

Journal acceptance rates: A cross-disciplinary analysis of variability and relationships with journal measures

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Abstract

There are many indicators of journal quality and prestige. Although acceptance rates are discussed anecdotally, there has been little systematic exploration of the relationship between acceptance rates and other journal measures. This study examines the variability of acceptance rates for a set of 5,094 journals in five disciplines and the relationship between acceptance rates and JCR measures for 1,301 journals. The results show statistically significant differences in acceptance rates by discipline, country affiliation of the editor, and number of reviewers per article. Negative correlations are found between acceptance rates and citation-based indicators. Positive correlations are found with journal age. These relationships are most pronounced in the most selective journals and vary by discipline. Open access journals were found to have statistically significantly higher acceptance rates than non-open access journals. Implications in light of changes in the scholarly communication system are discussed.

Highlights

- Acceptance rates vary statistically significantly by discipline of journal, country affiliation of the editor, and number of reviewers per article.
- There is a negative relationship between acceptance rates and citation-based indicators.
- There is a positive relationship between acceptance rates and journal age.
- Open access journals have significantly higher mean acceptance rates than non-open access journals.

Keywords

Acceptance rates, open access, journal measures, citation analysis, scientometrics, scholarly communication

1. Introduction¹

The scholarly publication system operates on the basis of exchange. As in any market, there are suppliers (authors) and buyers² (journals) of goods (papers). In this exchange, authors are

¹ This article is an expansion of Sugimoto, Larivière, and Cronin's (2013) short conference paper for the 14th International Society for Scientometrics and Informetrics conference in Vienna. It has been substantially updated and expanded.

seeking journals with the highest impact in order to increase their stock of symbolic capital (Bourdieu, 1984), while journals attempt to capture papers that will increase their prestige. As a general rule, the best authors want to publish in the best journals, and the best journals want the best authors (those with the potentially best papers) to publish with them. In a perfect (i.e., optimally efficient) market, the best papers would gravitate to the best journals (Oster, 1980). But in this as so many other markets both suppliers and buyers lack perfect information. Absent perfect information, the various actors involved rely upon a range of indicators (bibliometric, sociometric, demographic) and tacit knowledge to guide decision-making. One such indicator is acceptance rate, the proportion of papers submitted to a journal that are subsequently accepted and published.

Space at the upper end of the market is highly sought after and in limited supply. Competition and ambition often drive scholars to submit papers to journals beyond their reach, creating a cascade of rejected papers that puts added pressure on reviewers and editors (Cronin & McKenzie, 1992; Kravitz & Baker, 2011; Craig, 2010). Economic models have been proposed to analyze, *inter alia*, research spillover effects, duality in scientific discovery and congestion in information processing (Besancenot, Huynh, & Vranceanu, 2009, p. 1). Such models highlight the “informational frictions” that occur when papers are being matched with journals (Besancenot, Huynh, & Vranceanu, 2009, p. 2).

Peer review is the established mechanism for allocating space to papers within a journal. Experts (editors, editorial board members and external reviewers) assess the quality of submitted papers and evaluate their suitability for publication. It is assumed that editors and reviewers are unbiased in their assessments and that the governing norm of impartiality is not violated, at least not egregiously (Lee, Sugimoto, Zhang & Cronin, 2013; Sugimoto & Cronin, 2013). In reality, it is not quite so straightforward, as variations in consensus as to what constitutes quality, broadly conceived, within and across fields, can have an effect on acceptance rates (Hargens, 1988; Kravitz, Franks, Feldman, Gerrity, Byrne & Tierney, 2010).

Variation in journal acceptance rates is an understudied area, not the least because of the difficulty in obtaining reliable data. One of the most comprehensive (and earliest) studies to date examined the rejection rates of 83 journals across a broad spectrum of disciplinary areas and found that humanities and social science journals have the highest and the biological sciences the lowest rates of rejection (Zuckerman & Merton, 1971, p. 77): “the more humanistically oriented the journal, the higher the rate of rejecting manuscripts for publication; the more experimentally oriented, with an emphasis on rigour of observation and analysis, the lower the rate of rejection.” Subsequent monodisciplinary studies have confirmed these findings (e.g., Cherkashin, Demidova, Imai, & Krishna, 2009; Seaton, 1975; Vlachy, 1981; Rotton, Levitt, & Foos, 1993; Schultz, 2010). One explanation for this is the degree to which a dominant paradigm exists in any given discipline, providing a consensus as to what constitutes valid research (Kuhn, 1970).

