The relationship of polarity of post-publication peer review to citation count

Evidence from Publons

Received 21 January 2019
Revised 27 July 2019
15 October 2019
Accepted 20 December 2019

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Abstract

Purpose – The purpose of this study is to investigate the relationship of the post-publication peer review (PPPR) polarity of a paper to that paper's citation count.

Design/methodology/approach – Papers with PPPRs from Publons.com as the experimental groups were manually matched 1:2 with the related papers without PPPR as the control group, by the same journal, the same issue (volume), the same access status (gold open access or not) and the same document type. None of the papers in the experimental group or control group received any comments or recommendations from ResearchGate, PubPeer or F1000. The polarity of the PPPRs was coded by using content analysis. A negative binomial regression analysis was conducted to examine the data by controlling the characteristics of papers.

Findings – The four experimental groups and their corresponding control groups were generated as follows: papers with neutral PPPRs, papers with both negative and positive PPPRs, papers with negative PPPRs and papers with positive PPPRs as well as four corresponding control groups (papers without PPPRs). The results are as follows: while holding the other variables (such as page count, number of authors, etc.) constant in the model, papers that received neutral PPPRs, those that received negative PPPRs and those that received both negative and positive PPPRs had no significant differences in citation count when compared to their corresponding control pairs (papers without PPPRs). Papers that received positive PPPRs had significantly greater citation count than their corresponding control pairs (papers without PPPRs) while holding the other variables (such as page count, number of authors, etc.) constant in the model.

Originality/value – Based on a broader range of PPPR sentiments, by controlling many of the confounding factors (including the characteristics of the papers and the effects of the other PPPR platforms), this study analyzed the relationship of various polarities of PPPRs to citation count.

Keywords Post-publication peer review, Review polarity, Citation count, Citation analysis, Altmetrics, Publons

Paper type Research paper

Introduction

Peer review has consistently been the foundation of academic communication (da Silva, 2019). From the perspective of the publication process of scientific papers, peer review can be

This work was supported by the National Natural Science Foundation of China (Grant No. 71704057) and Guangdong Planning Office of Philosophy and Social Science of China (Grant No. GD17YTS01). We would like to thank the two anonymous reviewers for their valuable comments. We would also like to thank the Editors for their support during the review process.

1468-4527
DOI 10.1108/OIR-01-2019-0027

divided into pre-publication peer review and post-publication peer review (PPPR). In the process of publishing, reviewers, who are regarded as guards for academic communication, play a key role in pre-publication peer review. Nevertheless, pre-publication peer review has been called into question in the scientific community recently due to a series of scientific issues such as non-reproducibility and fraud (Haffar *et al.*, 2019). PPPR has caught the attention of the scientific community (da Silva and Dobranszki, 2015).

In fact, PPPR is not a new concept (Tattersall, 2015). For example, the correspondence section of an academic journal, such as "Letters to the Editor," is a type of PPPR (Tierney *et al.*, 2015). In addition, PPPR has developed rapidly with the facilitation of websites hosting PPPRs. Websites for PPPR such as ResearchGate, F1000, PubPeer and Publons provide a number of methods for their users to comment on published papers.

Simultaneously, PPPR is identified as an impact indicator (Gorraiz *et al.*, 2014). Evaluating the quality of a researcher's work is always based on indicators such as the number of publications from the researcher, the Journal Impact Factor and the number of citations the researcher has received. However, these indicators are not as good for evaluating the quality of the researcher's work (Aksnes *et al.*, 2019). In several countries, an assistant professor seeking tenure track will have his or her representatives (e.g. published papers) reviewed by peer reviewers. PPPR offers a more direct indication of the quality of a researcher's work. Moreover, if PPPR is widely adopted, it could serve as an earlier indicator of research quality (Spezi *et al.*, 2018) because it appears much closer to the publication time of a paper than do citations. This study focused on the relationship of polarity of the PPPR of a paper to its citation count.

Literature review

Pre-publication peer review is criticized because it focuses excessively on deciding whether to publish a paper rather than on providing a high-quality evaluation of scientific merit and the information necessary to organize and prioritize the paper (Kravitz and Baker, 2011). In the present scientific performance evaluation system, "publish or perish" seems to be the only choice for scientists. As a consequence, a very small fraction of researchers will probably acquire publishing opportunities via scientific misconduct that is challenging to identify in the pre-publication peer review process (Stebbing and Sanders, 2018).

While issues of pre-publication peer review are being challenged (Peres-Neto, 2016), PPPR is offered as an effective supplement to pre-publication peer review (Bell, 2017). Its advantages outweigh those of pre-publication peer review: the quality control of scientific papers can be strengthened (Luo and Rubens, 2016), fraud and other scientific misconduct are more likely to be unearthed by crowdsourcing peer review (Pontille and Torny, 2015), PPPR addresses some of the concerns about transparency and reproducibility (Freedman and Inglese, 2014). Therefore, publication should not be the final step in the lifecycle of scientific papers (Hames, 2014) but rather the beginning of critical analysis by means of PPPR (da Silva, 2013). Expanding upon traditional PPPR such as "Letters to the Editor," methods for combining internet technologies to realize peer review have been widely discussed. Generally, there are three methods of PPPR that are based on the internet. The first is the use of social media as a tool of PPPR (Topf and Hiremath, 2015). The second is the PPPR functions provided by journal websites themselves (Tracz and Lawrence, 2016). The third is independent platforms for PPPR (da Silva, 2018).

