Scientometrics (2018) 115:1087–1095
https://doi.org/10.1007/s11192-018-2707-9

Proposal of a stochastic model to determine the bibliometric variables influencing the quality of a journal: application to the field of Dentistry

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Received: 18 November 2017 / Published online: 9 March 2018

Abstract On the basis of the Impact Factor of Journal Citation Reports developed by ISI as a journal quality indicator, this paper puts forth an ordinal regression model to estimate the journal's position by terciles. The set of explanatory variables includes the *H-index* of its Editor-in-chief, percentage of papers published in the journal that received external funding, average number of papers published yearly, and two factors concerning the scope and structure of the journal. The proposed model was applied to the field of *Dentistry, Oral Surgery and Medicine*, and led us to the conclusion that the above mentioned covariables alone had a significant input in the model, but not the factors. The essay performed on a sample of 30 Dentistry journals included in JCR provided a confirmatory correct classification rate (CCR) of 80%, with a predictive CCR of 75% on a sample of eight new journals not previously considered in the phase of model estimation.

Reports of my death are greatly exaggerated (Mark Twain).

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Keywords Dentistry · *H-index* · Ordinal regression · Journal Citation Reports · Correct classification rate

Introduction

The Journal Impact Factor (*JIF*) is an indicator of venerable antiquity, devised by E. Garfield in the fifties (Garfield 1955) and commercially launched more than forty years ago. Despite having been officially buried recently (Roberts 2017), the *JIF* provided by the Journal Citation Reports (Thomson Reuters) continues to be an object of attention and controversy. Just in 2017 it has been the main topic of roughly 100 articles, and since its publication more than 2000 articles have analyzed or used it, e.g. as part of the title of a paper. Measurements cover different disciplines (Meteorology, Environmental Sciences, Soils, etc.), distributed in 75 scientific categories, and articles that have received over 20,000 citations.

Proof of the interest aroused and the controversy provoked lies in the fact that *JIF* is a subject that produces more editorials than research articles (1089 versus 889, in our revision in Clarivate), when the proportion between the two document types is overwhelmingly greater for the latter in research overall. The most important journals continue to dedicate frequent attention to the *JIF*, for instance two letters in *Nature* in 2017 (Varki 2017; Roberts 2017). In short, it does not sit in a dusty corner of bibliometric research.

Though it is impossible to encompass the vast amount of publications, we can roughly divide it into three subgroups: those criticizing/condemning the *JIF*, those respecting it (Seglen 1997a) and its later revisions (Seglen 1997b, 1998), and those analyzing the limitations of its use due to differences in citation ways among disciplines (Hansson 1995; Vanclay 2012), looking at different aging speeds, the non-normal distribution of citation frequencies, self-citation bias, or other problems concerning citable items.

Criticism often stems from the notion that a research paper can only be evaluated in a qualitative way by experts, and that *JIF* generates antithetical attitudes (Simons 2008; Alberts 2013). This is essentially the message of the *DORA Declaration of San Francisco* (www.ascb.org/dora/) and recommendations contained in the recent report known as the metric (Wilsdon 2015). Yet this drawback would apply to any bibliometric indicator referring to journals, authors or papers. The papers using and justifying the *JIF*, following Garfield (2006), would include the work of Saha et al. (2003). Far fewer explicitly defend its use, or limited use, for instance serving as a unit of analysis under the classic conception (Moed 2002), or to predict the success of academic races in their early phase (Bornmann and Williams 2017). The third group takes in studies focusing on technical limitations (Moed and Vanleeuwen 1995; McVeigh and Mann 2009), possible improvements for design (Buela 2003; Zitt and Small 2008) or factors hindering the use of the JIF (Bordons et al. 2002), but without questioning its global utility.

Within the field of the journal evaluation, the proposals of alternative indicators generally involve comparison with the *JIF* as can be seen in Bollen et al. (2009), Falagas et al. (2008), Leydesdorff and Opthof (2010), Leydesdorff and Bornmann (2011), Bornmann et al. (2012), Leydesdorff (2012), Vanclay (2012), and Noorden (2016). Against this background, our work comes under the less frequent line of *JIF* justification, in ourcase to evaluate the research activity of journals, looking closely at this indicator as a means of grouping the journals of a field by quantiles (median, terciles or percentiles).