It has been noted that there exists little guidance for calculating acceptance rates (Moore & Perry, 2012). At face value, the calculation may seem simple enough—the number of papers accepted over the total number of papers submitted. However, this is complicated by the unreliability of self-report data, inconsistent definitions of a resubmission, the inclusion/exclusion of invited papers or special issues in the calculations, the timeframe used, and the inclusion/exclusion of book reviews, among other considerations (Moore & Perry, 2012). Additionally, many studies rely on individual surveys of editors/publishers, rather than using a standard source for evaluation. Cabell’s Directories of Publishing Opportunities

² Buyers is used here in a generic sense. We are aware that with the advent of Gold Open Access and author processing charges that authors and/or funders are now, in some instances, strictly speaking the buyers of journal space.

(Cabell's henceforth) is one such source, but has been used only rarely in empirical studies (e.g., Haensly, Hodges, & Davenport, 2008).

Acceptance rates ostensibly testify to the relative competitiveness of a journal and have been used as a quality indicator. Statistically significant negative correlations between acceptance rates and other proxies of quality (i.e., citation rates, Journal Impact Factor [JIF]) have been demonstrated (Lee, Schotland, Bacchetti, & Bero, 2002; Buffardi & Nichols, 1981; Haensly, Hodges, & Davenport, 2008). Rotton, Levitt, and Foos (1993) found that rejection rates were good predictors of citations, while Haensly, Hodges, and Davenport (2008) found acceptance rates to be statistically significantly correlated with both citations and survey-based rankings of journals. However, and with few exceptions, these have relied on small scale and monodisciplinary datasets and are somewhat dated.

More comprehensive studies are necessary to elucidate the relationship between acceptance rates and other indicators. The results of such studies can be used to assess the utility of journal acceptance rates and the degree to which these can be considered appropriate proxies for quality. To this end, the present paper provides the largest study of acceptance rates to date and investigates the following research questions and associated hypotheses:

1. What is the degree of variability in acceptance rates?
 - H1. Statistically significant differences in acceptance rates will be observable by discipline.
 - H2. Statistically significant differences in acceptance rates will be observable by country of editor's location.
 - H3. Statistically significant differences in acceptance rates will be observable by number of external reviewers.
 - H4. Statistically significant differences in acceptance rates will be observable between JCR and non-JCR journals.
2. What is the relationship between acceptance rates and JCR measures?
 - H5. Statistically significant negative correlations will be observable between acceptance rates and citation-based JCR measures.
 - H6. Statistically significant positive correlations will be observable between acceptance rates and size-based JCR measures (e.g., number of publications).
3. What is the relationship between acceptance rates and age of journal?
 - H7. Statistically significant negative relationships will be observable between acceptance rates and age of journal.
4. What is the relationship between acceptance rates and the open access status of journals?
 - H8. Open access journals will have statistically significantly higher acceptance rates.

The results of this analysis will inform scientometricians, policy makers, and scholars who employ these metrics to make decisions about where to publish and the relative quality of venues.

2. Materials and methods

2.1 Data. We used four main sources of data: Cabell's, Thomson Reuters' Journal Citation Reports (JCR) for both Science and Social Sciences, Ulrich's Periodicals Directory (Ulrich's), and the Directory of Open Access Journals.

Cabell's provides general descriptive information about journals (Cabell's Directories, 2013). It indexes journals in eleven specialties organized into five disciplines (Table 1); a journal can be assigned to multiple specialties. New journals can be recommended to the directory by emailing a form to Cabell's. Journal information is obtained by contacting editors and/or publishers, but is not independently verified.

Basic metadata for all the journals by specialty were downloaded from Cabell's in October to November of 2012. These included the journal name, type of peer review employed, number of external reviewers, acceptance rate, journal website, whether or not the journal was indexed in the JCR and/or ERIC, whether the journal charged fees, the editor's country of affiliation, and when the journal was last updated in Cabell's. In total, 7,015 records were downloaded for all specialties; these represented 5,094 unique journals, since some journals, as noted, appear in multiple specialties or multiple disciplines. More than one quarter ($n=1,301$) of unique journals were indexed in the JCR (Table 1).

Table 1. Number of unique journals and percentage indexed in the JCR by discipline

Discipline	Specialty	# of unique journals	# of unique journals in JCR	% of journals in JCR
Business	Accounting	464	30	6.5%
	Management	1,652	268	16.2%
	Marketing	217	23	10.6%
	Economics and Finance	1,221	269	22.0%
	Subtotal	2,630	527	20.0%
Computer Science	<i>Computer Science and Business Information Systems</i>	771	141	18.3%
Education	Educational Technology and Library Science	295	32	10.8%
	Educational Curriculum and Methods	626	103	16.5%
	Educational Psychology and Administration	519	105	20.2%
	Subtotal	1,215	220	18.1%
Health	Nursing	235	64	27.2%
	Health Administration	236	69	29.2%
	Subtotal	351	107	30.5%
Psychology	Psychology and Psychiatry	779	459	58.9%
TOTAL		5,094	1,301	25.5%