Nevertheless, PPPR still faces challenges. Joynson and Leyser (2015) demonstrated that the culture of "publish or perish" is the biggest challenge for PPPR today. This is mainly because publishing research papers is seen as a critical factor (Markie, 2015) to garner respect, prestige, recognition and professional opportunities. Scientists are working with the expectation of completing a study and then immediately moving on to the next one, which means that once a paper is published, the corresponding study is essentially complete (Markie, 2015). In PPPR, authors of a paper are supposed to be able to respond to doubts at any time, which apparently costs a great amount of time and leads to the condition of authors potentially not responding to the questions raised by peer reviewers after publishing (Shashok and Matarese, 2018). The second challenge is that scientists' contributions to PPPR are not recognized (Winker, 2015), and scientists have little motivation to participate in PPPR. On the one hand, critical comments about a paper from scientists who are identified are a risk for those who make them (Liu, 2007). Although comments can be anonymous or use pseudonyms on the internet, IP addresses and other personal data are still at risk of being leaked (Knoepfler, 2015). On the other hand, it is hard for an anonymous scientist to earn credit by participating in PPPR because a PPPR from an anonymous scientist would also prevent the reviewing scientist from getting credit. On PubMed Commons (a former PPPR service begun by PubMed in 2013), for example, commenters were required to identify themselves when they commented on a published paper on PubMed (Brown *et al.*, 2013). Unfortunately, PubMed Commons is closed because of the poor level of adoption (Lane, 2015) on March 2, 2018. The third challenge is the lack of connection between the PPPR of a paper and the paper itself (Winker, 2015). In other words, it is difficult to recognize whether a published paper has received PPPR. Moreover, a questionnaire aimed at junior doctors showed that compared with single-blind peer review, PPPR is considered to be less reliable (Patel *et al.*, 2017).

It should be noted that the relationship between PPPR and citation count has attracted much attention. Previous studies could be divided into three categories. The first one is to compare the two groups of papers (papers that received recommendations vs papers that did not receive recommendations) with respect to citation count by using descriptive statistics. Wardle (2010) found that the mean and median citation count of the 103 publications highlighted by F1000 was higher than for all 1,530 publications. However, the study revealed that 46 and 31 percent of all articles highlighted by F1000 were cited less often than the mean and median of all 1,530 articles, respectively. The conclusion of the study was that F1000 could not be reliably used as a means of post-publication evaluation of the ecological articles. The second one is to reveal the correlations between the peer's ratings of a paper and the paper's citation count in PPPR by using correlation analysis. Plenty of previous studies revealed that the peer's rating from F1000 had a significant correlation with the citation count of the paper (Li and Thelwall, 2012; Waltman and Costas, 2014). Bornmann and Leydesdorff (2013) found a significant medium correlation between the peers' ratings of a paper on F1000 and the paper's citation count ($N = 125$). A previous study of Mohammadi and Thelwall (2013) further discovered and verified the significant positive correlation between the citation count of a paper and its peers' ratings on F1000. Eyre-Walker and Stoletzki (2013) investigated the relationship among peer scores, the citation count gained by an article and the impact factor of the journal in which the article was published. They found that the mean of an article's peer score was significantly positively correlated with the article's citation count. However, the peer score of an article mainly depends on the impact factor of the journal in which the article was published. The third one is to reveal the relations of PPPRs between citations by using regression analysis. Based on 2,361 original research articles published in *Gastrointestinal Endoscopy*, Smith *et al.* (2019) conducted a multivariable linear regression to assess for the relationship between Altmetrics predictors (such as Facebook posts, number of F1000 reviews, etc.) and citations. The result of the study showed that the number of F1000 reviews was significantly associated with the citations. Bornmann and Leydesdorff (2015) conducted a negative regression analysis for estimating the influence of the recommendation scores (rated by F1000 faculty members) of an article on the article's citation count. The results of their study showed that the recommendation scores of an article had significant influence on the article's citations. Bornmann and Haunschild (2015) performed a regression analysis by using the F1000 paper ratings ("good," "very good," "excellent") as the independent variable and citation count as the dependent variable. The results showed that compared with the articles assessed as "good," those assessed as "very good" and "excellent" had higher citation count.

In summary, most previous studies focused on discussing the advantages and disadvantages of PPPR. There exists a number of empirical studies focusing on the relationship between PPPR and citation count by using correlation analysis. It should be noted that Bornmann and Haunschild (2015) established a regression model for evaluating the relationship of an article's rating level to F1000 ("good," "very good," "excellent") on the article's citation count. However, it is widely known that F1000 is a recommendation platform, and most of the comments are positive (Hunter, 2012). Therefore, it remains unclear what the relationship of other PPPR polarities (i.e., negative, neutral or comments with both positive and negative content) for a paper are to the paper's citation count. On the basis of establishing experimental groups and their corresponding control groups, by controlling the confounding factors (including the characteristics of the papers and the effects of the other PPPR platforms), our study investigates the relationship of a paper's PPPR polarity to the paper's citation count.

Methods

Overview of PPPRs on Publons

Currently, the major platforms for PPPR are PubPeer, F1000 and Publons. PubPeer is an anonymous PPPR platform whose comments are mainly negative (Pierson, 2016), while most of the comments on F1000 are positive (Hunter, 2012). Publons is a real-name and hybrid scientific community. Except for recording the pre-publication peer review records for peer reviewers, Publons provides the function of PPPR for its registered users to comment on the published papers. Generally, there are two ways to comment on a published paper on Publons. The first way is to create a new PPPR for a paper that has not been included in Publons. After signing into Publons.com, users can add a new PPPR for a paper that they want to comment on in the user's private dashboard. Users are required to fill in the paper's DOI (PubMed ID or title) in the textbox for the paper information, fill in the PPPR of the paper in the textbox for the review content and then click the button "create review" to submit the PPPR for the paper. The second way is to add a PPPR for a paper that has been included in Publons. Users can browse or search for a paper on the webpage titled "Publications" (https://publons.com/publon/?order_by=date). Once users click on a paper, they can create a PPPR for the paper on the webpage for the paper's detailed information. The polarities of PPPRs on Publons are diverse, including positive, negative and neutral comments. Hence, PPPRs on Publons were selected as the data set.

