Journal of Informetrics 13 (2019) 708–716

Contents lists available at ScienceDirect

Journal of Informetrics

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

The "invisible hand" of peer review: The implications of author-referee networks on peer review in a scholarly journal

Pierpaolo Dondio[a], Niccolò Casnici[e], Francisco Grimaldo[c], Nigel Gilbert[d], Flaminio Squazzoni[b,*]

[a] School of Computer Science, Technological University Dublin, Dublin, Ireland
[b] Department of Social and Political Sciences, University of Milan, Italy
[c] Department of Computer Sciences, University of Valencia, Spain
[d] Department of Sociology, University of Surrey, Guilford, UK
[e] Department of Economics and Management University of Brescia Italy

ARTICLE INFO

Article history:
Received 18 October 2018
Received in revised form 26 March 2019
Accepted 27 March 2019

Keywords:
Peer review
Author-referee networks
Co-authorship network
Collaboration
Scholarly journals

ABSTRACT

Peer review is not only a quality screening mechanism for scholarly journals. It also connects authors and referees either directly or indirectly. This means that their positions in the network structure of the community could influence the process, while peer review could in turn influence subsequent networking and collaboration. This paper aims to map these complex network implications by looking at 2232 author/referee couples in an interdisciplinary journal that uses double blind peer review. By reconstructing temporal co-authorship networks, we found that referees tended to recommend more positively submissions by authors who were within three steps in their collaboration network. We also found that co-authorship network positions changed after peer review, with the distances between network neighbours decreasing more rapidly than could have been expected had the changes been random. This suggests that peer review could not only reflect but also create and accelerate scientific collaboration.

1. Introduction

Peer review has recently been under the spotlight (Bohannon, 2013; Bornmann, 2013; Grimaldo, Marušić, & Squazzoni, 2018). On the one hand, the immense importance of publications and citations for academic tenure and promotion has raised concerns about the reliability and transparency of editorial processes in scholarly journals (Teele & Thelen, 2017; Tennant et al., 2017). On the other hand, the proliferation of competitive resource allocation schemes based on productivity assessments have distorted incentives by establishing the primacy of quantity over quality, and publications over other activities (e.g., reviewing) (Bianchi, Grimaldo, Bravo, & Squazzoni, 2018; Edwards & Siddhartha, 2017; Sobkowicz, 2017). This is challenging the sustainability of scholarly publishing system in a period of academic hyper-competition (Kovanis, Porcher, Ravaud, & Trinquart, 2016; Righi & Takács, 2017). This context has led certain analysts to suggest that peer review is not fit for purpose, as it cannot ensure that only innovative, valid and reliable research is published (Macdonald, 2015; Sobkowicz, 2015).

However, the current debate is characterised by a dominant narrative that considers peer review only as a quality screening mechanism (Cowley, 2015). This has contributed to a "rhetoric of doom", according to which peer review will never be

* Corresponding author.
E-mail address: flaminio.squazzoni@unimi.it (F. Squazzoni).

https://doi.org/10.1016/j.joi.2019.03.018

optimal because of the subjectivity of scientists' opinions and other sources of bias (King, Avery, Helb, & Cortina, 2018; Lee, Sugimoto, Zhang, & Cronin, 2013; Teplitskiy, Acuna, Elamrani-Raoult, Körding, & Evans, 2018). Because it may be assumed that bias would spread under conditions of confidentiality, many analysts have suggested forms of open peer review as a means to mitigate these problems by increasing the transparency of editorial processes (Ross-Hellauer, 2017)

However, a more in-depth analysis suggests that peer review has always performed multiple functions as well as quality screening (Lamont, 2009; Moxham & Fyfe, 2017). For instance, peer review is often expected to increase the value of scientific manuscripts by enacting scientific collaboration among (often previously unrelated) knowledgeable scholars (e.g., Casnici, Grimaldo, Gilbert, Dondio, & Squazzoni, 2017; Casnici, Grimaldo, Gilbert, & Squazzoni, 2017; Rigby, Cox, & Julian, 2018; Siler, Lee, & Bero, 2015). While recent studies have revealed that editorial processes can be even influenced by pre-existing scientific collaboration patterns (Bravo, Farjam, Grimaldo, Birukou, & Squazzoni, 2018; King et al., 2018; Lee et al., 2013; Sarigöl, Garcia, Scholtes, & Schweitzer, 2017; Teplitskiy et al., 2018), to our knowledge, there is no quantitative study that fully reconstructs the network implications of peer review over time using internal data on editorial processes in scholarly journals (Squazzoni, Brezis, & Marušić, 2017). Barriers against data sharing have discouraged empirical research, leaving the debate on peer review open to anecdotal discourses (Casnici, Grimaldo, Gilbert, Squazzoni, 2017; Squazzoni, Grimaldo, & Marušić, 2017).