There are a lot of works devoted to reveal factors or elements affecting the JIF such as the *H-index* of members of the journal editorial board (Kay et al. 2017), mean time elapsed between submission of a paper and final decision on acceptation or rejection (Garfield 1999) and language (Kurmis 2003). All of them can be considered as positive factors to the extent that they are congruent with the apparent measure of the quality attibuted to JIF. On the other hand, there are also structural factors to be taken into account that lead to modify the way of calculation in order to fit it to theses peculiarities (Fassoulaki et al. 2002; Zitt and Small 2008) among which are disciplinary field (Althouse et al. 2009) or item classification (Golubic 2008). And finally, there are a group of factors that border the ethics limits such as excesive self-citations (Fassoulaki et al. 2000) or even transgress them (Falagas and Alexiou 2008). In fact, as Malay (2013) indicates, journal editors can also manipulate the JIF by encouraging or coercing authors to omit citations to reports published in competing journals or, if a citing journal, to cite articles published in their own journal (self-citation). Some attempts to explain the JIF behaviour by using statistical models have been done by Wagner et al. (2006) by proposing a generalized linear regression model based on 214 literature reviews that evidences that factors on the author level (e.g., expertise, collaboration, and conceptual feedback) and on the article level (e.g., methodological rigor) are significant and robust predictors of scientific impact over and above journal level factors. And more recently by Mutz and Daniel (2012a, b) suggesting a generalized propensity score methodology based on the Rubin causal model to solve the bias problem of the JIF introduced by factors such as document type, papers age, authors social status (due to the authors institution, for instance), subject matter, and the time interval of observation, that have nothing to do with the prestige or quality of a journal.

In an earlier paper, Valderrama et al. (2017) studied an optimal criterion for dividing the *JIF* in two groups, and estimated a log-regression model to explain the *JIF* rank from the above mentioned covariables and factors. The set of journals pertained to a field of increasing interest in bibliometric studies, namely Dentistry (Lucena et al. 2017).

Here we go beyond by considering a division of journals in the field by terciles, related to 2015 (as is usual for the *Spanish Agency of Scientific Evaluation*), and introducing new explanatory variables. Then, a way to select the most influential variables when estimating journal location by terciles was developed. It entailed an ordinal regression model in the framework of 30 journals sampled by terciles in a stratified procedure.

In a first stage we included as covariables the *H-index* of the Editor-in-chief, the percentage of papers published in the journal whose research received public or private financial support (Bornmann et al. 2011), and the average number of papers yearly published in a journal. Meanwhile, the factors taken into account include qualitative characteristics such as the scope of the journal (specialized in a concrete topic or generalistic) and internal structure (including survey papers, theoretical, applied…). Information about indicators was obtained from the data base InCites^{TM} Journal Citation Reports, edition 2016, and from the Institute for Scientific Information with free access for the University of Granada. In turn, the percentage of papers funded by external institutions as well as average number of papers per issue and number of issues each year were estimated by sampling.

The conclusion of the research is that the considered factors have not any significant input on the model, while the *H-index* of Editor-in-chief, percentage of papers with external fund and the average number of papers yearly published in a journal have significant effect on the ordinal response variable, and then the model provides a correct classification rate of 80%. Furthermore, a forecasting study has been developed for journals not included in the sample.

Methodology

The field *Dentistry, Oral Surgery and Medicine* of JCR includes 91 journals in the edition of 2015. If ordered by decreasing *JIF*, two of them, *Dental Materials Journal* and *Medicina Oral, Patolog ía Oral y Cirugía Bucal* occupy the same place, 60, with an *JIF* of 1.087. They can therefore easily be divided in terciles. Moreover, a stratified sampling by terciles was performed, randomly choosing 10 journals in each stratum, obtaining in this way a sample size of 30, corresponding to a sampling fraction of 33%.