Experimental group and control group design

First, the general rules for selecting papers in the experimental group and the control group were set as follows. The first rule was that none of the papers had received any comments from PubPeer or ResearchGate, nor had they received recommendations from F1000 or ResearchGate. The second rule was that papers in the experimental group and the control group were in the same journal and the same issue (volume) and were of the same document type and access type (gold open access or not). All of the above attempts were aimed at reducing the confounding factors so that the papers in both the experimental and control group were, as much as possible, in the same condition.

Second, we obtained the PPPRs and metadata (including title, DOI, etc.) of each paper from Publons on July 28, 2018.

Third, parameters for each paper's publication date and the date of its first PPPR were chosen. Since Publons was founded in 2012 and the delay between publication and citation is taken into consideration, papers published from 2013 to 2016 were selected preliminarily. It is well known that the length of time after publishing may have an effect on a paper's citation count. For example, one paper was published in 2013 and received its first PPPR in 2017. The citation count of that paper as of 2018 did not accurately reflect the effect of PPPR on the paper's citation count. Hence, we selected those papers that had not been retracted by the day of data collection and whose gap between first publication date and the first PPPR was within 365 days as the experimental group. For the papers published in the second half of 2016, we set June 30, 2017, as the date by which they needed to have received their first PPPR. It should be noted that editorials, letters to editor and comments were excluded from the experimental group.

Fourth, papers in the experimental group were manually matched 1:2 with papers without PPPR as the control group; the matched papers were published by the same journal and in the same issue (volume), were of the same document type and had the same access type (gold open access or not). By manually searching on the journal websites, we found each paper in the experimental group and added the previous and next paper within the same issue (volume) that were of the same document type and had the same access type to the control group. Simultaneously, the DOI, date of first publication and access type of each paper in the control group and in the experimental group were recorded. Special cases were as follows. First, if an experimental group paper (e.g. named *T*) was the first paper of an issue, the next two papers without PPPR after *T* were included in the control group. Second, if *T* was the last paper of an issue, the previous two papers without PPPR were included in the control group. Third, if the previous paper (e.g. *S*) before *T* received PPPR, then the previous paper before *S* (e.g. *R*) without PPPRs was added to the control group. Fourth, if the next paper after *T* (e.g. named *U*) had received PPPR, the next paper after *U* (e.g. named *V*) without PPPR was included in the control group and so on.

Classifying the polarity of PPPRs and similarities between pre-publication peer review and PPPR

Content analysis was performed to classify the polarity of the PPPRs of the papers in the experimental group. First, the polarities of the PPPRs were classified into four categories: neutral, negative, both negative and positive and positive. The neutral PPPRs mainly focused on demonstrating the findings of the paper or supply extra information for that paper (e.g. a website URL), but they did not comment on the paper with any emotional polarity. The negative PPPRs commented negatively on the paper without any positive emotion, such as a review stating the following: "This publication is seriously flawed, both methodologically as well as technically." PPPRs that were both negative and positive contained both negative and positive emotions, such as review with the following information: "[It] is very useful for the researcher… However, there are some minor weaknesses." The positive PPPRs commented positively on the paper without any negative emotions, such as a review that read, "This paper presents a novelty in the field of … I recommend it." After classifying the polarity of the PPPRs, two coders read the PPPRs of each paper in the experimental group and judged the polarity of each PPPR.

For coding the similarities between pre-publication peer reviews and PPPRs, if a PPPR was structured like a pre-publication peer review, such as "I think this work can't be accepted until [there are] major revisions," it was labeled as 1, otherwise it was labeled as 0.

It should be noted that a small number of papers had two or more PPPRs. For example, one paper had two PPPRs. In the first case, if one PPPR was negative and the other one was positive, then the polarity of the PPPRs of the paper was labeled as "both negative and positive." In the second case, if both of the PPPRs were negative, then the polarity of the PPPRs of the paper was labeled as "negative" and so on. The same is true for the coding of similarities between pre-reviews and PPPRs.

Variables and data processing

The dependent variable of this study was the citation count not including authors' self-citations (hereafter referred to as "citation count"). Scopus is one of the largest citation databases (Elsevier., 2018). Therefore, Scopus was chosen as the data source of citation count. Google Scholar was chosen as the supplemental data source for a minority of papers (29 papers and their corresponding pairs) that were not included in Scopus. The citation data were manually collected on July 15, 2019.

The independent variable of the current study was "group." Group was a binary variable (0 = control group; 1 = experimental group). After coding for the polarity of the PPPRs of the papers in the experimental groups, combined with their corresponding control groups, four subsets of data were generated: papers with neutral PPPRs and their corresponding control group (hereinafter referred to as CG-$EG_{neutral}$), papers with both negative and positive PPPRs and their corresponding control group (hereinafter referred to as CG-$EG_{negative\ and\ positive}$), papers with negative PPPRs and their corresponding control group (hereinafter referred to as CG-$EG_{negative}$) and papers with positive PPPRs and their corresponding control group (hereinafter referred to as CG-$EG_{positive}$).

Previous studies have revealed that the characteristics of a paper itself, such as page count (Hafeez *et al.*, 2019), number of authors (Ahmed *et al.*, 2016), affiliation count (Azer and Azer, 2016), word count of title (Gnewuch and Wohlrabe, 2017), word count of abstract (Hafeez *et al.*, 2019), number of references (Didegah *et al.*, 2018), keyword count (Uddin and Khan, 2016), days since publication (Clements, 2017), funding (Patience *et al.*, 2017) and free access (Hafeez *et al.*, 2019), had an effect on the paper's citation count. Therefore, the control variables of the current study were the page count, number of authors, affiliation count, word count of title, word count of abstract, number of references, keyword count, days since publication, funding and free access. Web of Science integrates the metadata of papers and provides a friendly interface. Based on Web of Science, we used DOIs as the search strategy to obtain most of the detailed characteristics of the papers, including their title, abstract, keywords and so on. For the missing data of a number of papers, we complemented the existing data manually. Based on the data set of the metadata, the values of the control variables were calculated. The page count, number of authors, affiliation count and number of references were calculated directly from the metadata. The word count of title and of abstract were generated by calculating the number of spaces (plus one) in the title and abstract. Keyword count was generated by calculating the separator counts (plus one) between keywords. Days since publication was the number of days between the first published date of a paper (the date was manually obtained one-by-one on each paper's webpage on the publisher's website) and the date of the citation count collection (July 15, 2019). Funding was a binary variable (0 = papers without funding; 1 = papers with funding). Free access (the data were manually obtained one-by-one on each paper's webpage on the publisher's website, i.e. free access papers in this study were gold open access papers) was a binary variable (0 = the paper cannot be accessed freely; 1 = the paper can be accessed freely). We would love to share the data set of the current study.