Our paper aims to fill this gap by presenting a study on 3508 author/referee couples in a journal dataset. We reconstructed a network structure and the dynamics of collaboration using temporal co-authorship networks. We considered the editorial matching of authors and referees as a series of discrete events that linked experts who had specific positions in the scientific community and pre-existing connections (Sarigöl et al., 2017). On the one hand, when editors match authors and referees, they could connect experts who had never collaborated previously. On the other hand, the increasing specialisation of research would make random connections less probable considering that specialists cannot be fully disconnected from each other, especially in small communities.

Our hypothesis is that studying these connections could reveal the network structure and dynamics of the community surrounding a journal and so show: (1) if pre-existing collaboration networks have an influence on referee recommendation and (2) if subsequent collaboration networks could reflect the exposure of experts to new knowledge and potentially new connections during the peer review process. While research has begun to consider peer review as a "distributed cognition" social technology, which serves to frame knowledge claims collectively through established practices of epistemic value (e.g., Cowley, 2015; Pontille & Torny, 2015; Secchi & Cowley, 2018), we claim that as well as being "cognitive", these practices are also socially 'transformational'. As such, they can reveal, strengthen and change scientists' connections and their structural positions in the community. By measuring connections between experts before and after peer review, who could also learn from each other during the process, we can expand the 'quality screening' canonical view of peer review and reconsider the multiplicity of functions that this mechanism accomplishes for the community, either directly or indirectly.

The rest of the paper is structured as follows. The next section presents data and methods, and the following one, the results about connections among scientists before and after peer review. It should be noted that connections were measured through co-authorship networks, which are only one of the means by which scholars collaborate (e.g., Börner, Glänzel, Scharnhorst, & Van den Besselaar, 2011). The last section discusses findings and some limitations of the study.

2. Data

The dataset included information about all manuscripts submitted to a journal from 1998 to 2015. The journal is an open-access, interdisciplinary journal that published research on the application of computer simulation in the social sciences. It is indexed by all major citation databases, e.g., WoS and Scopus. It strictly followed double blind peer review with editorial notifications to both authors and referees, who had full information, including all referee reports, once fully anonymised.

Data included manuscript title, author and referee names, referees' recommendation and number of review rounds for a total of 1433 submissions and 3025 reviews, which were made by 1252 authors and 989 referees respectively. Note that we excluded all submissions that were desk rejected by the journal editor. The sample included 1949 individual scientists. Following previous research (Bravo et al., 2018; Casnici, Grimaldo, Gilbert, Squazzoni, 2017), we focused only on the first round of reviews to avoid correlation and learning effects, which are typically triggered by subsequent rounds. We therefore selected 920 manuscripts submitted to the first round of review. After removing 159 withdrawn manuscripts, we concentrated on 761 manuscripts and 1678 scientists, composed of 842 only-authors, 387 only-referees and 449 authors-referees. Considering only valid reviews (i.e. reports with a recommendation), we identified 2232 distinct referee-author couples with an average of 2.03 reviews per manuscript. Fig. 1 shows the editorial decisions and referee recommendations after the first round of reviews.

As regards to the number of referees per manuscript, note that most manuscripts were reviewed by two or three referees (51.6% and 41.9% respectively), while only a few manuscripts were reviewed by one or four referees (3.7% and 2.8% respectively).

In order to study connections among scientists before and after peer review, we built a set of time-dependent co-authorship networks starting from our sample of journal authors and referees by using various external data sources. These co-authorship networks were time-dependent as we considered all publication traces of scholars until the time *t* in which they submitted or reviewed a manuscript for the journal. We computed every co-authorship network from1998 to 2015 using a time interval of three months. This allowed us to approximate the position of each author and referee in the net-

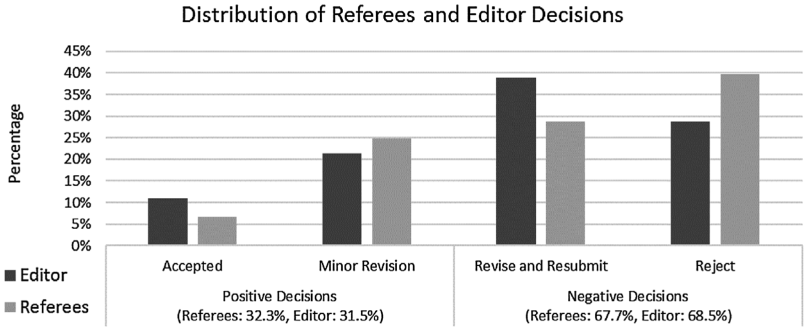

Fig. 1. Distribution of referees and editorial decisions.