The 2011 data for both the Science and Social Sciences JCR were downloaded from Thomson Reuters (variables collected are shown in Table 2). However, all of these data were associated with the abbreviated name of the journal. A conversion table and title matching were used to reconcile the Cabell's and JCR data. The JCR data were located for 1,301 unique journals. This number is lower than the number of journals listed by Cabell's as appearing in the JRC. Journals could not be matched for several reasons: 1) incomplete information was provided in Cabell's (e.g., the title did not include the subtitle, so could not be distinguished from other journals with the same initial title); 2) no such journal could be found in the JCR (due either to an erroneous assumption on the part of the editor or because the journal had ceased to appear in the JCR since the time the editor was surveyed); and 3) the journal was indexed in the Arts & Humanities index of Web of Science for which Journal Impact Factors are not calculated.

Journal start dates were gathered from Ulrich's using the "Start Year" field in the database. In the case of journal name changes, the start date of the initial journal was used, not the date at which the journal became associated with the current name.

Journals from the entire Cabell's list were matched against the list of nearly 10,000 journals provided by the Directory of Open Access Journals (DOAJ)³ using ISSN and the full journal title if the ISSN was unavailable. This yielded a set of 369 journals.

2.2 Analysis. Cabell's provided acceptance rates in various forms. While some editors provided an exact figure (e.g., 17%) others provided a range (e.g., 10-15%). Of the 5,094

³ www.doaj.org

unique journals in Cabell's, 3,612 (71%) provided an exact figure, 1,188 (23%) provided a range, and 294 (6%) did not provide any information on acceptance rate. Therefore, prior to analysis, this field was expanded to three measures: minimum, median, and maximum. A sensitivity analysis was performed to ensure that different results would not be achieved using just one of these three. Table 2 (in Results section) displays the correlations between journal measures and acceptance rates for the 1,301 unique journals found in the JCR and Cabell's (using Pearson correlation analysis). As shown, there are no statistically significant differences in the results using minimum, median, or maximum acceptance rates. We used the median rate in subsequent analyses.

Analyses were conducted in three stages: the first analysis was applied to all 5,094 journals indexed in Cabell's; the second set of analyses was conducted using only those 1,301 journals appearing both in the JCR and Cabell's; the third analysis applied only to those identified as open access journals.

Box-and-whisker plots are used to demonstrate the varying acceptance rates by discipline, country of editor, and number of reviewers⁴. This is a convenient way of graphically displaying the quartile data for each category, particularly for data that are non-parametric as it demonstrates the skewness for each variable. The "top" and "bottom" of the box represent the 75th and 25th percentiles of the data, respectively (i.e., lower and upper quartiles). The dark line in the middle of the box represents the median, or the 50th percentile. Whiskers are calculated at $Q3 + 1.5IQR$ and $Q1 - 1.5IQR$, where $Q3$ is the 75th quartile, $Q1$ is the 25th quartile, and IQR (Inner Quartile Range) is the distance between $Q3$ and $Q1$.

An ANOVA was conducted to determine whether the differences observed by discipline, location of editor, and number of reviewers per article was statistically significant. Post-hoc analyses (using Bonferroni corrections) were conducted. Pearson correlation analyses were conducted to examine the relationship between the JCR and Cabell's data. A t-test (two-sample assuming equal variances) was conducted to analyze the difference in mean acceptance rates between open access and non-open access journals.

2.3 Limitations. The major limitation of the study is our inability to accurately assess the validity of the Cabell's data. These data are provided by editors via a survey and not subject to any assessment, nor is a standard calculation for acceptance rate provided. This is most evident by the fact that only 71% of editors supplied an exact figure, while the rest provided a range. As a survey, this is also a convenience sample, relying on the interest of editors. This leads to incomplete discipline coverage and possible self-selection biases. However, this remains the largest compilation of available acceptance rates to-date and therefore was chosen for analysis. We strongly encourage publishers and other corporations who have access to such data to make them more readily available to the scientific community.

3. Results

The results are split into three sections. The first section describes and analyzes all journals indexed by Cabell's, using the fields available from this source. The second section describes and analyzes only those journals found in both Cabell's and the JCR and also incorporates journal age information from Ulrich's. The final section analyzes the difference in acceptance rates between open access and non-open access journals.

3.1 Cabell's journals. Figure 1 demonstrates the variation in acceptance rates by discipline for all journals listed in Cabell's, with health disciplines having much higher acceptance rates

⁴ Not all editors supplied all of this information; therefore, each figure is constructed using those journals for which these data are available. This explains the discrepancy between the total number of journals in each figure and the number indexed by Cabell's.

than the other disciplinary areas. This reinforces earlier findings which noted a correlation between the empiricism of a field and rates of acceptance (e.g., Zuckerman & Merton, 1971). Business and Computer Science had the lowest median acceptance rates, although a higher number of outliers than the other disciplines. A post-hoc analysis revealed statistically significant differences between the acceptance rates of: a) Business and all other disciplines except Computer Science, b) Computer Science and Health and Psychology; c) Education and all disciplines except Computer Science; d) Health and all disciplines; and e) Psychology and all disciplines except Education.