Statistical procedures

Descriptive statistics were used to quantitatively describe features of the data set. Spearman correlation analysis was conducted to investigate the relationship between the control variables and the citation count. Except for the three binary variables (group, funding and free access), all of the variables were count data. Count models (e.g. the Poisson regression model, negative binomial regression model) are appropriate estimation techniques for count data. Moreover, the data set of the current study was over-dispersed (Table III and Table V). As a result, the Poisson regression model was rejected; instead, negative binomial regression models were conducted to reveal the relationship of the polarities of PPPRs to citation count. In fact, a negative binomial regression model has been used in several bibliometrics studies for estimating the relationship of various factors to citation count (Hanssen and Jorgensen, 2015; Bornmann; Leydesdorff, 2015).

Results

Coding reliability of the polarity of PPPRs and similarities between pre-publication peer review and PPPR

We obtained 3,401 papers from Publons.com. Based on the above criteria of papers in the experimental group, a total of 191 eligible papers (with 198 PPPRs) were selected as papers in the experimental group.

We examined the coding reliability of the polarity of PPPRs and the similarities between pre-publication peer reviews and PPPRs. It should be noted that there are a number of reliability measurements for content analysis (Bolognesi *et al.*, 2017). We chose Krippendorff's alpha, as proposed by Krippendorff (2004), for estimating the reliability in the current study. Krippendorff's alpha of the polarity of the PPPRs and the similarities between pre-publication peer reviews and PPPRs were calculated using a software developed by Freelon (2013), and the alpha values were 0.887 and 0.941. Both alpha values were greater than 0.8, which demonstrated acceptable interrater reliability between the judgments of the two coders (Beckler *et al.*, 2018).

As for the different judgments of the polarities of the PPPRs and the similarities between pre-publication peer reviews and PPPRs, a third coder was trained to participate in the coding. In comparing the judgment from the third coder with the former two coders, we chose the judgments that two of the three coders agreed upon. After the comparison, there were three PPPRs with conflicting polarity left. In this situation, the three coders determined the final results of the judgment for the data set of this study by discussion.

Descriptive statistics of the data set

The 191 papers of the experimental group were published in 152 journals. Specifically, 131 journals had one paper, and 21 journals had two or more papers in the experimental group (details are shown in Table I).

Of the 191 papers in the experimental group, there were 18 papers with neutral polarity PPPRs, 108 papers with both negative and positive polarity PPPRs, 22 papers with negative

Journals	Number of papers
MedEdPublish	9
PLOS ONE	6
Cochrane Database of Systematic Reviews	5
Journal of Ethnopharmacology	4
English Language Teaching	3
PeerJ	3
Andrologia	2
Bioinformatics	2
BMJ Open	2
Construction and Building Materials	2
International Journal of English Linguistics	2
International Journal of Molecular Sciences	2
Journal of Alloys and Compounds	2
Journal of Neurology, Neurosurgery & Psychiatry	2
Leukemia Research	2
Nature	2
PLOS Biology	2
Proceedings of the National Academy of Sciences	2
Scientific Reports	2
The American Society of Tropical Medicine and Hygiene	2
The Knee	2

Table I. The journals had two or more papers in the experimental group polarity PPPRs and 43 papers with positive polarity PPPRs. According to the 1:2 pairing, there were 382 papers in the control group, making a total of 573 papers in both the experimental and control groups. The overview of the characteristics of each experimental and control group, including the number of papers, publication year, funding, free access status, number of PPPRs and number of PPPRs, which were structured like pre-publication peer reviews, is presented in Table II. For brevity, papers with neutral polarity PPPRs in the experimental group are abbreviated to $EG_{neutral}$, and their pairs in the control group are abbreviated to $CG_{neutral}$ and so on.

As shown in Table II, more than 50 percent of the papers in each group were supported by funding and could be accessed on the publisher's website for free.

It should be noted that a tiny fraction of the ratios of papers in the experimental group to papers in the control group in the same publication year is not 1:2 in Table II. For example, the number of papers (published in 2014) in $EG_{negative\ and\ positive}$ and $CG_{negative\ and\ positive}$ were 11 and 23, respectively. The reason was that many of the papers were first published online before they were assigned to a volume or an issue. Additionally, some papers (in the experimental group) were first published online in December or January, and as a result, the publication years of its pair papers (in the control group) in the same issue (volume) might be the next year or the previous year compared to the publication year of the paper in the experimental group.

The descriptive statistics of the variables of the control groups and the experimental groups are presented in Table III.

As shown in Table III, the *SD* of citation count was higher than the mean of citation count in all groups, except $EG_{neutral}$ and $EG_{negative}$. This suggests that the citation count of each group (except $EG_{neutral}$ and $EG_{negative}$) was over-dispersed.

Correlation analysis

Spearman correlation analysis was conducted to analyze the correlations between the variables of each group. The results are shown in Table IV.

