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Directionality of paper reviewing and publishing of a scientist: A Granger causality inference

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ABSTRACT
It has been evidenced that peer review activities are positively correlated to scientists' bibliometric performance (e.g., Ortega, 2017, 2019). However, how the number of paper 'reviewing' interacts with a scientist's 'publishing' has not been addressed in previous studies. This paper attempts to employ the Granger causality inference to explore the directionality between a scientist's publication performance and his/her review activities. Our dataset comprises scientists' reviewed articles derived from Publons in the Web of Knowledge database, and their publications retrieved from PubMed. We find that scientists who reviewed less or published less tend to have Granger causality between reviewing and publishing activities. In addition, compared with early-career researchers, reviewing advances publishing for senior scientists.

KEYWORDS
Granger Causality Inference; Peer Review; Scientific Publications; Science of Science

1 Introduction

Peer review is a process of subjecting an authors' scholarly work, research, or idea to the scrutiny of others who are experts in the same field (Ware, 2008). This procedure improves the quality of manuscripts and filters the scientific community's scientific outputs. It is the heart of all science through which papers are published, grants are allocated, researchers are promoted, and prizes are awarded (Smith, 2006).

According to the recent peer review system, scholars' activity to review submitted manuscripts is underpaid. There exist at least two reasons why scholars are willing to review activities. On the one hand, some scholars considered peer review as one important part of their academic job; on the other hand, it is believed that the peer review process is an invaluable approach for researchers to stay up-to-date with research trends in their fields. However, the number of submitted manuscripts is increasing rapidly year by year, which has caused the demand for reviewers to outstrip the supply. The overload reviewing work for each scholar may cause their declining review invitations. The primary reason is that the effort put into this procedure has not been adverted into a reward system among the scientific community (Ortega, 2017). The lack of recognition for reviewers can be attributed to the difficulty of identifying or quantifying the quality of review activity because the personal information

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about reviewers and review records in the current peer review system is anonymous. Consequently, There are no metrics to measure reviewing activities of scholars and it is more difficult for researchers to explore relationships between reviewing activities and other academic activities. By this time, scholars will weigh up the pros and cons of reviewing activity to decide whether they accept the request of reviewing manuscripts from journal editors and/or conference chairs.

To this end, some online websites, such as Publons[1], a peer review platform, attempted to identify scholars' contributions for their reviewing activities. In this platform, reviewers' devotion can be acknowledged, and journal editors can find appropriate reviewers for submitted manuscripts (Cuellar, 2018). In the meantime, such a platform has provided an opportunity for scholars to dive into peer review activity and relationship with other research activities profoundly, such as paper publishing.

The relationship between reviewing activity and other research activities, such as publishing activity, has been discussed in recent years (Ortega, 2017, 2019). They primarily implemented correlation-level analyses between reviewing and publication activities. Yet, the directional effect between the two activities has been ignored. In another word, it is unclear whether more review tasks lead to more papers published, more papers published result in more review tasks, or bidirectionality between two activities. Apart from directionality, the time lag between the two time series (i.e., the monthly numbers of publications/reviews) is also neglected. For example, as there is a life cycle of one scientific publication, the number of reviewing articles in this year may affect the number of articles published in the next year. Simultaneously, the lag time should vary for different scholars in various disciplines rather than a fixed value for all scholars.

Therefore, this study aims to explore the directional effects between reviewing and publishing activities based on the publication records derived from PubMed and the reviewing records acquired from Publons from 2012 to 2018. We conducted Granger-causality test to examine directionality between two activities. Although Granger-causality inference cannot indeed illustrate the "real causality" of peer review and publication of scholars, this model's result could still offer us more significant information, such as the directionality between two activities, than correlation analysis. In the meantime, we will conduct Granger-causality inference case by case to identify the fittest lag time for each scholar.

2 Related Studies

In academia, scholars tend to publish academic manuscripts in journals or attend academic meetings to improve the knowledge reserve in professional disciplines and support their scholarly productivity (Newhart et al., 2020). Publications of scholars have become a significant indicator for rewards, funding grants, and promotion (Inoannidis et al., 2014). There exist quantities of subjective and objective factors influencing scholars' publication in their academic careers.