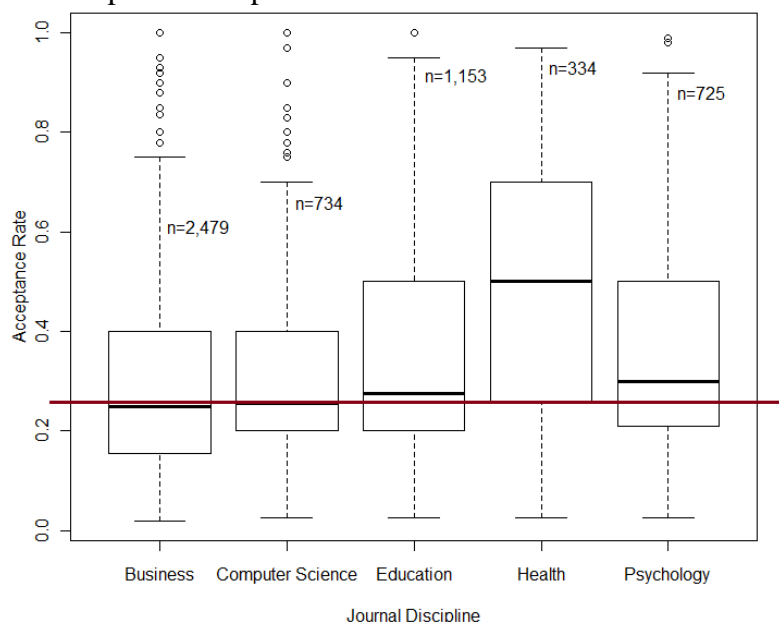


Figure 1. Acceptance rate of journals by discipline and median of all disciplines (redline)

There were statistically significant differences (at .01 significance level) in acceptance rates by the country affiliation of the editor ($p= 7.67\text{E-}30$), as shown Figure 2. North America accounts for more than half of all affiliations; thus, the median of the dataset reflects the North American median, which is lower than all other geographic areas. North American and European journals are also those most likely to be indexed in the JCR (Archambault et al., 2006)—another sign of prestige and of the uneven coverage of Thomson Reuters' databases.

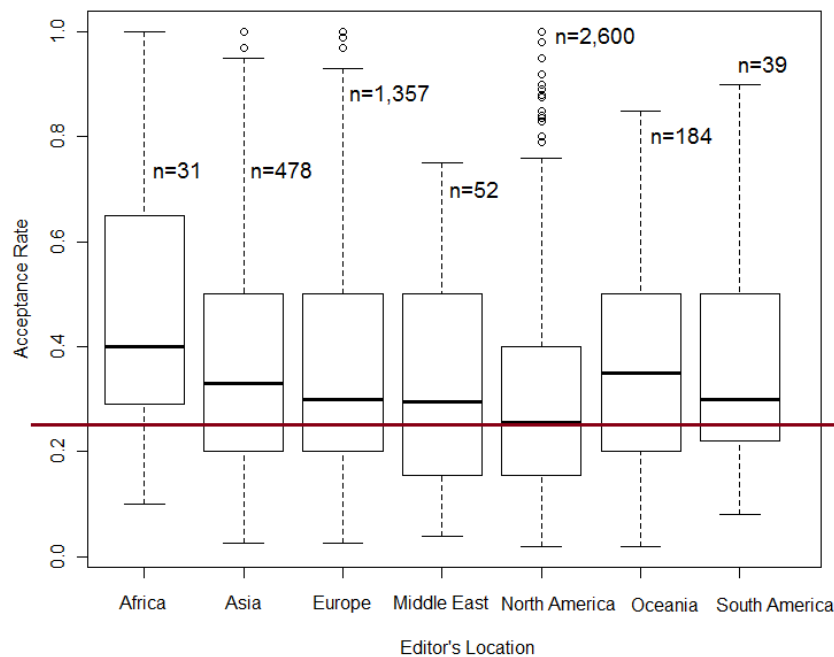


Figure 2. Acceptance rates of journals by editor's country affiliation and world median (red line)

A post-hoc analysis revealed that Africa, Asia, Europe, and Oceania were statistically significantly different from North America. Other statistically significant differences were found between the acceptance rates of Africa and the Middle East. For this analysis, all effects were statistically significant at the .05 significance level.