Table IV shows that page count is significantly and positively correlated with citation count in $CG\text{-}EG_{negative\ and\ positive}$, but it has no statistically significant correlation with citation count in the other groups. The number of authors is significantly and positively correlated with citation count in all of the groups, except $CG\text{-}EG_{negative}$. Affiliation count is significantly and positively correlated with citation count in $CG\text{-}EG_{negative\ and\ positive}$ and $CG\text{-}EG_{positive}$, while it has no statistically significant correlation with citation count in $CG\text{-}EG_{neutral}$ or $CG\text{-}EG_{negative}$. The word count of title is significantly and negatively correlated with citation count in $CG\text{-}EG_{positive}$ but has no statistically significant correlation with citation count in the other groups. The word count of abstract is significantly and positively correlated with citation count in $CG\text{-}EG_{neutral}$ and $CG\text{-}EG_{negative}$, while it has no statistically significant correlation with citation count in $CG\text{-}EG_{negative\ and\ positive}$ or $CG\text{-}EG_{positive}$. The number of references is significantly and positively correlated with citation count in all of the groups. Keyword count has no statistically significant correlation with citation count in any of the groups, except $CG\text{-}EG_{positive}$. The number of days since publication is significantly and positively correlated with citation count in $CG\text{-}EG_{negative\ and\ positive}$ and $CG\text{-}EG_{positive}$, while it has no statistically significant correlation with citation count in $CG\text{-}EG_{neutral}$ or $CG\text{-}EG_{negative}$.

Negative binomial regression analysis

All of the variance inflation factors (VIFs) were less than 10, which indicated that there was no serious multicollinearity problem. The results of the four negative binomial regression models are presented in Table V.

Table II. The overview of the characteristics of each experimental and control group

	$CG_{neutral}$	$EG_{neutral}$	$CG_{negative\ and\ positive}$	$EG_{negative\ and\ positive}$	$CG_{negative}$	$EG_{negative}$	$CG_{positive}$	$EG_{positive}$
N	36	18	216	108	44	22	86	43
Number of papers published in 2013	8	4	12	6	0	0	16	8
Number of papers published in 2014	6	3	23	11	8	4	16	8
Number of papers published in 2015	10	5	63	32	14	7	16	8
Number of papers published in 2016	12	6	118	59	22	11	38	19
Number of papers with funding (rate)	29 (0.810)	13 (0.7222)	141 (0.653)	72 (0.667)	26 (0.591)	13 (0.591)	55 (0.640)	29 (0.674)
Number of free access papers (rate)	26 (0.7222)	13 (0.7222)	122 (0.565)	61 (0.565)	26 (0.591)	13 (0.591)	54 (0.628)	27 (0.628)
Number of PPPRs (mean of PPPRs per article)	–	18 (1.000)	–	113 (1.046)	–	24 (1.091)	–	43 (1.000)
Number of PPPRs that were structured like pre-publication peer reviews (rate)	–	0 (0.000)	–	80 (0.708)	–	12 (0.500)	–	13 (0.302)

Table III.
The descriptive statistics of the variables of the experimental and control groups

Groups	Statistics	Page count	Number of authors	Affiliation count	Word count of title	Word count of abstract	Number of references	Keyword count	Days since publication	Citation count
$CG_{neutral}$	*Min*	2	1	1	3	74	10	0	966	0
($N = 36$)	*Max*	167	26	15	25	698	170	10	2205	104
	Mean	17.583	5.111	3.583	11.639	214.472	44.889	2.667	1585.222	15.194
	SE	4.664	0.918	0.538	0.795	22.330	5.125	0.506	66.169	3.622
	SD	27.982	5.507	3.228	4.770	133.978	30.752	3.033	397.013	21.732
$EG_{neutral}$	*Min*	2	1	1	3	26	8	0	972	0
($N = 18$)	*Max*	60	23	15	19	360	171	8	2205	29
	Mean	16.889	7.444	4.000	11.944	196.611	45.667	2.111	1579.111	8.611
	SE	4.127	1.673	0.832	0.846	21.982	10.408	0.588	93.859	2.012
	SD	17.509	7.098	3.531	3.589	93.264	44.156	2.494	398.212	8.535
$CG_{negative\ and}$	*Min*	3	1	1	3	0	3	0	935	0
$_{positive}$ ($N = 216$)	*Max*	120	28	20	34	847	219	15	2195	258
	Mean	12.343	5.940	3.171	13.630	217.676	44.773	3.806	1347.736	12.412
	SE	0.743	0.292	0.174	0.343	6.791	1.982	0.193	21.563	1.818
	SD	10.920	4.296	2.556	5.041	99.809	29.125	2.837	316.913	26.719
$EG_{negative\ and}$	*Min*	3	1	1	4	0	4	0	944	0
$_{positive}$ ($N = 108$)	*Max*	142	26	14	35	955	176	10	2203	110
	Mean	13.343	6.148	3.287	14.444	220.444	47.111	3.833	1346.574	11.259
	SE	1.594	0.459	0.230	0.531	11.506	3.059	0.271	30.686	1.813
	SD	16.567	4.773	2.388	5.517	119.575	31.790	2.814	318.902	18.839
$CG_{negative}$	*Min*	4	1	1	6	57	9	0	952	0
($N = 44$)	*Max*	115	26	27	25	845	78	7	1967	39
	Mean	12.341	5.795	3.614	13.886	194.614	36.386	3.682	1384.341	8.932
	SE	2.505	0.797	0.678	0.677	18.027	2.253	0.313	47.607	1.409
	SD	16.615	5.290	4.499	4.489	119.579	14.944	2.077	315.790	9.350
$EG_{negative}$	*Min*	6	1	1	6	100	9	0	953	0
($N = 22$)	*Max*	46	16	9	19	522	262	10	1966	32
	Mean	12.909	3.909	2.364	12.091	204.000	52.545	4.182	1386.364	9.909
	SE	1.796	0.720	0.472	0.909	18.791	10.670	0.486	68.272	2.036
	SD	8.423	3.379	2.216	4.264	88.136	50.046	2.281	320.224	9.551

(*continued*)

Table III.