Subjective factors, including gender, family, and time constraint, may affect scholars' publication productivity (Newhart et al., 2020). Although the gender difference in scholars' publications has been decreased over the last 30 years (Caplar et al., 2017), gender inequality still

[1] https://publons.com/.

exists in some disciplines. For instance, in astronomy (Mayer et al., 2017), female authors write 19 ± 7% fewer papers in seven years following their first paper than their male colleagues. In the meantime, publication productivity is related to marriage. For example, for women particularly, the relationship between productivity and marriage varies by type of marriage: first compared with subsequent marriage and spouse's occupation in science (compared with non-scientific employment). Women with preschool children have higher productivity than women without children or school-age children (Fox, 2005). Besides, the publication process is a demanding and take-consuming activity, and time constraints may be the most common barrier to publication of scholars (Chen, 2011).

Objective factors, containing faculty ranks and source of funding, also have a significant influence on publication productivity (Newhart et al., 2020). Historical literature illustrated that researchers with upper levels performed more remarkable than those with lower ranks. For instance, based on all Italian university researchers' performance in the hard sciences for the period 2004-2008, Abramo et al. (2011) found that lower academic ranks typically owned less output than higher grades. The higher levels holding greater seniority and more incredible experience in the professional fields contributed to this apparent phenomenon. Furthermore, funding is positively correlated with increased output, and researchers who received funding from the aerospace engineering program published 2.59 articles more than those not receiving funding support (Goldfarb, 2008).

Peer review is fundamental and essential in the scientific process. It can provide quality control of what science should be published, funded, and who should be promoted (Wagner, 2006). Meanwhile, the peer review is underpaid for reviewers. Therefore, a successful peer review system depends on the reviewer's willingness to review manuscripts. Rapid growth in scientific production puts a burden on the scientific peer review system, and the system is facing a crisis (Kovanis, 2016). Editors have assumed that it is the overload of reviewing activity that makes researchers less willing to perform the anonymous, time-consuming yet underpaid tasks associated with reviewing papers (Breuning, 2015). Fortunately, some online platforms such as Publons attempted to give scholars credit for their reviewing activities and provided a new research perspective matching bibliometrics indicators to assess scholars' output.

Scholars have dived into the relationship between publication activities utilizing bibliometrics indicators and reviewing activity based on the scholars' reviewing records from Publons. For instance, based on publishing records derived from Google Scholar and reviewing data from Publons, Ortega (2017) found that there seems to be a weak correlation between bibliometric indicators, such as the number of publications. Similarly, Ortega (2019) explored the relationship between Publons metrics and altimetric counts, and there is also a week relationship between them. Based on the previous studies, it is obvious that the correlation does not uncover the directionality of two variables or consider the lag time of two-time series. This paper will utilize the Granger-causality inference method to discover the directional relationship between reviewing activity and publication productivity of scholars (Granger, 1969).

The Granger causality inference has been applied into quantities of discipline, such as business economics (Akkemik & Göksa, 2012; Rahimi et al., 2017),mathematics (Inglesi-Lotz et al., 2014), neurosciences neurology (Barnett et al., 2014; Chen et al., 2006), behavior science (Schippers et al., 2011), Psychology (Wang et al., 2007; Zhou et al., 2009), public administration (Altuzarra & Esteban, 2011; Beyzatlar et al., 2014; Bilen et al., 2017). For example, based on Spanish quarterly data for 1977-1998, Bajo-Rubio (2001) analyzed the relationship between outward foreign direct investment (FDI) and exports. The results indicated that the relationship between two variables is from outward FDI to exports in the short run and bilateral Granger causality in the long run (ajo-Rubio & Montero-Muñoz, 2001). Zhang (2011) utilized some econometric techniques, including the Granger causality test, etc., to explore the influence of financial development on carbon emissions and found that China's economic development acts as an important driver for carbon emissions increase. However, in management science, there seem just a few papers applying this method (Chang et al., 2018). For instance, by tracking 3,390 products on Amazon.com over two months, Ren (2018) found that the volume of negative consumer reviews drives consumers' purchasing decisions, but the magnitude of positive consumer reviews only marginally affects purchasing decisions.