The selected journals are included in Table 1 together with the following variables:

- Impact factor in the field (*JIF*)
- *JIF* rank in the field (*R*)
- *H-index* of the editor-in-chief (*H-Ed*)
- Average number of papers yearly published in a journal (*Aver*)
- Sections (*S*): homogeneous framework (1) or including sections (2)
- Scope of the journal (*T*): generalist (1) or specialized (2)
- Percentage of papers with external finantial support (*P*)
- Anscombe transformation (*AnsP*)

Variables *JIF*, *R* and *H-Ed* were obtained from Scopus database, while information about *S* and *T* was derived by reading the journals themselves. To estimate *P*, a sample of 100 papers for each one of the 30 sampled journals corresponding to the same time interval of the *JIF's* were looked up. In order to deal with a quantitative Gaussian variable, the Anscombe (1948) transformation was applied to the binomial parameter *P*:

$$P \longrightarrow \arcsin\sqrt{\frac{P}{100}}$$

Similarly, *Aver* was estimated by sampling issues of each journal published during the interval 2014–2017.

Statistical calculations were performed by means of program R.

The final stage of analysis entailed estimation of an ordinal regression equation taking as response the tercil; as covariates *H-Ed* (x_1), *AnsP* (x_2), *Aver* (x_3), and as factors *S* (x_4) and *T* (x_5). The distribution function is given by:

$$F_s(x_1, x_2, \ldots, x_p) = P(Y \le Y_s / x_1, x_2, \ldots, x_p) = \frac{1}{1 + \exp\{-\alpha_s + \sum_{i=1}^{p} \beta_i x_i\}}$$

where Y_s with s=1,2,3 denotes the tercil, so that the probability of a journal being in tercil s is given by:

$$\begin{aligned}
P_1 &= P(Y = Y_1 / x_1, x_2, \ldots, x_5) = F_1(x_1, x_2, \ldots, x_5), \ s = 1 \\
P_2 &= P(Y = Y_2 / x_1, x_2, \ldots, x_5) = F_2(x_1, x_2, \ldots, x_5) - F_1(x_1, x_2, \ldots, x_5), \ s = 2 \\
P_3 &= P(Y = Y_3 / x_1, x_2, \ldots, x_5) = 1 - F_2(x_1, x_2, \ldots, x_5), \ s = 3
\end{aligned}$$

Because the model gives the probability of a journal belonging to tercils, we select the one with the highest probability.

Table 1 Data on JIF and explanatory variables included in the study

Sampled Journal	*JIF*	*R*	*H-Ed*	*Aver*	*S*	*T*	*P* (%)	*AnsP*
First tercil								
J. Dent. Res.	4.602	2	48	206.16	1	1	63	0.91691
Dent. Mater	3.931	5	41	188.04	1	2	62	0.90658
J. Clin. Periodontol.	3.915	6	55	138.00	2	2	56	0.84554
Clin. Oral Implant. Res.	3.464	7	29	195.60	1	2	34	0.62253
Mol. Oral Microbiol.	3.061	9	39	40.92	1	2	83	1.14581
J. Endod.	2.904	10	52	398.40	2	2	39	0.67449
Int. Endod. J.	2.842	12	35	128.40	2	2	67	0.95886
Int. J. Oral Sci.	2.595	15	58	34.12	1	1	36	0.64350
Clin. Oral Investig.	2.207	21	33	312.75	1	2	36	0.64350
Int. J. Oral Maxillofac. Implants	1.690	25	25	200.40	1	2	54	0.82544
Second tercil								
J. Oral Maxillofac. Surg.	1.231	32	8	529.20	2	2	19	0.45103
J. Adhes. Dent.	1.194	34	34	70.20	1	2	33	0.61194
J. Cranio-Maxillofac. Surg.	1.182	35	37	295.20	1	2	20	0.46365
Odontology	1.640	38	8	53.73	1	1	40	0.68472
J. Evid.-Based Dent. Pract.	1.563	41	27	65.08	2	1	42	0.70505
Eur. J. Orthodont.	1.272	42	21	86.28	1	2	26	0.53507
Gerodontology	1.262	44	29	64.36	1	1	30	0.57964
Dent. Traumatol.	1.237	45	26	78.00	1	2	21	0.47603
J. Esthet. Restor. Dent.	1.231	50	28	46.80	1	2	34	0.62253
Med. Oral Patol. Oral Cir. Bucal	1.162	60	32	108.60	2	2	38	0.66422
Third tercil								
Implant Dent.	1.117	64	8	134.16	1	2	31	0.59050
Brit. Dent. J.	0.844	65	3	170.04	1	1	20	0.46365
Head Face Med.	0.800	67	19	33.82	1	1	27	0.54640
Aust. Endod. J.	0.795	68	2	18.54	1	2	25	0.52360
J. Adv. Prosthodont.	0.791	70	12	61.80	1	2	28	0.55760
Quintessence Int.	0.789	72	25	92.70	1	1	14	0.38350
J. Oral Sci.	0.784	73	18	70.40	1	1	37	0.65389
Pediatr. Dent.	0.767	74	12	80.50	2	1	28	0.55760
J. Dental Sci.	0.449	75	31	81.60	1	2	51	0.79540
Int. J. Dent. Hyg.	0.421	76	15	42.20	1	2	28	0.55760