Groups	Statistics	Page count	Number of authors	Affiliation count	Word count of title	Word count of abstract	Number of references	Keyword count	Days since publication	Citation count
$CG_{positive}$	*Min*	2	1	1	4	0	3	0	955	0
($N = 86$)	*Max*	30	21	17	26	430	87	11	2324	76
	Mean	10.186	5.442	3.116	13.593	197.628	34.895	2.721	1500.419	9.605
	SE	0.621	0.427	0.263	0.546	8.102	1.884	0.271	47.004	1.420
	SD	5.757	3.960	2.437	5.063	75.131	17.471	2.514	435.900	13.172
$EG_{positive}$	*Min*	3	1	1	4	0	11	0	958	0
($N = 43$)	*Max*	31	76	74	35	389	146	10	2323	64
	Mean	10.302	7.070	4.767	13.140	196.488	42.395	3.372	1501.116	15.116
	SE	0.833	1.740	1.687	0.816	11.400	4.817	0.461	67.277	2.825
	SD	5.462	11.409	11.060	5.352	74.755	31.584	3.024	441.166	18.524

Table IV. Spearman correlations between variables of each group

	(No.) variables	1	2	3	4	5	6	7	8	9
CG-EG$_{neutral}$ (N = 54)	1 Page count	–	0.010	0.198	−0.096	0.294*	0.392**	0.103	−0.010	−0.172
	2 Number of authors		–	0.666**	0.255	0.414**	0.275*	−0.067	0.158	0.289*
	3 Affiliation count			–	0.329*	0.333*	0.424**	0.024	0.059	0.229
	4 Word count of title				–	0.128	0.388**	−0.114	−0.029	0.097
	5 Word count of abstract					–	0.613**	−0.295*	0.000	0.313*
	6 Number of references						–	−0.189	−0.115	0.273*
	7 Keyword count							–	0.102	−0.134
	8 Days since publication								–	0.111
	9 Citation count									–
CG-EG$_{negative\ and\ positive}$ (N = 324)	1 Page count	–	−0.144**	0.052	−0.035	0.258**	0.600**	0.171**	−0.223**	0.176**
	2 Number of authors		–	0.607**	0.130*	0.023	−0.025	−0.145**	0.028	0.215**
	3 Affiliation count			–	0.061	0.091	0.087	−0.126*	0.050	0.271**
	4 Word count of title				–	0.129*	−0.002	0.003	−0.012	−0.041
	5 Word count of abstract					–	0.186**	0.237**	0.009	0.074
	6 Number of references						–	0.156**	−0.052	0.376**
	7 Keyword count							–	0.054	−0.007
	8 Days since publication								–	0.329**
	9 Citation count									–
CG-EG$_{negative}$ (N = 66)	1 Page count	–	−0.265*	−0.288*	−0.251*	0.236	0.452**	0.299*	−0.001	0.180
	2 Number of authors		–	0.721**	0.198	0.218	−0.112	−0.012	0.263*	0.185
	3 Affiliation count			–	0.184	0.228	−0.039	−0.132	0.114	0.168
	4 Word count of title				–	0.246*	0.055	−0.052	0.152	−0.038
	5 Word count of abstract					–	0.306*	0.028	0.091	0.353**
	6 Number of references						–	0.207	0.044	0.386**
	7 Keyword count							–	−0.112	0.046
	8 Days since publication								–	0.176
	9 Citation count									–

(*continued*)

Table IV.

	(No.) variables	1	2	3	4	5	6	7	8	9
CG-EG$_{positive}$ (N = 129)	1 Page count	–	−0.134	0.053	−0.025	0.177*	0.396**	0.293**	−0.181*	−0.038
	2 Number of authors		–	0.594**	0.107	0.230**	0.164	−0.096	0.043	0.302**
	3 Affiliation count			–	0.078	0.085	0.198*	−0.039	0.015	0.286**
	4 Word count of title				–	0.194*	−0.132	0.057	−0.003	−0.270**
	5 Word count of abstract					–	0.198*	0.164	−0.146	−0.051
	6 Number of references						–	−0.096	0.071	0.449**
	7 Keyword count							–	−0.129	−0.204*
	8 Days since publication								–	0.349**
	9 Citation count									–

Notes: *Correlation is significant at the 0.05 level (two-tailed); **Correlation is significant at the 0.01 level (two-tailed)