3 Data and Methods

Our dataset consists of time series of scholars' publishing and reviewing records. The two metrics indicators are the number of publishing and reviewing articles per month. The publication data is derived from the PubMed database. PubMed is a free source developed and maintained by the National Center for Biotechnology Information (NCBI), a division of the U. S. National Library of Medicine (NLM), at the National Institutes of Health (NIH). PubMed citations and abstracts include biomedicine and health fields and cover portions of the life sciences, behavioral sciences, chemical sciences, and bioengineering (Canese & Wei, 2013). Simultaneously, the peer-reviewing records are acquired from the platform, called Publons. Publons is the world's leading peer review platform to officially recognize the reviewer's contribution to the Journal of Transcultural Nursing (JTCN) (Cuellar, 2018). In this platform, scholars can create a personal profile to display the information of manuscripts they have reviewed, such as, the journal and numbers of reviewing articles.

The reviewing records covered all the scholars' activity in the Publons database from January 2012 to December 2018. The publication records are also between January 2012 to December 2018 from the PubMed database to ensure the two time comparability series. Firstly, we excluded the review records without ORCID in the Publons database (1,192,255 review records remained). Then, we acquired 4,072,414 articles with ORCID and information about manuscripts' publication time from the PubMed database. We obtained the monthly numbers of publishing and reviewing articles between January 2012 to December 2018 by matching ORCID (1,467,950 records of 49,379 scholars remained). Finally, we excluded the time series pairs whose lengths are less than 15 to ensure that a sufficient length of time series for further analyses (1,219,507 records of 23,126 scholars remained) (Hoffmann et al., 2005). Subsequently, our samples comprised all series whose sizes are at least 15 time points for both variables without missing value. The max length of the series equals 226 months. In other words, the length of time series is between 15 months to 226 months. Finally, we utilized Granger causality inference step by step and case by case to uncover directional effects between reviewing and publishing activities. This model's core concept is to introduce accurate lagged variables for every time series and examine the effect from the lagged form of one variable on the other.

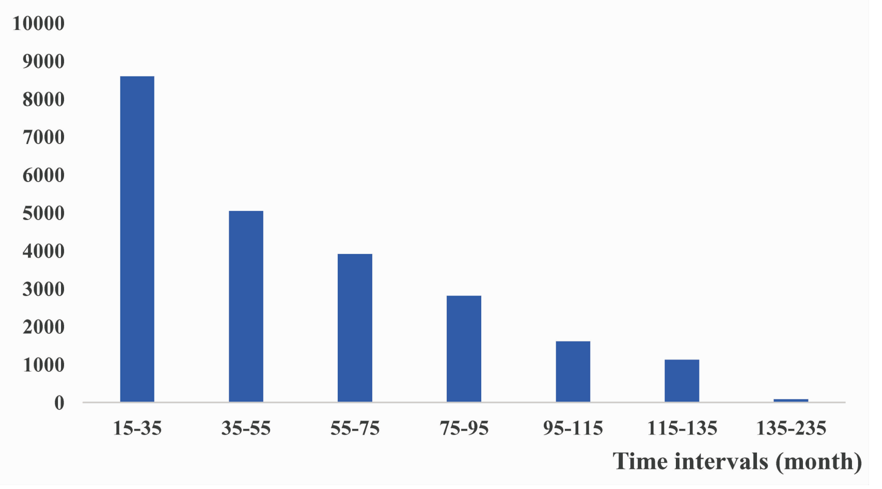


Figure 1 Length of time series in our dataset

Moreover, we examined the different directional effect patterns with different academic ages, different productivity of reviewing and publishing activity utilizing One-way ANOVA.

4 Empirical results

Table 1 has displayed the statistic descriptive of our data sample. Then, we conducted the Granger-causality test to explore the directional relationship between reviewing activities and publication productivity of scholars. This method consists of four steps (Hu et al., 2021), including the stationarity test, confirming each time series pair's accurate lag time, cointegration tests, and Granger-causality tests.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
year	1,219,507	2015.147	2.535	2012	2018
month	1,219,507	6.711	3.406	1	12
# pub	1,219,507	.351	.477	0	1
# review	1,219,507	.223	.478	0	15

4.1 Stationarity tests

Time series analysis has an assumption that the utilized time series should be stationary. In fact, in many cases, the time series are non-stationary. If we run a non-stationary time series, a spurious result will be acquired, and then we will fail to speculate the true trend of the time series. The core idea of stationarity tests is to check whether both time series for each scholar has a unit root. If there is a unit root, the time series seems non-stationary.