Table 1
DBLP Co-authorship network statistics.

Size	1,314,050 vertices (authors)
Edges	18,986,618 edges (collaborations)
Average degree	28.898 edges / vertex
Diameter	24 edges
90-percentile effective diameter	7.14 edges
Effective diameter	7.4786 edges (estimated)
Mean shortest path length	6.09 edges

work depending on each manuscript's submission date t_s and thus to consider the variation of each position over time. The inclusion of a temporal dimension in author-referee network estimates is a major improvement compared to previous research in which referee-author distances were calculated using a single cumulative network without any time dynamics (e.g., Teplitskiy et al., 2018).

We combined several data sources to obtain more reliable scientist-to-scientist connections. We first used the DBLP dataset (Ley, 2005), which includes almost 3 million papers by over 1.3 million authors from 4313 conferences and 1489 scientific journals. This allowed us to access 1.31 million authors and about 19 million node-to-node links, with a mean shortest path length just above six (see Table 1). While DBLP had a unique identifier for each author and covered all articles from JASSS, we built a script to match authors and referees and used each available data-source to avoid name ambiguity. Using the DBLP network, we were able to measure the geodesic distance (length of the shortest path) of 1771 out of 2232 distinct referee-author couples. The missing distances were due to scholars who did not have any record in the DBLP database.

Since DBLP is a repository mainly for computer science publications, some of the connections between scholars present in the Journal dataset could not be sufficiently represented in DBLP. In order to reduce the incompleteness of data, we located scholars in Google Scholar, a freely accessible repository of scientific publications representing social scientists and other specialists more completely than DBLP (Martin-Martin, Orduna-Malea, Harzing, & Delgado López-Cózar, 2017; Moed, Bar-Ilan, & Halevi, 2016). Google Scholar includes more than 100 million publications, covering 90% of the production of academic papers written in English having a digital trace on the Web (Khabsa & Giles, 2014). However, comprehensive network statistics are not available from Google Scholar. While the size and the difficulty of collecting temporal data prevented us using Google Scholar as our main data source, this database was key to obtaining a refined more accurate distance for 340 of the 1771 author-referee couples.

To do so, we first expanded the co-authorship network by two steps around each referee and author who had a Google Scholar account (see Fig. 2). When the expanded set of scholars for each referee and author did not overlap with the previous one (see graph A), we assumed that authors and referees were at $\geq$5 degrees of separation, otherwise $\leq$4 (note that in the example of Graph B, the distance was = 4). When distance values found via Google Scholar were smaller than the DBLP networks, we preferred to use Google Scholar distances to approximate actual networks distances better. Finally, using the distance between each referee and author, we defined the distance, $N_D(r,p)$, between referee r and paper p as the minimum of the geodesic distances between referee r and each author of the paper p (see Fig. 3).

3. Results

3.1. Connections among scientists before peer review

In a study of 7981 manuscripts submitted to PLoS ONE, Teplitskiy et al. (2018) identified three types of connections between authors and referees: close (direct connections), distant (co-authors of co-authors) and very distant (co-authors of co-authors of co-authors etc.). However, Teplitskiy et al. (2018) did not consider the temporal dimension in their co-authorship networks, and therefore the distances between scholars used in their study are significantly smaller than the actual distances at the time of paper submission.