Models	Variables	Coefficient	Standard error	z	$P>z$	[95% confidence	interval]
CG-EG$_{neutral}$	Group	−0.559	0.342	−1.630	0.102	−1.228	0.111
Note: N = 54; LR χ^2(11) = 30.42,	Page count	−0.013	0.007	−1.810	0.070	−0.027	0.001
Prob > χ^2 = 0.0014; Likelihood-ratio	Number of authors	0.028	0.052	0.540	0.590	−0.074	0.130
test of α = 0: chibar2(01) = 425.62,	Affiliation count	−0.088	0.106	−0.830	0.408	−0.296	0.120
Prob ≥ chibar^2 = 0.000.	Word count of title	0.010	0.038	0.270	0.788	−0.065	0.085
	Word count of abstract	0.001	0.002	0.350	0.727	−0.003	0.005
	Number of references	0.009	0.006	1.550	0.122	−0.002	0.021
	Keyword count	−0.055	0.052	−1.060	0.288	−0.157	0.047
	Days since publication	0.001	0.000	1.590	0.112	0.000	0.001
	Funding	2.071	0.434	4.780	0.000	1.222	2.921
	Free access	−0.074	0.425	−0.170	0.863	−0.908	0.760
	_cons	−0.373	0.928	−0.400	0.688	−2.191	1.446
	α	0.850	0.182			0.559	1.293
CG-EG$_{negative\ and\ positive}$	Group	−0.083	0.140	−0.590	0.557	−0.358	0.193
Note: N = 324; LR χ^2 (11) = 128.15,	Page count	−0.009	0.009	−1.010	0.314	−0.026	0.008
Prob > χ^2 = 0.0000; Likelihood-ratio	Number of authors	0.058	0.018	3.170	0.002	0.022	0.094
test of α = 0: chibar2(01) = 3912.80,	Affiliation count	0.014	0.039	0.350	0.728	−0.063	0.091
Prob ≥ chibar^2 = 0.000.	Word count of title	−0.010	0.014	−0.740	0.461	−0.037	0.017
	Word count of abstract	0.001	0.001	1.650	0.099	0.000	0.003
	Number of references	0.016	0.003	5.320	0.000	0.010	0.022
	Keyword count	−0.051	0.025	−2.020	0.043	−0.100	−0.002
	Days since publication	0.001	0.000	6.780	0.000	0.001	0.002
	Funding	0.619	0.148	4.180	0.000	0.329	0.909
	Free access	0.087	0.141	0.620	0.537	−0.189	0.363
	_cons	−1.278	0.462	−2.770	0.006	−2.183	−0.373
	α	1.224	0.105			1.035	1.447
CG-EG$_{negative}$	Group	0.055	0.253	0.220	0.827	−0.441	0.551
Note: N = 66; LR χ^2 (11) = 21.55,	Page count	−0.031	0.015	−2.150	0.031	−0.060	−0.003
Prob > χ^2 = 0.0281; Likelihood-ratio	Number of authors	−0.023	0.052	−0.440	0.662	−0.125	0.079
test of α = 0: chibar2(01) = 220.70,	Affiliation count	−0.020	0.059	−0.340	0.734	−0.136	0.096
Prob ≥ chibar^2 = 0.000.	Word count of title	−0.059	0.032	−1.850	0.064	−0.121	0.003
	Word count of abstract	0.007	0.002	2.990	0.003	0.002	0.012
	Number of references	0.000	0.007	−0.040	0.964	−0.013	0.013
	Keyword count	0.076	0.071	1.070	0.286	−0.064	0.216
	Days since publication	0.000	0.000	0.980	0.328	0.000	0.001
	Funding	0.398	0.239	1.660	0.096	−0.071	0.868
	Free access	−0.552	0.309	−1.790	0.074	−1.157	0.053
	_cons	1.265	0.714	1.770	0.076	−0.133	2.664
	α	0.611	0.127			0.406	0.920
CG-EG$_{positive}$	Group	0.498	0.199	2.500	0.012	0.108	0.888
Note: N = 129; LR χ^2(11) = 63.25,	Page count	−0.009	0.022	−0.420	0.677	−0.053	0.035
Prob > χ^2 = 0.0000; Likelihood-ratio	Number of authors	0.034	0.034	0.980	0.328	−0.034	0.101
test of α = 0: chibar^2(01) = 874.90,	Affiliation count	−0.017	0.042	−0.400	0.687	−0.098	0.065
Prob ≥ chibar^2 = 0.000.	Word count of title	−0.038	0.016	−2.360	0.018	−0.070	−0.006
	Word count of abstract	−0.001	0.001	−0.660	0.511	−0.004	0.002
	Number of references	0.012	0.005	2.210	0.027	0.001	0.023
	Keyword count	−0.070	0.039	−1.780	0.076	−0.148	0.007
	Days since publication	0.001	0.000	2.990	0.003	0.000	0.001
	Funding	0.762	0.239	3.190	0.001	0.294	1.230
	Free access	−0.337	0.211	−1.600	0.110	−0.750	0.077
	_cons	0.967	0.497	1.940	0.052	−0.008	1.941
	α	0.927	0.131			0.702	1.222

Table V.
The results of the four negative binomial regression models

As shown in Table V, the alpha values of all four models were significantly different from zero (p < 0.001). All of the regression models were statically significant (p < 0.05).

The relationship of the control variables to citation count varied with the different models. For example, the variable "page count" had a significant negative relation with the citation count in the model of CG-EG$_{negative}$, but it had no significant relation with citation count in the models of CG-EG$_{neutral}$, CG-EG$_{negative\ and\ positive}$ or CG-EG$_{positive}$.

Table V shows that the citation count of the experimental group was significantly greater than the citation count of the control group in the model of CG-EG$_{positive}$ (p < 0.05, *coef.* = 0.498) while holding the other variables (such as page count, number of authors, etc.) constant in the model. However, the citation count of the experimental group had no significant differences between the citation count of the control group in the models of CG-EG$_{neutral}$, CG-EG$_{negative}$ and CG-EG$_{negative\ and\ positive}$ (p > 0.05) while holding the other variables (such as page count, number of authors, etc.) constant in the models.

Discussion

No significant differences in citation count were observed between the papers without PPPRs in the control group and the papers with neutral PPPRs in the experimental group while holding the control variables (such as page count, number of authors, etc.) constant in the model. Those PPPRs containing neither positive nor negative polarity mainly demonstrated the methods and findings of the papers rather than making comments about the papers themselves. There was also a small number of PPPRs containing neither positive nor negative polarity, as these only contained URL links, which may lead to a situation in which the differences between this group and the control group are only due to there being more exposure opportunities on Publons, which increases the visibility of the papers. However, previous studies have revealed that the correlations between the visibility of a paper and its citation count are not very stable. Liu *et al.* (2013) found a significant positive relation between papers' page views and the papers' citation count; however, there was no significant relation between papers' page views and citation count in the study conducted by Allen *et al.* (2013). Therefore, this may be the reason there are no significant differences in the citation count between papers with neutral PPPRs and papers without PPPRs in the control group.

The results of this study indicated that there was no significant difference in citation count between papers without PPPRs (control group) and papers with PPPRs that contained both negative and positive polarity while holding the control variables (such as page count, number of authors, etc.) constant in the model. In Publons, a considerable fraction of those PPPRs with both negative and positive polarity were probably pre-publication peer reviews that were copied by reviewers as the PPPRs. Table II shows that 70.8 percent of the PPPRs with both negative and positive polarity were structured like pre-publication peer reviews. In other words, compared with papers in the control group, those papers with PPPRs that contained both negative and positive polarity merely added content that was similar to that found in a pre-publication peer review. As is widely known, each scientific paper should be peer reviewed before publication (Voight and Hoogenboom, 2012). Previous studies revealed that of the new submissions of a journal, the portion of the major revision decision and minor revision decision was greater than the portion of the accept decision (Rosenkrantz and Harisinghani, 2015; Lamb and Mai, 2015). That is, the pre-publication peer reviews of the majority of papers contained both negative and positive reviews simultaneously. Hence, compared with the papers in the control group, those papers with both negative and positive polarity in PPPR might not be obviously distinct in terms of overall quality, so there is no significant difference in citation count between the two groups.