This paper will utilize the augmented Dickey-Fuller tests (ADF) to test each time series pair case by case. If a time series passes the ADF test as p values are significantly less than a threshold (the value of the threshold is set as 0.05 in this paper), we can identify that the time series is stationary.

We checked the two time series, which describe monthly publication records and reviewing records for scholars case by case. Finally, based on the results of the test for all scholars, we divided scholars into three types :

- Type 1: The publication records and reviewing records both passed the ADF test, which suggested that both time series are stationary;
- Type 2: Neither the publication records nor reviewing records passed the ADF test, illustrating that neither time series is stationary;
- Type 3: The publication records and reviewing records don't pass the ADF test, which indicated that publication and reviewing time series are both non-stationary.

Because time serials pair of type 1 are stationary, the next step for this kind of pair is to confirm the accurate lag time. Concerning types 2 and 3, we should conduct first-order differences for both time series, and then we retested differential time series. Finally, we excluded the scholars whose time serials after first-order differences still don't pass the ADF test.

Table 2 Stationarity test results.

Stationarity test		Stationary	Non–stationary
Before difference	# scholars	22238	888
	% scholars	96.16%	3.84%
After difference	# scholars	23103	23
	% scholars	99.01%	0.99%

Table 2 shows that 99.01% of scholars have stationary time series pairs after first-order differences. Finally, the 23,103 scholars' records will be utilized in the following steps.

4.2 Confirming the fittest lag time for each time series pair

Many researchers have analyzed two time series and compared their relations in different fields. However, the time lag is often a fixed or a simple value (Moed, 2016). This paper will confirm a more accurate time lag for each scholar's time series pair.

An approach, called vector autoregression, has been introduced to confirm the lag time for time series pairs in Granger-causality tests. There exist amounts of indicators as the criterion for us to identify the fittest lag time for time series, such as AIC (Akaike Information Criterion) (Aho et al., 2010), BIC (Bayesian Information Criterion) (Bhat & Kumar, 2010) and LR (likelihood ratio) test (McGee, 2002). These indicators estimate prediction error and speculate the relative quality of statistical models for a given set of data. In this paper, we utilized AIC and BIC as the criteria to select the fitness lag time for each time series pair. If the values of AIC and BIC in one model are the minimum compared to other models for one time series pair, the lag time in this model is the fittest one for this scholar.

We conducted a VAR model for each series time pair that has remained after being filtered before and set the maximum lag to eight. Ultimately, we acquired an accurate lag time for each scholar's time-series pair. Figure 1 showed the time lag distribution for all scholars in our dataset.