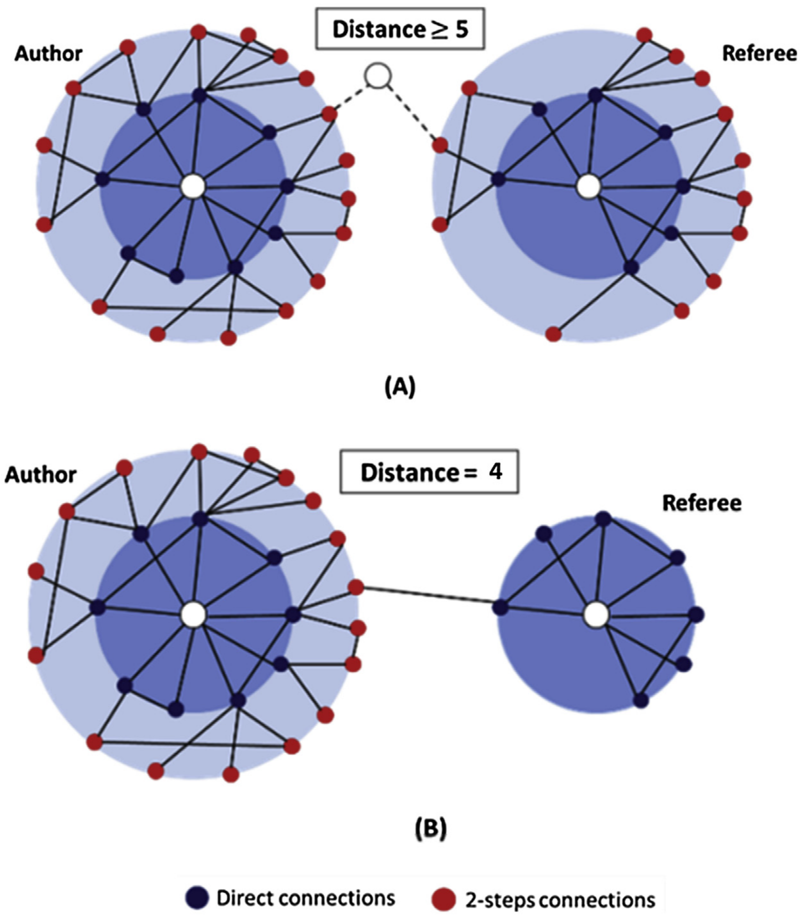

Fig. 2. Estimating network distance using Google Scholar.

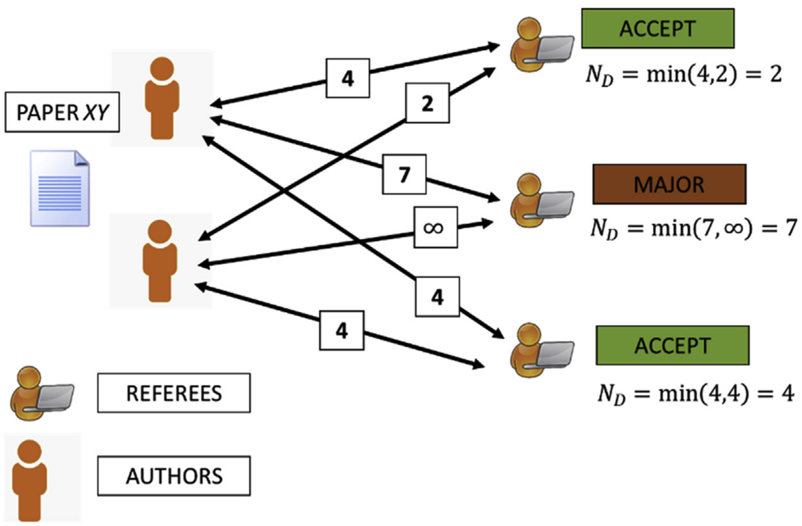

Fig. 3. The network distance $N_D(r,p)$ between referee *r* and paper *p*. The distance is the minimum of the geodesic distances computed on a co-authorship network between the paper's authors and each referee.

Table 2
Network distance vs. acceptance rate (χ^2 (1) = 18.81, p < 0.001 ; 95% confidence interval: [10.14%, 26.61%]).

	Distant ($\boldsymbol{N_D} > 3$)	Close ($\boldsymbol{N_D} \leq 3$)
Positive Review (accept or minor)	532 (32.69%)	69 (51.11%)
Negative Reviews (reject, revise or major)	1095 (67.31%)	66 (48.89%)
Total	n = 1627	n = 135