An interesting finding was that no significant difference in citation count was found between papers without PPPRs (control group) and papers with negative PPPRs while holding the control variables (such as page count, number of authors, etc.) constant in the model. We examined the papers citing several papers with negative PPPRs and found that very few papers were cited in negative ways in the citing papers. Most importantly, it should be noted that 50 percent of PPPRs with negative polarity were structured like pre-publication peer reviews (Table II). Therefore, there are two possible reasons that explain this result. The first reason, which is the most important reason, is that half of the PPPRs with negative polarity are structured like pre-publication peer reviews. On the one hand, for those papers that received PPPRs structured like pre-publication peer reviews, although the reviews were negative, the papers were finally published in the journals. This may imply that there was some merit in the papers. On the other hand, those PPPRs structured like pre-publication peer reviews may have had no effect on the citation count (which was discussed in the previous paragraph). The second reason, however, which is not as important a reason, is that citations that a paper (with negative PPPRs) received are cited in partly negative ways. Citations can be identified as positive, negative or neutral (Bar-Ilan and Halevi, 2017). A reference can sometimes be made to point out limitations, inconsistencies or flaws that are even more serious (Catalini *et al.*, 2015). Moreover, the citation count could be produced by the publication of low-quality work that attracted some criticism (Garfield, 1979).

The citation count of papers with positive PPPRs was significantly greater than the citation count of papers without PPPRs ($p < 0.05$, *coef.* = 0.498) while holding the other variables (such as page count, number of authors, etc.) constant in the model. The result of the current study is consistent with the previous three regression analyses (Bornmann and Haunschild, 2015; Smith *et al.*, 2019; Bornmann and Leydesdorff, 2015). That is, comparing to papers without PPPRs, papers with positive PPPRs receive more citation count. For the possible explanations, on the one hand, papers with positive PPPRs probably are of a higher quality. A previous study conducted by Bornmann and Leydesdorff (2013) revealed that the assessment of a paper's quality by a peer consists of three aspects, that is, impact (namely, citations), importance and accuracy. The result of the study showed that the impact (citations) can explain one-third of the variance in the peer ratings. Moreover, previous studies have shown that there is a significant positive correlation between the peer recommendation of a paper and the citation count of the paper (Waltman and Costas, 2014; Bornmann and Leydesdorff, 2013). For example, Bornmann and Haunschild (2018) found that the articles' citations were significantly and positively related to peers' quality of F1000Prime. One the other hand, on real-name platforms of PPPR, such as Publons, endorsement by peers can further enhance a paper's significance and quality and strengthen the reliability of the research. Generally, citations are usually based on the assessment of papers that can be considered to have credibility (Bornmann and Marx, 2014; Greenberg, 2011). Therefore, papers with positive PPPRs are able to receive more citations than those papers without PPPR (control group).

Conclusions

This study investigated the relationship of a paper's PPPR polarity to the paper's citation count by conducting a negative binomial regression by controlling the confounding factors from various PPPR platforms (PubPeer, F1000 and ResearchGate) and the characteristics of each paper, including page count, number of authors, affiliation count, word count of title, word count of abstract, number of references, keyword count, days since publication, funding and free access status. Papers that received neutral PPPRs, those that received negative PPPRs and those that received both negative and positive PPPRs had no significant differences in citation count when compared to their corresponding control pairs (papers without PPPRs). Papers that received positive PPPRs were expected to have significantly greater citation count than their corresponding control pairs (papers without PPPRs).

This study indicated that the polarities of PPPRs (especially positive PPPRs) from Publons can potentially serve as a useful indicator for evaluating papers' academic impact. The study provides several practical implications for publishers and research administration departments. First, publishers and indexers such as Web of Science should consider making a link between a paper and the PPPRs it has received from Publons. For example, the PPPRs could be displayed on the webpage of a paper once it receives PPPRs. Doing so would be convenient for readers in identifying whether the papers they are reading have received PPPRs. If the paper they are reading has received positive PPPRs, it can help improve the academic impact of the paper. Second, PPPRs could serve as an earlier indicator for estimating a paper's academic impact because the PPPRs might appear earlier than the citations would. Therefore, research administration departments, such as scientific funding committees, might consider positive PPPR as an earlier indicator for evaluating the academic impact of a researcher's work.

This study still has its limitations. First, the sample size of the current study is small. The results may be influenced by extreme higher citation count values. We tried to remove papers (and their corresponding pairs) with extreme higher citation count (greater than 100) from the models that contained extreme higher citation count and re-examined the results. There were one paper and five papers that citation count was greater than 100 in the model of $\text{CG-EG}_{\text{neutral}}$ and $\text{CG-EG}_{\text{negative and positive}}$. We removed those papers and their corresponding pairs from the two models and conducted negative binomial regression analysis. The results were consistent with the results of the current study. However, future studies should be conducted on a larger sample with further time and increased PPPR numbers on Publons. Second, the page count of the papers in experimental group were different with the page count of their corresponding pairs. The variable page count was included in the regression model, but selection of control group papers with different page count might still distort the analysis. Third, in Publons, reviewers may transfer the pre-publication peer reviews of papers they reviewed to the PPPRs of the papers. With the increase in PPPRs in Publons, to eliminate interference, it is better to consider removing those PPPRs that are structured like pre-publication peer reviews in future studies. Four, the variable free access (gold open access) was included in the models; however, the other forms of free access (green open access) were not included in the models. Therefore, the impact of green open access on the results should be examined in future studies.

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