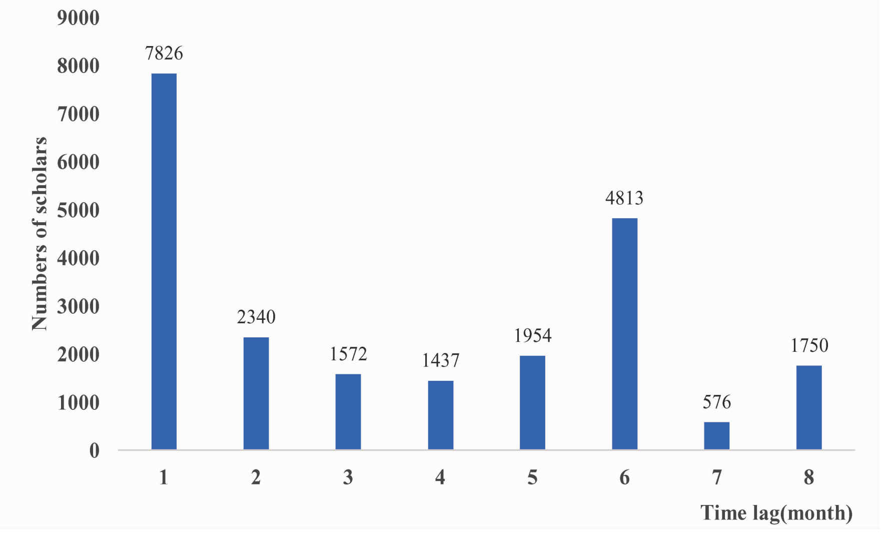


Figure 2 Distribution of time lag in our dataset

4.3 Cointegration tests

We have acquired the 23,103 scholars' stationary time-series records. These records can be divided into two categories: One is the raw time series, which are both stationary, and another one is the time series whose raw time series are non-stationary but stationary after first-order difference. As for the former series, we don't need any extra operation in this step. But it is possible that although time-series pairs are non-stationary, there may remain a statistically significant connection between the two variables. Therefore, we need to conduct cointegration tests case by case for latter records to check for a cointegrated combination of the two series.

There are three main methods for cointegration tests: Engle-Granger two-step method (Engle et al., 1987), Johansen test (Johansen, 1995), and Phillips-Ouliaris cointegration test (Phillips & Ouliaris, 1990). The Johansen test is a test for cointegration that allows for more than one cointegrating relationship for a large sample (Pesaran et al., 2001). This paper will apply the Johansen test to check the cointegrated combination of two series.

There are 1000 scholars' monthly time series pairs whose raw records are non-stationary, yet the differential records are stationary that should be conducted with cointegration tests. Finally, 146 scholars passed the test, and the rest are excluded.

4.4 Granger–causality test

The Granger causality test is a statistical hypothesis test for determining whether one-time series is useful in forecasting another, first proposed in 1969 (Granger, 1969). According to Granger causality, if a signal X1 "Granger-causes" (or "G-causes") a signal X2, then past values of X1 should contain information that helps predict X2 above and beyond the information contained in past values of X2 alone (Granger, 1969). The Granger-causality test's null hypothesis is that X1 doesn't Granger cause X2, or X2 doesn't Granger cause. If the time series pair passes the grange-causality as the *p*-value is significantly less than 0.05, we will reject the hypothesis. For example, If the number of publications "Granger-causes" (or "G-causes") the number of reviewing articles, the number of publishing articles of a scholar has a significant effect on the reviewing articles.

Based on the stational time series pairs, and the fittest time lag of each time series pair, we can conduct the Granger-causality test for all stationary series pairs in our dataset. Table 3 shows the Granger-causality test result based on monthly publication and reviewing records for scholars. In Table 3, "Publication→Reviewing" means that the publication productivity of scholars "Granger-causes"the reviewing activity, while"Reviewing→Publication" indicates that reviewing activity may influence the bibliometric performance of scholars." Publication⟷Reviewing" suggests that the number of reviewing articles and publishing manuscripts affect each other bidirectionally. As shown in Table 3, 42.3% of scholars have no significant effect between two-time series. 32.5% of scholars show a one-way product between two-time series, including 3720 scholars whose reviewing activity Granger cause publication productivity and 3518 scholars whose publication activity influences reviewing activity. In the meantime, 25.2% of scholars show a bidirectional effect between two-time series pairs.

Table 3 The result of Granger-causality test

	Reviewing→ Publication	Publication→ Reviewing	Publication⟷ Reviewing	No sig.
# scholars	3720	3518	5601	9422
% scholars	16.7%	15.8%	25.2%	42.3%
Academic age	5.50	5.43	4.39	5.63
# publishing articles per year	1.70	1.73	1.72	2.18
# reviewing articles per year	2.71	2.63	2.87	3.47