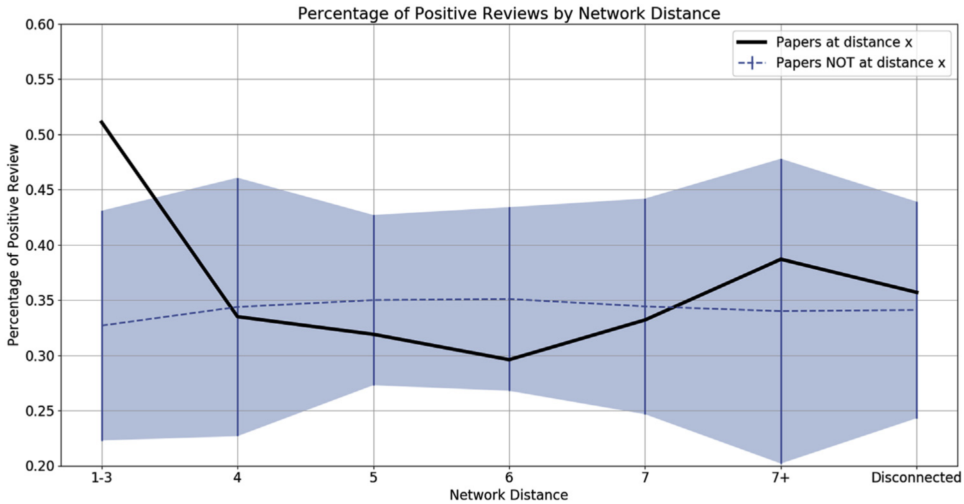

Fig. 4. Network distance vs. percentage of positive recommendations. Blue region indicates the 95% confidence interval of the test (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 3
Positive recommendations and referee-author distances. Note that each row reports a chi-square test on the difference between the percentage of positive recommendations related to a given referee-author distance and the percentage of positive recommendations related to all other referee-author distances.

Distance	χ^2	p-value	C.I.	C.I
1 to 3	18.81	0.00001	0.080	0.288
4	0.02	0.902	−0.126	0.108
5	1.33	0.248	−0.107	0.047
6	3.01	0.083	−0.130	0.036
7	0.03	0.855	−0.110	0.085
7+	1.32	0.250	−0.091	0.185
Disconnected	0.25	0.618	−0.082	0.114

In our dataset, for instance, there are only three cases where author and referee have a distance of two steps, while only one case where there is a direct connection between author and referee at the time of submission. Therefore, in this study we divide the sample into only two categories: *close* (degree of separation ≤3) and *distant* (degree of separation ≥4) scholars.

We estimated the association between referee-author distances and referees' recommendations for each manuscript. We first calculated the percentage of positive and negative recommendations, depending on the relative distance between authors and referees (see Table 2). While distant referees tended to assign more negative than positive reviews (67.3% versus 32.7% of cases), the opposite happened for close referees, since they tended to assign more positive than negative reviews (51.1% versus 48.9% of cases). The association between distance and recommendation was statistically significant (see Table 2).

Furthermore, we considered the difference between the frequency of positive recommendations assigned by referees at a given referee-author distance x and the frequency of positive recommendations assigned by referees at referee-author distances $\neq x$. Fig. 4 shows multiple chi-square test between the frequency of positive recommendations and referee-author distances. Results indicate that closer referees tended to assign positive recommendations more frequently compared to all other referees. Note that referees at four, five, six steps, or greater distance from authors assigned positive recommendations with the same frequency as all other referees. Table 3 shows chi-square values in detail.

Moreover, our analysis shows that the referee-author distance was associated with the number of citations collected by the eventually published manuscripts. Indeed, we found that manuscripts which received negative reviews by closer referees have been cited more frequently (average citations = 73.5, SD = 69.9) than articles which received negative recommendations by distant referees (average citations = 36.6, SD = 42.2). On the contrary, we did not find a positive association between the referee-author distance and the number of citations of manuscripts that received positive reviews (see Table 4 for details). It is worth noting that these results, albeit significant, must be considered cautiously and are mainly explorative. On the

Table 4
Network distance vs. logarithmic citations of published manuscripts (t-tests). The number of reviews referred only to published articles.

Review Outcome	Distance Group	Average Citations	Std Dev Citations	Number of reviews	t-test
Negative Review	Close ($N_D \leq 3$)	1.48	0.77	20 (12 manuscripts)	1.32* (p-value 0.094)
	Distant (N_D>3)	1.27	0.61	126	
Positive Review	Close ($N_D \leq 3$)	1.31	0.53	46	−0.97 (p-value 0.165)
	Distant (N_D>3)	1.42	0.33	346	

* $p < 0.1$.

Table 5
Composition of referees and citations. The number of articles includes only published manuscripts for which we could estimate the network distance for all referees. We excluded published manuscripts for which we could not estimate at least one author-referee network distance.

Composition of Referees	# articles	Avg. Citations
All Close referees	21	57.83
All Distant referees	387	37.89
Mixed (at least one of the referees was close and at least one was distant)	38	47.4

Table 6
Average reduction of the geodesic distance between scholars. Columns 2 and 3 show the difference between the average distance at t_0 and the distance at time of t (paper submission). For instance, the distance between referees and authors decreased on average by 0.45 steps after 1 year, and by 0.78 steps after 2 years.