Ordinal regression model and results

As mentioned before, in a first step of the study we introduced all the considered covariables and factors, but the estimated ordinal model concluded that neither factors S nor T were significant at the level 0.05. Following a step-wise procedure, the final regression model therefore provided as estimated parameters with their respective p values:

Table 2 Probabilities of the forecasted tercil for journals included in the initial sample

Journals included in the initial sample	Probab 1st tercil	Probab 2nd tercil	Probab 3rd tercil	Estim. Tercil	Real Tercil	Result
J. Dent. Res.	1.00	0.00	0.00	1	1	Ok
Dent. Mater	0.99	0.01	0.00	1	1	Ok
J. Clin. Periodontol.	0.99	0.01	0.00	1	1	Ok
Clin. Oral Implant. Res.	0.29	0.68	0.03	2	1	Failure
Mol. Oral Microbiol.	0.99	0.01	0.00	1	1	Ok
J. Endod.	1.00	0.00	0.00	1	1	Ok
Int. Endod. J.	0.96	0.04	0.00	1	1	Ok
Int. J. Oral Sci.	0.87	0.12	0.00	1	1	Ok
Clin. Oral Investig.	0.83	0.17	0.00	1	1	Ok
Int. J. Oral Maxillofac. Implants	0.70	0.29	0.01	1	1	Ok
J. Oral Maxillofac. Surg.	0.14	0.79	0.08	2	2	Ok
J. Adhes. Dent.	0.14	0.79	0.08	2	2	Ok
J. Cranio-Maxillofac. Surg.	0.48	0.50	0.01	2	2	Ok
Odontology	0.00	0.24	0.76	3	2	Failure
J. Evid.-Based Dent. Pract.	0.12	0.79	0.09	2	2	Ok
Eur. J. Orthodont.	0.01	0.41	0.58	3	2	Failure
Gerodontology	0.04	0.73	0.23	2	2	Ok
Dent. Traumatol.	0.01	0.42	0.57	3	2	Failure
J. Esthet. Restor. Dent.	0.05	0.74	0.21	2	2	Ok
Med. Oral Patol. Oral Cir. Bucal	0.26	0.71	0.04	2	2	Ok
Implant Dent.	0.00	0.23	0.76	3	3	Ok
Brit. Dent. J.	0.00	0.05	0.95	3	3	Ok
Head Face Med.	0.00	0.23	0.77	3	3	Ok
Aust. Endod. J.	0.00	0.01	0.99	3	3	Ok
J. Adv. Prosthodont.	0.00	0.13	0.86	3	3	Ok
Quintessence Int.	0.00	0.21	0.79	3	3	Ok
J. Oral Sci.	0.02	0.57	0.41	2	3	Failure
Pediatr. Dent.	0.00	0.17	0.83	3	3	Ok
J. Dental Sci.	0.48	0.51	0.01	2	3	Failure
Int. J. Dent. Hyg.	0.00	0.16	0.84	3	3	Ok