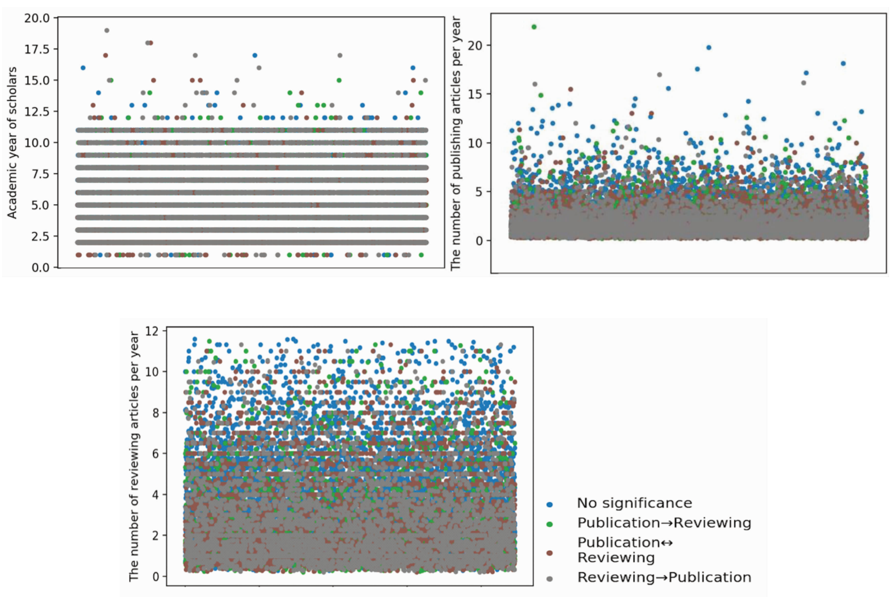


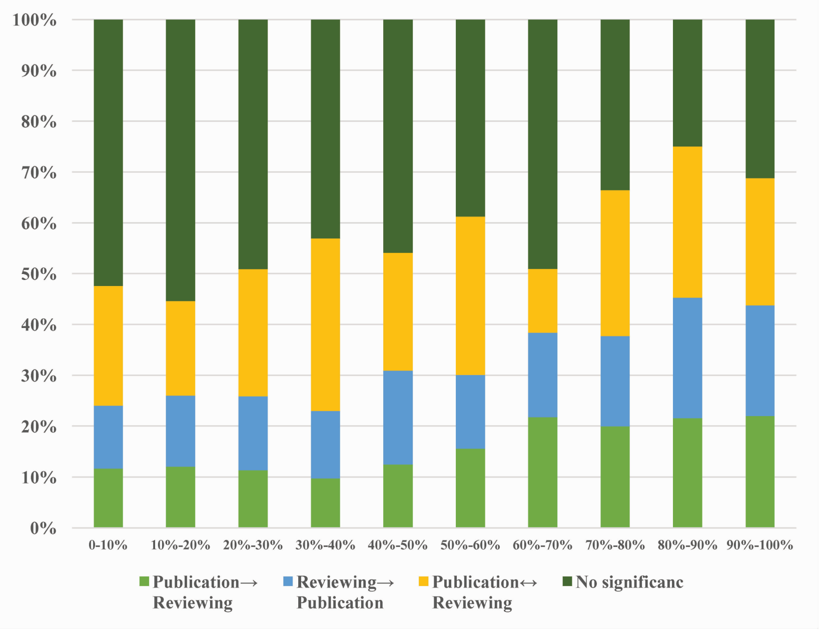
Figure 3 The left upper corner of the figure displays the distribution of academic year of scholars in four groups, and the right upper one displays the distribution of publishing productivity of scientists in four group. The distribution of academic year of scholars has been displayed on the lower.

Moreover, we conducted One-way ANOVA to demonstrate the difference in publishing articles, reviewing articles, and academic age of scholars among four groups, including "Publication→ Reviewing," "Reviewing→ Publication," "Publication↔Reviewing," and "No significance." As shown in Table 4, we compared the number of publishing articles of scholars among four groups. We identified that the scientists in the "no significance" group own more publishing articles per year than in other groups with $p<0.05$. We also compared the numbers of reviewing items per year among four groups and found that scholars showing no significance between publishing and reviewing activities owned more reviewing articles than others. Meanwhile, scientists who displayed a bidirectional effect between two activities had more publishing articles than those who owned a one-way influence. Surprisingly, the scholars in "Reviewing→ Publication" group is significantly older than other groups.

