On Collective Dynamics of Academic Journals: Polarization, Fluctuation, and Robustness

N. Cai, *Senior Member, IEEE*, L. Liu, *Student Member, IEEE*, and J.-W. Cao, *Senior Member, IEEE*

***Abstract*—The dynamics of academic journals are observable from time series of citation indices, such as journal impact factor (JIF), which are quantitative emergence of the citation network topology ever growing. It is meaningful to study the variation of citation indices and quality of journals through computational studies. In this paper, an experimental system is developed to generate virtual citation networks by simulating key social activities, including manuscript submission, peer review, journal publication, and article citation. The system is built upon a model grounded solely in basic individual behavioral dynamics and free from reliance on specific technical assumptions, ensuring broad generality. By incorporating bibliometric attributes such as article quality scores and temporal publication data, the system enables replication of journal behaviors and citation dynamics. A series of computational experiments are conducted on the system, revealing and analyzing various phenomena under different scenarios. Key findings include the identification of dynamic patterns such as stationarity, inertia, and polarization tendencies in journal performance over time. The experiments further demonstrate the robustness of journal dynamics against moderate external disturbances, such as self-citation behavior, and highlight a gradual weakening of volatility in journal citation indices. These findings are further explained through a semi-analytical approach. The study offers actionable insights for journal management, policy design, and long-term evaluation strategies, contributing to a deeper understanding of the temporal evolution of academic journal communities.**

***Index Terms*—citation index, citation network, computational experiment, collective dynamics**

I. Introduction

EACH academic journal functions as a dynamic system, with its relevant indicators constantly fluctuating and forming time series. Additionally, every journal operates as an open social system, influenced by the activities of various social roles, including individual roles such as editors, reviewers, authors, and readers, as well as institutional roles like publishers and sponsors. Those journals related to a specific discipline collectively form an ecosystem, identified by interactions and competition among them.

The development of a journal is a shared aspiration among editors. They aim to elevate their journal to a prestigious status, showcasing cutting-edge achievements and setting the course for research in their field, while garnering widespread recognition within the relevant community. A prestigious journal is able to attract submissions from accomplished scholars or based on significant research, and is characterized by strong competitiveness and promising long-term sustainability.

The competitiveness of academic journals can be attributed to their internal quality and potential. However, these factors are not directly observable. In practice, the dynamics of academic journals are usually assessed through time series data of citation indices. Among the various indices, the Journal Impact Factor (JIF) is particularly influential as a commonly employed metric in evaluating journal competitiveness. Despite their differences, typical citation indices, such as JIF, CiteScore, Scimago Journal Rank (SJR), Source Normalized Impact per Paper (SNIP), and Eigenfactor Score (ES) are mostly highly correlated [1]-[3].

Citation indices like JIF are quantitative macroscopic emergence of the topology of citation network, which is shaped by numerous individual publication and citation behaviors. Comprehending the individual behavioral dynamics is crucial for effective modeling. In turn, the modeling process feeds back insights and enhances the understanding of these dynamics. During the past decade or so, some models are proposed that can dynamically generate citation networks. BA (Barabási Albert) scale-free network as a kind of dynamically growing network constitutes a source of origin for the science of complex network, with citation network being its most typical instance [4]. However, there is still gap between real instances and abstract concept. Since citation network is essentially acyclic due to the strict timing sequence for vertices, its motif is no more with the triangular cyclic structure as in traditional networks, but a third-order feedforward loop [5]. Refs [6]-[7] amended the generation rule of scale-free network addressing the specialty of citing behaviors. Later, the topological properties of citation network are further studied [8]-[9]. It is well-accepted that the generation of citation network is mainly based on three mechanisms, namely preferential attachment [10], aging [11], and fitness [12]. The theory on citation network generation was early proposed by Wu and Holme [13], with the link probability between vertices being jointly determined by two factors: aging and copying behavior

This work is supported by National Natural Science Foundation (NNSF) of China (Grant 61867005), by National Key Basic Research and Development Program of China (Grant 2017YFE0132100), by BUPT Excellent Ph.D. Students Foundation (Grant CX20242084), and by BUPT innovation and entrepreneurship support program (Grant 2025-YC-A071). (*Corresponding authors: N. Cai; L. Liu.*)

Ning Cai and Li Liu are with the School of Artificial Engineering and Automation, Beijing University of Posts and Telecommunications, Beijing 100876, China (e-mail: caining91@tsinghua.org.cn; liuli1175298635@bupt.edu.cn).