The majority of journals had two or three external reviewers per article (Figure 3). Our data showed that acceptance rates were lower for journals that employed three or more reviewers per submission and higher for those journals which used only one or two. Previous research has shown low degrees of consensus in peer review (Lee, Sugimoto, Zhang, & Cronin, 2012). The lack of consensus among reviewers may lead to rejections, thus reducing the acceptance rates in journals with high number of reviewers per paper. Alternatively, journals with more reviewers per paper may be considered more rigorous and thus be associated with lower acceptance rates.

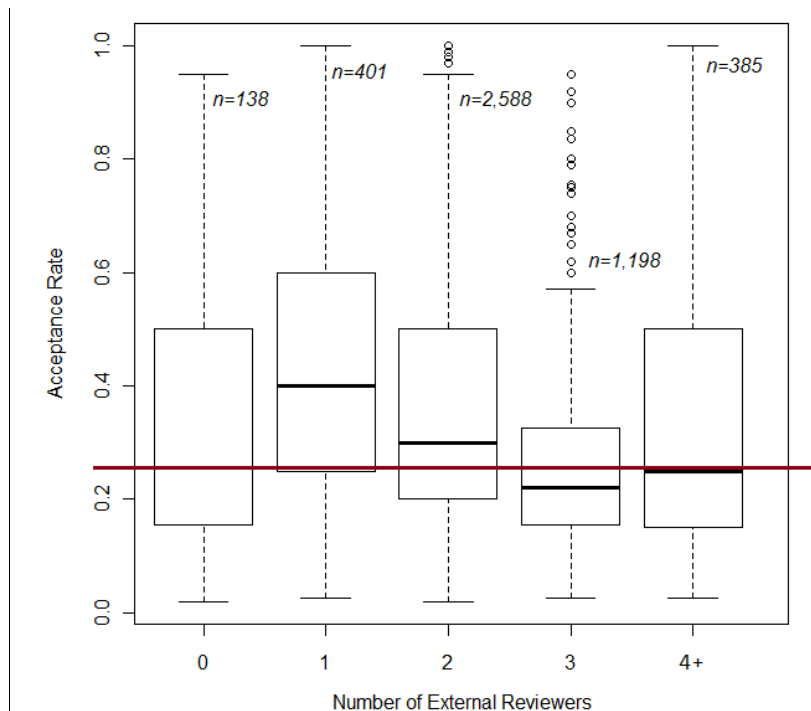


Figure 3. Acceptance rates of journals by number of external reviewers

A post-hoc analysis revealed differences in acceptance rates between: a) 0 reviewers and 3 reviewers; b) one reviewer and all other categories except zero reviewers; c) two reviews and one and three reviewers; d) three reviewers and all other categories; and e) four reviewers and one and three reviewers. Differences in acceptance rates by discipline, editor's location, and number of reviewers were all statistically significant at the .01 level⁵.

3.2 Cabell's and JCR journals. The first analyses examine whether there were differences in acceptance rates between those journals indexed in the JCR and those not indexed in the JCR by discipline. As shown in Figure 4, JCR journals had lower median acceptance rates in all disciplines⁶, with the most marked difference found in Health. Furthermore, the range of acceptance rates was more compressed in these journals—that is, the maximum was lower and the interquartile ranges were closer to the median. If one accepts the premise that JCR-indexed journals are of higher quality than non-JCR-indexed journals, then these results may suggest that lower acceptance rates are similarly a sign of higher quality in most disciplines. Computer Science is the one discipline with relatively little difference between the non-JCR and JCR median. This may be a result of the fact that some of the most prestigious venues for publication in Computer Science are conference proceedings (Lisée, Larivière and Archambault, 2008), rather than journal articles.

⁵ The results of the ANOVA were statistically significant at .01 level (p-values of 3.61E-52 (discipline), 7.67E-30 (editor's location), and 4.79E-40 (number of reviewers). The effect sizes for all the ANOVAs were small to medium: Eta square for discipline = 0.044461, editor's location = 0.03118, and number of reviewers = 0.039686.

⁶ Note that the *n* for each discipline is different from the *n*'s reported in Table 1 as journals without acceptance rates were removed.

