige indicators that cover a target publication period of 5 years instead of 2 years. This allows a more fair evaluation, in particular for those disciplines in which the citation flow is slow;
- our analysis covers 14 macro-disciplines in the sciences and 6 macro-disciplines in the social sciences, whereas Bollen et al. consider only science journals and highlight results only for 3 macro-disciplines (physics, computer science, and medicine);
- we use the classification method proposed by Leydesdorff and Rafols (2009), which exploits factor analysis on the category citation matrix, in order to assign journals to macro-disciplines. Bollen et al., by contrast, use a less involved syntactic method (the author themselves realize that their classification is only an approximation and refer to an earlier work of Leydesdorff for a more quantitative classification method, see footnote 1 in Bollen et al. (2006a)).

The results we obtained for medicine confirm also those found by Davis (2008), where the rankings according to Eigenfactor and 2-year impact factor methods are contrasted for 165 journals from the category medicine (general and internal). The author finds a significant correlation between the two measures (Spearman 0.84), and an even higher association (Spearman 0.95) between Eigenfactor and the total number of citations. The author concludes that, for medical journals, the concepts of popularity and prestige appear to provide very similar information.

Two papers recently apply the PageRank algorithm to find the influence of scientific papers instead of that of scientific journals. Chen, Xie, Maslov, and Redner (2007) analyze all publications in the Physical Review family of journals from 1863 to 2003. Although they measure a significant Spearman correlation of 0.91 between the PageRank and the total number of citations rankings, the authors also find a number of papers with a modest number of citations that stand out as exceptional according to the PageRank ranking; interestingly, these *scientific gems* are familiar to almost all physicists because of their very influential contents. Ma, Guan, and Zhao (2008) analyze papers published in period 2000–2005 in the field of molecular chemistry and molecular biology that are included in Web of Science and find a high correlation (Spearman 0.98) between PageRank and total number of citations.

The SCImago journal rank indicator is another index that implements the PageRank algorithmic schema (SCImago, 2007). It has been developed by the SCImago group at the University of Granada in collaboration with Elsevier and it is based on data from Elsevier's Scopus citation database. Falagas, Kouranos, and Karageorgopoulos (2008) retrieve the top 100 journals according to impact factor from JCR 2006 and compare the impact factor journal ranks with the SCImago journal ranks computed on Scopus; they find a median absolute change of rank of 32 positions. Conversely, regarding the top 100 journals according to the SCImago journal rank indicator, the median absolute change of rank with respect to the use of impact factor is 29. Furthermore, López-Illescas, de Moya-Anegn, and Moed (2008) contrast Web of Science impact factor with SCImago journal rank and find a Spearman correlation of 0.69 for the journals indexed by both data sources in 2006 in all fields of science, and a higher correlation of 0.93 for oncological journals. Interestingly, the coefficient for science journals is similar to the one obtained by Bollen et al. (2006a) using the journal PageRank instead of SCImago journal rank.

A couple of papers perform a factor analysis with the aim of clustering different scientific impact measures including impact factor, journal PageRank, and SCImago journal rank. Bollen, de Sompel, Hagberg, and Chute (2009) include in the study both bibliometric and social network centrality indexes computed on both citation and usage networks. The usage network is constructed from usage log data available at web portals of scientific publishers and institutional library services. They cluster impact factor and SCImago journal rank together, while journal PageRank is aggregated with betweeness centrality measures. They claim that usage-based measures are actually stronger indicators of scientific prestige than many presently available citation measures, e.g., impact factor and SCImago journal rank, which appear to express popularity instead. The study of Leydesdorff (2009) comprises different citation indicators as well as social network centrality measures. Impact factor and SCImago journal rank are placed in the same factor, while journal PageRank is surrounded by social network measures (in particular betweeness centrality). These results confirm the above mentioned analysis of Bollen et al. (2009). Both studies seem to indicate that SCImago journal rank is a journal impact indicator quite similar to the impact factor, while journal PageRank has important interactions with social network centrality measures.

4. Conclusion

We have measured the difference between the bibliometric concepts of popularity and prestige across disciplines, as captured by the impact factor and the Eigenfactor, respectively. We found that, although the two bibliometric measures are generally statistically correlated, they also significantly diverge in some cases, in particular for the hard sciences. The investigation reveals that journals can be classified in four categories according to the two bibliometric metrics of popularity and prestige:

1. journals that are both popular and prestigious; they are highly cited and receive their citations from prestigious journals;
2. journals that are neither popular nor prestigious; they are poorly cited and the few endorsements they receive are from obscure journals;
3. journals that are popular but not prestigious; these journals have a high citation rate per article, but they receive their endorsements by journals with low prestige. These journals are not necessarily highly cited;
4. journals that are prestigious but not popular; these journals receive relatively few citations compared to the number of articles they publish, but their citations come from highly esteemed journals. These journals are not necessarily poorly cited.

Whereas there is no much discussion about the quality of journals in the first two categories, the status of journals in the third and fourth categories is more controversial. For these journals, the Eigenfactor metric, as well as its average per article, can be useful yardsticks to evaluate and compare the overall importance of science and social science journals.

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