$$\beta_1 = -0.163\ (0.005),\ \beta_2 = -11.472\ (0.021),\ \beta_4 = -0.013\ (0.018)$$
$$\alpha_1 = -15.356\ (0.001),\ \alpha_2 = -11.029\ (0.002)$$

with a Nagelkerke pseudo R^2 equal to 0.807. Hence, the probabilities that a journal be in the first, second or third tercil on the basis of explanatory covariables are:

Table 3 Probabilities of the forecasted tercil for journals not included in the initial sample

Journals not included in the initial sample	Probab 1st tercil	Probab 2nd tercil	Probab 3rd tercil	Estim. Tercil	Real Tercil	Result
Comm. Dent. Oral Epidem.	0.96	0.03	0.01	1	1	Ok
J. Orofacial Pain	0.69	0.31	0.01	1	1	Ok
Oral Oncology	0.95	0.05	0.00	2	2	Ok
Int. J. Prosthodontic	0.45	0.54	0.01	2	2	Ok
J. Public Health Dent.	0.66	0.33	0.01	1	2	Failure
Oral Radiology	0.00	0.23	0.77	3	3	Ok
Int. J. Period. Rest. Dent.	0.07	0.78	0.15	2	3	Failure
Seminars in Orthodontics	0.00	0.01	0.99	3	3	Ok

$$P_1 = \frac{1}{1 + \exp\{5.356 - 0.163 \cdot H - Ed - \ 11.472 \cdot AnsP - \ 0.013 \cdot Aver\}}$$

$$P_2 = \frac{1}{1 + \exp\{11.029 - 0.163 \cdot H - Ed - \ 11.472 \cdot AnsP - \ 0.013 \cdot Aver\}} - P_1$$

$$P_3 = 1 - (P_1 + P_2)$$

This model was tested on the journals sampled in this study, giving a correct classification rate of CCR = 80% and the probabilities of a journal belonging to each tercil that are shown in Table 2. We moreover applied ordinal regression to forecast the tercil of eight journals not included in the initial sample and the predictive ability of the model provided a success rate of 75% as can be seen in Table 3.

Discussion of results and conclusions

Departing from a set of variables explaining the impact factor tercil to which a journal included in the list of *Journal Citation Reports* belongs, an ordinal model considering the tercil as a response variable (with three categories) is described in this paper. It is based on 30 journals randomly sampled in a stratified way from the JCR list. The initial covariables that were taken into account are: *H-index* of Editor-in-chief, percentage of papers with external funding, and the average number of published papers. Two additional factors included were the scope of the journal and internal structure.

Our estimation procedure led us to the conclusion that none of the factors of study had a significant effect on the response, meaning that a journal being divided into sections (review papers, original research, clinical studies…) does not affect its *JIF*. A similar argument could explain the fact that a journal has a generalistic scope, including several fields versus a specialized goal in a concrete field. On the other hand, the three covariables must be included in the model, all of them positively correlating with the response regarding journal editors classified in the top positions of the ranking; on average they have a higher *H-index* than the ones of lesser impact factors. The same reasoning may be applied to the average number of papers published in a year, because it logically increases the citations and therefore the impact factor.

Finally, the influence of the percentage of papers published in a journal that received external funding deserves mention. Initially, the fact that a research receives support from an external institution or company is not of higher quality in regard to another one. Usually, however, teams with an excellent level of scientific production, thus a broad set of papers published in top-cited journals, tend to get financing from external agents willing to develop their ideas or products. Thus, the existing association between the response and this explanatory variable might be considered a spurious correlation.

Acknowledgements This work was supported by MTM2017-88708-P of Secretaría de Estado de Investigación, Desarrollo e Innovación, Ministerio de Economía y Competitividad de España.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflicts of interest.

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