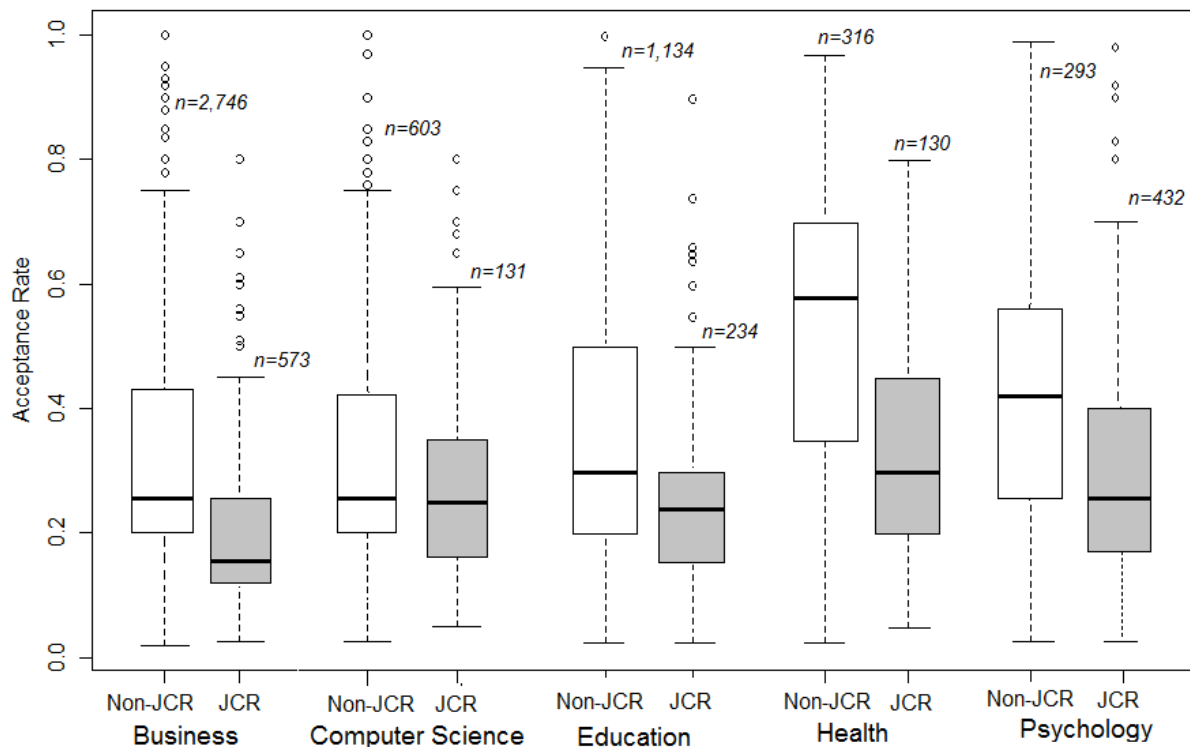


Figure 4. Acceptance rates of journals by discipline (JCR and non-JCR Indexed)

The relationships between journal measures provided by JCR and acceptance rates are shown in Table 2. As described in the Methods, the minimum, median, and maximum rates were calculated. However, finding no statistically significant difference in outcome based on these ($p > 0.05$), we selected the median for subsequent analyses.

Table 2. Correlations between journal measures and acceptance rates

	AcceptLow	AcceptMed	AcceptMax
2011TotalCites (n=1,242)	-0.035	-0.042	-0.048
ImpactFactor (n=1,238)	-.059*	-.062*	-.065*
5YearImpactFactor (n=1,029)	-.146**	-.150**	-.151**
ImmediacyIndex (n=1,153)	-.071*	-.069*	-.066*
2011Articles (n=1,238)	.126**	.128**	.128**
CitedHalfLife (n=877)	-0.055	-.062*	-.069*
EigenfactorScore (n=1,239)	-.229**	-.236**	-.239**
ArticleInfluenceScore (n=1,028)	-0.018	-0.025	-0.032
Longevity (n=1,232)	-0.035	-0.042	-0.048

*. Correlation is statistically significant at the 0.05 level (2-tailed)

**. Correlation is statistically significant at the 0.01 level (2-tailed)

Given Cohen's (1988) interpretation of correlations, the relationships shown in Table 2 can be considered weakly correlated.⁷ There was a negative relationship between acceptance rates and all citation-related metrics—that is, when the acceptance rate decreases, the citation rate tends to increase. There was a positive relationship between the number of articles and the acceptance rate—that is, acceptance increased as the number of articles in a given journal

⁷ Cohen (1988) suggests the following interpretation for correlations: 0.1 is associated with small or weak association, 0.3 is a moderate association, and 0.5 is a large or strong correlation. It should be noted that significance tests are dependent on sample size. Given the large size of our data, significant relationships are shown even in the cases of weakly correlated data.

increased. There was also a positive relationship between journals' age and acceptance rate—that is, younger journals tended to have higher acceptance rates. The strongest correlations were between acceptance rates and Eigenfactor score, which is likely a consequence of the fact that the Eigenfactor increases with journal size, as would the acceptance rate. There was no statistically significant relationship between acceptance rates and total cites, Article Influence Score, and journal longevity; Cited Half Life were not statistically significantly correlated with the low acceptance rate, and all the other relationships were statistically significant at either the .05 or .01 significance level.