Year (t)	Journal	Random	z crit	Confidence Interval 99%	Cohen's d
1	0.45	0.29	6.35 ***	[0.095,0.224]	0.21
2	0.78	0.56	6.04 ***	[0.126,0.313]	0.22
3	1.03	0.84	4.32 ***	[0.077,0.303]	0.18
4	1.43	1.21	3.84 ***	[0.072,0.367]	0.17
5	1.6	1.45	2.35 **	[-0.014,0.31]	0.11

** $p < 0.05$; *** $p < 0.01$.

one hand, the distribution of citations is skewed and characterised by high standard deviations. On the other hand, our observations were partially dependent because manuscripts could be reviewed by more than one referee. Furthermore, it is worth noting that referee-author distances could reflect temporal processes: tighter distances between authors and referees could be more probable at the beginning of the journal development, when the community was relatively smaller, and this could affect the temporal association between distances and citations.

With all these caveats, our results suggest that having a negative review from a close reviewer may be beneficial for manuscripts. Probably, this is because close critical referees were competent on the manuscript topics but independent in their judgement and so more demanding for authors, who probably received useful comments that increase the value of the manuscript, when eventually published as reported in Casnici, Grimaldo, Gilber, Dondio et al. (2017). This could be confirmed by comparing manuscripts which were assessed by all close, all distant or a mix of close/distant referees (see Table 5). Although we had numerous missing cases (i.e., manuscripts with missing referee-author distances or missing citation data), manuscripts that were reviewed by referees who were closer to authors were significantly more cited than those reviewed by all distant or a mix of close/distant referees. This suggests that author-referee distances could reveal more the presence of sub-communities of scholars working on the same topics, with more consistent standards of judgement according to which negative reviews are valuable for manuscript improvements.

3.2. Network implications

Our previous analysis showed that connections between scholars in peer review change over time and this could even be either a direct or an indirect implication of peer review. For instance, referees can access relevant research when reviewing a manuscript, discover recent literature in their field of interest and identify potential collaborators when the article is eventually published (Grimaldo et al., 2018; Tennant et al., 2017). If peer review is a form of collaboration between knowledgeable scholars in a value generating processes, it is reasonable to expect that the process may have consequences on scientists' positions and connections later.

In order to examine this, we looked at the network distances after authors and referees were matched by the journal editor during the peer review process. We calculated the geodesic distance of each author-referee couple every three months, starting from the day in which peer review took place, t_0. Note that the network distance between author and referee could only reduce over time because by adding new nodes (new scholars) and links (new co-authorships), the shortest path between each referee and author can only get shorter.

Table 6 shows the average reduction of the geodesic distance between authors and referees of the same manuscript in number of steps per year after t_0 (see a graphical representation in Fig. 5). The estimated effect decreases slightly over time (column 2 of Table 6). To test the significance of this finding, we compared the decreasing trend of the distance of all the

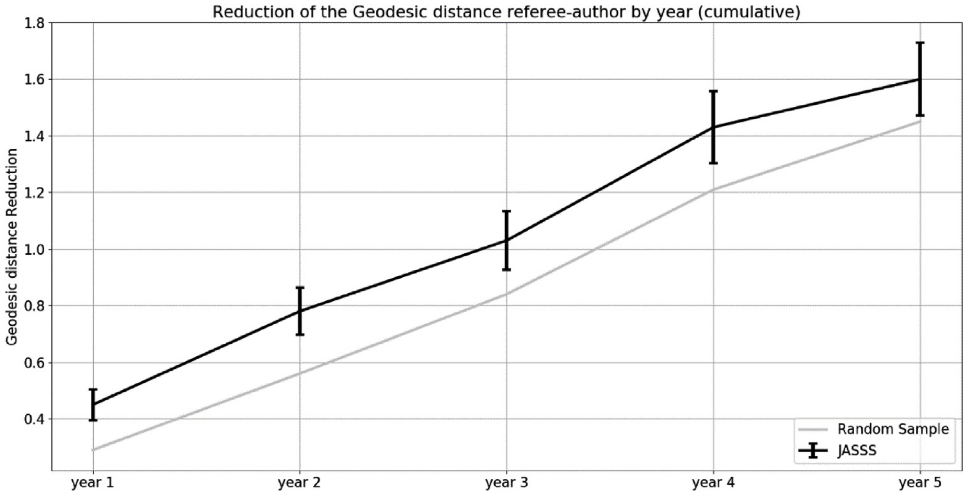

Fig. 5. The reduction of the geodesic distance of JASSS scholars vs. the random sample by year. The vertical black lines indicate the 99% confidence interval for a paired t-test for the null hypothesis between the mean reduction in the geodesic distance observed in the JASSS dataset vs the random sample.