Jun-Wei Cao is with the Beijing National Research Center for Information Science and Technology, Tsinghua University, Beijing 100084, China.

(preferential attachment). Ren *et al.* [14] improved the work of [13] such that the motif generated is more consistent with feedforward loop. The concept fitness of complex network was raised by Bianconi and Barabási [12]. For citation network, the fitness of vertex can be regarded as a quantitative measure of the quality of article, which is an internal state being difficult to observe. Medo *et al.* [15] endeavored to evaluate fitness value based on the ratio of the counted versus expected number of citations. Peterson *et al.* [16] formulated the probability density function of citations based on simple rule of preferential attachment, and the resulted distribution conforms to the power-law principle, with possibility of a phase transition burst after transcending certain threshold. Eom and Fortunato [17] modeled the link probability as being proportional to the sum of both the effects of the preferential attachment and the time-decaying fitness. They then considered the influence of academic reputation of authors by taking personal accrued citations as the corresponding indicator [18] and found the phase transition burst too. Golosovsky and Solomon [19] reformulated the model in [17] into the product of two effects, with the preferential attachment term being a power function. Later, Golosovsky [20] analytically proved their model based on queueing theory, while their idea might also enlighten designing observer to evaluate hidden internal states such as fitness. Via mechanism modeling, Wang *et al.* [21] derived a functional expression for citation pattern, which could forecast future citations to article through existing ones. However, it is said that the forecast is not satisfactory in practice [22]. This might be attributed to the over-simplicity of model, without the evolution of system and the coupling between sub-systems being considered. Through extensive empirical analysis, [23] demonstrates that the evolution of scientific paradigms exhibits robustness, guided by strong self-organizing trends. Kuhn *et al.* [24] identified the memes within existing physical literature, uncovering a clear correlation between their frequency of occurrence and propagation along the citation graph, offering valuable insights into the copying behavior. Sinatra *et al.* [25] observed that the time for the most excellent work of a scholar to appear is evenly distributed over his/her entire career. Based on this observation, they proposed a model to quantitatively measure personal talent from the citation series of a scholar. They further discovered [26] that temporal dependency exists between different excellent products of any scholar. Their discovery may be relevant to the transition of both personal interest and research hotspot of community [27]. Paying attention to the aging effect, Lorenz-Spreen *et al.* [27] built a dynamical model for the fluctuation of topic heat based on eco-systematical competition model under limited resource, and they found that the fluctuation includes three stages: imitation, saturation, and competition. Also addressing the aging mechanism, Candia *et al.* [28] counted the collective memory of any specific subject as the sum of a short-term “communicative memory” and a long-term “cultural memory”, and built a dynamical equation for memory decaying. Abramo *et al.* [29] employed a linear bivariate regression model to forecast future citations to given article, with the two variables being the impact factor of publication and the number of citations already accumulated, respectively. Sunahara *et al.* [30] discovered six productivity patterns throughout the careers of scientists, complementing the research in [25] by providing deeper comprehension on temporal behavioral dynamics. Recently, other factors affecting citation behavior are concerned, such as collaboration network [31]-[32].

When facing complex systems dynamics, the result of mode identification by statistics or machine learning usually lacks sound interpretability and bears less generality and reliability so long as merely data analysis is employed [33]-[34], due to the essential paradox between complexity and the finiteness of data sampling. After all, the roles of domain knowledge about the principles of systems and corresponding scientific theories should by no means be underestimated. A parallel experimental system is regarded as stand-alone instance belonging to the same class with its real-world counterparts. Experimental analysis based on parallel models has been becoming a mainstream methodology in modern social sciences [35]. On one hand, it is the only way that can improve interpretability, generality, and reliability in the case of missing or insufficient data [36]. On the other hand, general laws and phenomena can be revealed via repeatable experiments and demonstrations under scientifically controlled conditions.