In order to ensure that elite journals were not skewing the results, we divided the journals into quartiles by acceptance rate and analyzed each quartile. Table 3 shows that only a few of the pairs of variables are statistically significantly correlated. The first quartile contains those journals with the lowest acceptance rates; the fourth quartile those with the highest. The strongest relationships between the indicators and acceptance rates are in the first quartile, particularly in terms of citation-based indicators, suggesting that there is a relationship between highly selective journals (those with low acceptance rates) and high impact journals (those with high citation counts). However, the relationship is much more nuanced for less selective journals; as shown in Table 3, very few statistically significant relationships are found below the first quartile. Exceptions are the significance of the cited half-life and acceptance rates in the 3rd and 4th quartile.

Table 3. Correlation between journal factors and median acceptance rates

Variable	1 st quartile	2 nd quartile	3 rd quartile	4 th quartile
2011TotalCites	-.119*(275)	0.083(332)	0.037(303)	-0.078(304)
ImpactFactor	-0.076(275)	-0.022(332)	0.049(303)	-0.013(304)
5YearImpactFactor	-0.056(239)	-0.031(285)	0.087(253)	0.019(230)
ImmediacyIndex	-0.047(273)	-0.092(332)	-0.008(303)	-0.005(303)
2011Articles	-0.007(273)	0.072(332)	0.109(303)	0.012(303)
CitedHalfLife	-0.04(169)	-.229**(223)	-0.092(226)	-.226**(242)
EigenfactorScore	-.152*(275)	0.082(332)	0.075(303)	-0.073(304)
ArticleInfluenceScore	-.171**(239)	-0.11(285)	0.046(253)	-0.018(230)
StartYear	-.162**(275)	0.011(332)	-0.033(303)	-.180**(304)

*. Correlation is statistically significant at the 0.05 level (2-tailed)

**. Correlation is statistically significant at the 0.01 level (2-tailed)

The relationships between journal measures and acceptance rates were also analyzed by discipline (Table 4). Acceptance rates are statistically significantly and negatively correlated with the *article influence score* across all disciplines. The five-year IF is statistically significantly and negatively correlated with all disciplines, and the cited-half life is statistically significantly and negatively correlated with all disciplines except Computer Science, where it is a positive relationship—suggesting perhaps that for Computer Science rigor is associated with speed. The lack of a statistically significant relationship between acceptance rates and journal age in Computer Science demonstrates that older journals may not be as prestigious in this field as in others. The JIF is statistically significantly and negatively related to acceptance rates in Business, Health, and Computer Science, but not in Education or Psychology. While in the first case, this is likely a consequence of the very low Impact Factors values journals have in this discipline, in the second case, it might be due of the many specialties of psychology—combining social sciences, natural sciences and medical sciences—with each of them having its own hierarchy of journals and different citation practices.

Table 4. Relationships between journal factors and acceptance rates by discipline

Variable	Business	Computer	Education	Health	Psychology
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		Science			
2011TotalCites	-.145**(511)	-0.106(131)	-0.095(214)	-.316**(105)	-0.035(432)
ImpactFactor	-.267**(511)	-.307**(131)	-0.132(214)	-.418**(105)	-0.049(432)
5YearImpactFactor	-.279**(409)	-.407**(108)	-.159*(186)	-.453**(78)	-0.076(389)
ImmediacyIndex	-.224**(510)	-0.155(130)	-0.046(213)	-.200*(105)	-.099*(431)
2011Articles	0.067(510)	0.019(130)	.181**(213)	-0.07(105)	.166**(431)
CitedHalfLife	-.167**(331)	0.043(103)	-.284**(145)	-.252*(95)	-.326**(302)
EigenfactorScore	-.175**(511)	-0.109(131)	-0.108(214)	-.305**(105)	0.002(432)
ArticleInfluenceScore	-.288**(409)	-.406**(108)	-.256**(186)	-.485**(78)	-.150**(389)
Longevity	-.117**(511)	0.008(131)	-.157*(214)	-.281**(105)	-.199**(432)

3.3 Open access journals. A t-test was conducted to examine the difference in acceptance rates between the 369 open access journals and the 4,465 non-open access journals in Cabell's. The result showed that open access journals had significantly higher acceptance rates than non-open access (statistically significant at the .01 level; Cohen's $d = 0.232$).

Table 5. Difference between acceptance rates between open access and non-open access journals by discipline.

Discipline	Mean Acceptance rate		Number of journals		p-value (one-tail)	Cohen's d
	OA	Non-OA	OA	Non-OA		
Business	0.384	0.304	191	2725	7.44494E-09	0.210
CS	0.418	0.308	98	636	6.44811E-08	0.394
Education	0.374	0.337	98	1058	0.036	0.106
Health	0.578	0.463	37	300	0.002	0.314
Psychology	0.512	0.348	29	696	1.67641E-06	0.348

T-tests by discipline demonstrate that open access journals in all disciplines have significantly higher acceptance rates at the .05 level (see Table 5 for detailed p -value). The differences between the acceptance rates of open access journals are most pronounced (per Cohen's d) in the cases of Computer Science, Psychology, and Health.