referee-author couples against a random sample of about 30,000 nodes from the co-authorship. To do so, we first removed each author-referee couple that was disconnected at t_0, identifying 1488 suitable author-referee couples (a, r) in the journal dataset. We called $d(a, r, t_0)$ the distance between each author a and referee r at time t_0. For each couple (a, r), we sampled 20 random nodes n_i (for a total of 29,760 nodes) considering two conditions. First, each random node n_i should have the same distance to author a as referee r at t_0, i.e., $d(a, n_i, t_0) = d(a, r, t_0)$. Secondly, each random node n_i should have the same degree centrality of referee r at t_0, i.e., $deg(r, t_0) = deg(n_i, t_0)$. Selecting the random node that had the same author-referee distance and the same centrality degree was necessary in order to compare scholars with similar co-authorship networks and so likely similar seniority. We then calculated the geodesic distance over time and compared the reduction of the distance of the random sample with the journal sample.

Table 6 (columns 4 and 5) shows the result of a statistical comparison of the average distance reduction in the journal dataset versus the random sample. We found that the average distance in the co-authorship structure between each author and referee of the journal was significantly different from the random one for all years. The difference was largest in the first two years after peer review. The effect size, measured using Cohen's *d*, (Cohen, 1988) is moderate.

More specifically, we found that 99 referee-author couples (6.65% of the total) reduced their distance from >3 to $\leq$3 degrees, against only 0.84% of couples in the random sample. 284 couples (19.08% of the total couples) that had a >4 distance during peer review reduced their distance to $\leq$4 over time, against 6.61% of the random sample. 28 couples took less than a year to reduce their distance by more than one step, and 44 took less than two years. Furthermore, 28 couples (1.88% of the total couples) reduced their distance to 2 degrees, against only 0.13% of couples in the random sample. Seven couples arrived at step 1 by publishing an article together a year later.

Fig. 6 shows an example of the network position dynamics for an author and a referee who were matched by the journal editor on a submission at time t_0 with a network distance of 6 steps and who moved closer over time to reach 2 steps in t_5. Obviously, it is worth noting here that inferring a causal effect of peer review on complex, time-dependent patterns, such as scientific collaboration structures, is far from the scope of our analysis.

Finally, in order to estimate the link between referee recommendation and network distance reduction, we divided the author-referee couples into two groups: one included referees who made negative recommendations, and the other included referees who submitted positive recommendations. We did not find any significant difference between the two groups, except for the first year, when the average distance reduced by 0.51 in case of positive reviews and 0.41 in case of negative reviews. This 22.5% gap was statistically significant (95% confidence interval is [0.045-0.15]). After one year, 42 couples reduced their distance by 2 or more steps in the positive set (9.52% of the total number of *positive* couples) and 41 couples in the negative set (4.55% of the total number of *negative* couples).

4. Conclusions

Although the debate in academia, the social media and the press mostly concentrates on the quality screening function of peer review, our findings suggest that peer review is also a collaboration process between experts (Cowley, 2015; Tennant et al., 2017). While connections could bias referees' judgment, especially in contexts of hyper-competition (Bravo et al., 2018; Bianchi et al., 2018; Casnici, Grimaldo, Gilbert, Squazzoni, 2017), they could also reflect the inevitable concentration of expertise in certain fields. Our study confirms that even when peer review is double blind and scientists' identity is at least in principle mutually unknown, the respective positions of authors and referees in the pre-existing collaboration structure might influence the process. However, this is not necessarily bad for science (Bravo et al., 2018).