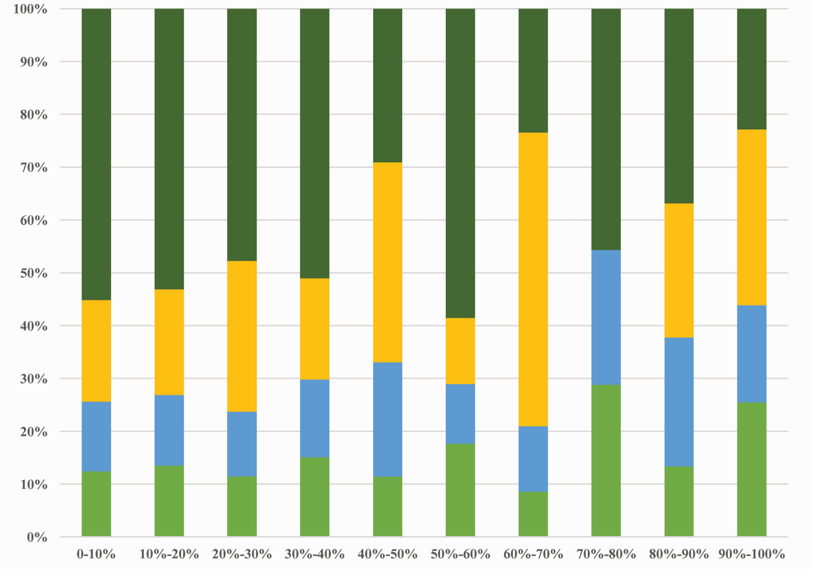
Table 4 Result of One-Way ANOVA

	Mean	Std. Err.	t	P>|t|
The number of publishing articles per year				
Publication→ Reviewing vs No significance	–.450	.029	–15.38	–0.000*
Reviewing→ Publication vs Publication⟷Reviewing	–.011	.031	–0.36	0.984
Publication→ Reviewing vs Publication⟷Reviewing	.019	.032	0.60	0.934
Publication→ Reviewing vs Reviewing→ Publication	.030	.034	0.87	0.822
No significance vs Publication⟷Reviewing	.470	.025	18.77	–0.000*
No significance vs Reviewing→ Publication	.480	.029	16.74	–0.000*
The number of reviewing articles per year				
Publication→ Reviewing vs No significance	–.836	.041	–20.29	–0.000*
Publication→ Reviewing vs Publication⟷Reviewing	–.243	.045	–5.41	0.000*
Reviewing→ Publication vs Publication⟷Reviewing	–.167	.044	–3.77	0.001*
Publication→ Reviewing vs Reviewing→ Publication	–.076	.049	–1.55	0.407
No significance vs Publication⟷Reviewing	.594	.035	16.87	–0.000*
No significance vs Reviewing→ Publication	.760	.040	18.82	–0.000*
Academic age				
Publication→ Reviewing vs No significance	–.212	.052	–4.04	0.000*
Publication→ Reviewing vs Reviewing→ Publication	–.075	.062	–1.20	0.627
No significance vs Reviewing→ Publication	–.137	.051	2.67	0.038*
Publication→ Reviewing vs Publication⟷Reviewing	1.033	.057	18.09	–0.000*
Reviewing→ Publication vs Publication⟷Reviewing	1.108	.056	18.74	–0.000*
No significance vs Publication⟷Reviewing	1.245	.045	27.80	–0.000*