4. Discussion and Conclusion

The first research question related to variability. Examining more than 5,000 journals, statistically significant differences in acceptance rates were found by discipline, country affiliation of the editor, and number of reviewers. This variability suggests that acceptance rates, like many other scientometric indicators, are highly contextualized and should be used accordingly. Health journals had the highest acceptance rates—this may be a result of the particular specialties (i.e., Nursing and Administration) covered by Cabell's. Business journals had the lowest acceptance rates—this may reflect the competition for publication in the top journals in Business. Given the publicized stratification of journals and the coupling of tenure requirements for publishing in these venues (Dennis, Valacich, Fuller, & Schneider, 2006), it is to be expected that the elite journals will receive many more submissions than they can publish, resulting in lower acceptance rates.

The second and third research questions addressed the relationship between acceptance rates and other journal measures, particularly those provided by the JCR. The results indicate that older journals and those that attract more citations are also those which are more selective. These relationships are exaggerated when examining the journals with the most selective acceptance rates. This may reflect the reinforcement cycle of acceptance rates and indicators like the Impact Factor, with individuals continuing to submit to those with the highest impact factor, thereby reducing the acceptance rate, which, in turn, raises the profile of the journal

and enhances its likelihood of being cited. Recently, Bruce Alberts, editor in chief of *Science*, complained that the obsession with impact factors “wastes the time of scientists by overloading highly cited journals such as *Science* with inappropriate submissions from researchers who are desperate to gain points from their evaluators” (Basken, 2013, para. 12).

Most authors would like to see their work appear in a prestigious journal such as *Science* or *Nature*, but probabilistically that will occur only rarely, if ever. In all likelihood authors have an intuitive sense of how journals in their field stack up—if they don’t there is a growing number of discipline-specific rankings on which to rely (e.g., Harris, 2008)—in terms of reputation and quality and will take a path somewhere between idealism and pragmatism when it comes to submitting their papers, neither aiming too high (waste of time and effort) nor setting their sights too low (bad from a career advancement perspective and perhaps for one’s morale). In any case, rejected papers, which will likely have had some value added as a result of their being subjected to peer review, will eventually find a home elsewhere, albeit at a lower level in the overall journal pecking order (e.g., Bornmann, Weymuth, & Daniel, 2010; Sugimoto & Cronin, 2013; Cronin, 2012), though also, sometimes, in higher-end journals (Calcagno et al., 2012). Not everyone can publish in *Nature*; not everyone should try. Unrealistic expectations, when scaled up, translate into system inefficiencies and disequilibria, which is bad news all round.

In response to our fourth research question, we found that open access journals have higher acceptance rates than non-open access journals. The strength of this difference varied by discipline, being most pronounced in Computer Science, Health, and Psychology. As our data suggest, low acceptance rates are typically correlated with older journals, with limited output, and high citation receipt. Space is consistently mentioned in studies of acceptance rates (e.g., Zuckerman & Merton, 1971; Hargens, 1988). Our research finds a direct correlation between number of articles published per year and acceptance rates, confirming the relationship. However, this may be challenged recent developments in scholarly communication. PLoS ONE, for example, has an acceptance rate around 69%⁸, a high Impact Factor, and published 23,468 papers last year⁹. It is also relatively young. The established correlations may not hold in an age of rapidly growing publishing space.

The introduction of author processing charges is shifting the burden of payment from the consumer (individual or institutional) to the author (Solomon & Björk, 2012). Open access requires us, as Suber (2008) has observed, to think more closely about the relationship between journal *prestige* and journal *quality* in an evolving, mixed-mode publishing market, i.e., one combining toll access and open access journals. As a result of accelerating developments in OA and the rapid adoption of alternative metrics of scholarly influence and impact (e.g., Cronin & Sugimoto, in press) we are seeing an expansion of the indicator set that can be used to assess journal quality. Acceptance rates and Journal Impact Factor are now only two of the indicators available to authors to evaluate journal quality and inform their submission behavior (e.g., Lozano, Larivière & Gingras, 2012). Work has also been undertaken to explore the relationship between cost and prestige (eigenfactor.org, 2013), as well as other journal indicators (e.g., Ni, Shaw, Lind, & Ding, 2013). By the same token, journals can deploy a wider range of indicators to signal their ~~their~~ quality to prospective authors and readers. However, it is important that each of these measures be analyzed as to their utility and validity—do they provide new insight on the value of the product? Do they tell a fundamentally different story from previous indicators? With such analysis, the market will likely become more transparent.

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⁸ <http://www.plosone.org/static/information>

⁹ <http://blogs.plos.org/everyone/2013/01/03/2012review/>

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