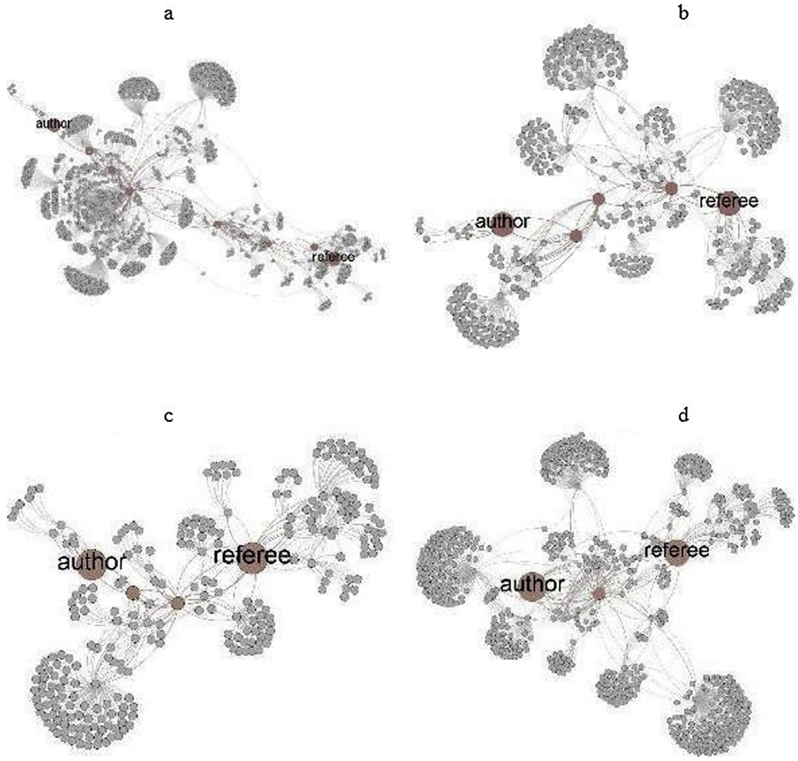

Fig. 6. Examples of network position dynamics for a referee/author distance paths by year. The author and referee nodes represent their mutual distance in the co-authorship network, while the smallest nodes indicate their co-authors. Network snapshots must be read left to right, top to bottom, starting from the top left snapshot (Fig. 6a), which represents the author-referee position when the journal editor matched them during the peer review process. Fig. 6b and c represent the network structure after one and two years. Fig. 6d represents the final connection structure of the two connected scholars after three years.

Disentangling the good from the bad in network effects will require further research. In a recent study on more than 100,000 submissions between 2007 and 2015 in PLoS ONE, Sarigöl et al. (2017) found that prior relationships between submission authors and handling editors could speed up manuscript handling times by 19 days on average. While this case is clearly a sign of editorial bias, our author-referee network effects on recommendations could simply indicate a concentration of expertise in certain small sub-communities. Reconstructing each referee's expertise and performing a structural analysis of the temporal composition of the community via topic modelling could help verify this hypothesis (Ding, 2011) and discriminate between referees' subjectivity or antagonistic motivations, or the tendency of experts in the field to collaborate either side-by-side or mediated by bridges. However, the effects we found could also result to some degree from limitations in our ability to sample all author-referee couples.

Our findings suggest that peer review could not only reflect but also change scientific collaboration patterns. This is probably because experts learn from the process by being exposed to new ideas and sources, while diffuse and complex standards of judgement and competence help them either to corroborate their position or develop new insights (Lamont, 2009). Our findings could be complemented by reconstructing the fragmentation of scientists into sub-communities with different endogenous processes of growth (Grimaldo et al., 2018). Unpacking these sub-communities could reveal exogenous effects on our sampled relationships and help us estimate in more detail the pure effect of peer review on future collaboration patterns. However, controlling for all confounding factors leading to temporal modification of collaboration patterns between scholars is difficult. Furthermore, co-authorship is only one of the many means through which scholars collaborate (e.g., Börner et al., 2011). For instance, cross-references and citations could reflect indirect collaboration via knowledge sharing and credit recognition (e.g., Hauke, Lorscheid, & Meyer, 2017).

Finally, despite all these caveats, network visualisations of peer review could have two other important functions. First, once incorporated in journal management systems, they could help to map positional effects, estimate potential bias and assist journal editors in referee selection (Bravo et al., 2018). Unfortunately, peer review management systems have not yet fully incorporated advanced tools and data applications, although such tools would help all those involved to manage the process better and more responsibly. While available workflow management systems for scholarly journals, such as *ScholarOne*, *Editorial Manager* or *Evise*, have internal tools to check previous manuscripts by authors or locate referees from external data sources upon manuscript keywords (e.g., Web of Science) (Kim, Choi, Kim, Chung, & Lee, 2018), these do not still incorporate rich structural and positional factors like those ones considered in this study. Secondly, these network tools could also offer insights about the temporal evolution of the scientific community surrounding a journal, with potentially positive effects on learning and self-awareness of journals (e.g., Batagelj, Ferligoj, & Squazzoni, 2017; Bravo et al., 2018). In this respect, we hope that our findings will stimulate large-scale applications of network research to improve our understanding of the impact of the social context on peer review and promote innovations in the journal management of the process.

Author contributions

Pierpaolo Dondio: Conceived and designed the analysis; Collected the data; Contributed data or analysis tool; Performed the analysis; Wrote the paper.

Niccolò Casnici: Collected the data; Contributed data or analysis tool; Performed the analysis.

Francisco Grimaldo: Collected the data; Contributed data or analysis tool.

Nigel Gilbert: Collected the data; Wrote the paper.

Flaminio Squazzoni: Conceived and designed the analysis; Wrote the paper.

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