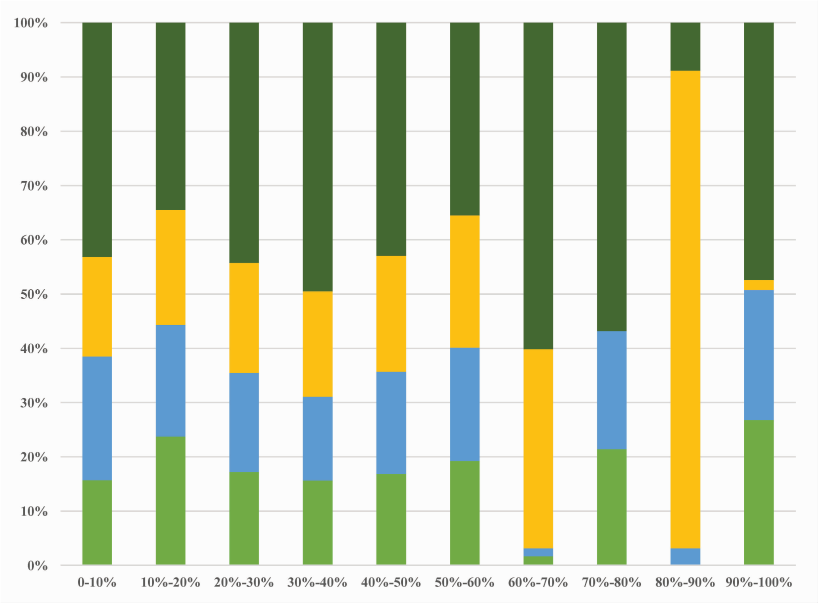
In the meantime, we also examined the directional patterns with various reviewing and bibliometric performance, different academic age in Figure 3. We divided all scholars in the dataset into 10 groups based on scholars' academic age, the number of publishing articles per year and the number of reviewing manuscripts per year, respectively: 0-10%, 10%-20%, 20%-30%, 30-40%, 40%-50%, 50%-60%, 60%-70%, 70%-80%, 80%-90% and 90%-100%. For instance, 0-10% denoted that the scholars whose academic age, number of reviewing or publishing productivity ranks among the top 10%. From Figure 4 (a), It is obvious that scholars with lower reviewing articles showed more Granger causality relationship between the two activities. It is consistent with the aforementioned findings in One-Way ANOVA. For example, for the scholars in group 90%-100%, 68.82% owned the Granger causality relationship between publishing and reviewing articles. However, for scholars whose numbers of reviewing rank among 0-10%, 47.62% displayed Granger causality inference. However, from Figure 4(b) and 4(c), There exists no apparent law in directional patterns of scholars with different publishing performance and various academic age.



(a)



(b)



(c)

Figure 4 Directional patterns with different groups (Figure (a) and Figure (b) illustrated the Granger causality result for the scholars with different numbers of reviewing and publishing articles, respectively. Figure (c) displayed the different directional patterns of scholars with various academic age)

5 Conclusions

This paper applied the Granger-causality test to uncover the directional relationship between scholars' publishing and reviewing articles. We focused on settling two issues. One is to confirm an accurate time lag for each time series, rather than a fixed value and the other one is to uncover directionality effect between two activities. We collected reviewing records and publishing records from Publons and PubMed, respectively, and utilized ORCID connecting publication records with reviewing records to acquire the time series pairs between January 2012 and December 2018 for each scholar. By conducting the Granger causality test step by step for each scholar, we found that 57.7% of scholars show a significant directional effect between publication and reviewing articles. The scientists who own fewer reviewing articles may have a Granger causality inference between reviewing and publishing activities compared to higher ones. Furthermore, the scholars who publish lesser articles tend to have more significant causality between two activities. Surprisingly, scientists with elder academic age tend to be in the "Reviewing→ Publication" group.

The peer-review system played an essential role in academic development. Unfortunately, the system breaks down with the rapidly increasing submitted manuscripts and the lack of acknowledgment for reviewers. Therefore, the attempt to explore the directional relationship between peer review activity of scholars and publishing activity, can provide more valuable suggestions for editors to select appropriate reviewers and scholars to decide whether they should accept requests from journal editors.

Although the Granger-causality test can't uncover true causality between two variables, this approach can introduce accurate lag time into the model and uncover the directionality of effect between two-time series, which the correlation coefficient can't display. In the future, we can certainly focus on the causality of two activities to explore the intrinsic mechanism of unidirectional or bidirectional effect between two activities. For instance, if we can find the characteristic of scholars who shows the unidirectional effect from reviewing activity to publication productivity of scholars, It may provide scientific evidence for journal editors to allocate more manuscripts logically to improve the whole peer review system.

There also exits several limitations of this study. Publons is biased in disciplines and publishers (Ortega, 2019). For indiscipline, Health Sciences and Life Sciences, and Physical Sciences and Engineering are underrepresented in this platform. In publishers, Publons includes more articles from open access platforms. These biases could be one of the limitations of our study.

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