All academic journals belonging to a discipline form a complex social system, with the journals keeping on interacting and competing with each other. It is of both theoretical and practical importance to study the variation of citation indices and quality of journals via model-based experiments [37], since certain hidden laws can be revealed and mechanisms of some phenomena be illuminated thereby. Especially, a deeper understanding about the collective features of journal dynamics, such as differentiation, convergency, and fluctuation, would be instructive for sustainable development of journals under competition. As far as our knowledge is concerned, relevant studies are still rare and sporadic hitherto. Refer to [38] and the literature that cites and that is cited by it. [38] illustrates an endeavor on this research track, but the journal model wherein is isolated, without the inter-journal influences and constraints taken into consideration.

This paper presents an experimental system that comprehensively models various social activities within an academic community, such as manuscript submission, peer review, journal publication, and article citation, aiming to simulate the long-term evolution of journals of a discipline. Through this system, a series of computational experiments are conducted, resulting in the observation and study of several phenomena under different scenarios. The focus is particularly on the likelihood, universality, and regularity of two fundamental aspects: 1) the mutual divergence and Matthew effect among different journals; 2) the consistency in the temporal trend of any single journal.

The methodological novelties can be characterized as follows. Firstly, the process of citation network generation integrates various influencing factors into a relative citation probability, rather than an absolute probability, which is plainly advanced both in extendibility and reasonability. Secondly, the modeling is based solely on the fundamental behavioral criteria of individuals, resulting in sufficiently generalizable results without relying on any specific assumptions or settings. Thirdly, alongside experimental observations, analytical and semi-analytical interpretations are also provided, enhancing validation for the findings from composite perspectives. We believe that the second and third methodological novelties can enlighten extensive research addressing the complexities of social dynamics across diverse fields, with the current study serving as an illustrative example.

Based on behavioral dynamics, we address the exploration about the regular temporal patterns behind the process of academic publication, with article to article, article to journal, and journal to journal interactive couplings, and we indeed reveal some meaningful patterns which have rarely been noticed before. The study of temporal patterns of journal evolution is concentrated on inter-journal divergency and individual steadiness, which is from an original perspective emerging out of practical pursuits. In practice, both issues are of significant importance: one is the nature of development/ degradation of different journals, and the other is the steadiness of quality along with the numerical steadiness of quality indicator for individual journals.

The remainder of this paper is organized as follows: Sec. 2 provides a comprehensive description of the framework of model. Sec. 3 details the observation and analysis of several significant phenomena through computational experiments. Theoretical explanations for the dynamical patterns observed are presented in Sec. 4, supported by semi-analytical study. Sec. 5 is dedicated to conducting sensitivity analysis. Finally, this paper concludes with a concise summary of the findings in Sec. 6.

II. Experimental Modeling

The experimental model is discrete-timed, and the unit of time is a month, with each iteration representing a synchronous round of generation, submission, review, and publication of articles. Disciplines are differentiated by different parameter settings. For better understanding, the introduction to modeling will be discussed in two major aspects.

A. Relative citation probability

In the experimental cyber-scenario, articles are generated successively. Each article is a new vertex inserted into the citation network. When a new vertex is added, it should be linked to a number of previously existing vertices, representing the selected references of the newly published article. By this means, the citation network grows over time.

Suppose the overall journal community is comprised of N academic journals; each publishes a same number of articles synchronously.

The reference selection is stochastic. The connectivity of citation network is up to the relative probability for an article to be cited P_c, which is a multiplicative product of a series of factors, each corresponding to the effect from one specific influential factor affecting the citation behavior.

$$P_c = \prod_i F_i \tag{1}$$

Each factor F_i is normalized into a number within [0, 1], such that P_c never exceeds this interval.

In the current model, the four prime influential factors that jointly determine the citation behavior are: the key citation index x of publication, the number of citations n_c already achieved by article, the intrinsic article quality η, and the article age t. Each factor in (1) is a function of corresponding influential factor, namely, $F_1(x)$, $F_2(n_c)$, $F_3(\eta)$, and $F_4(t)$, respectively.

The factor functions follow some common principles. Firstly, they are generally monotonic. Secondly, they should be sufficiently smooth over the entire definitional domain. There is no reason for each of them to have any abrupt change at specific points. Thirdly, they are bounded by the prescribed limits. Lastly, they should be essentially simple in form, according to the Occam's Razor law.

Summing up the above principles, one knows that the basic configuration of the factor functions is of S-type. In the current study, hyperbolic tangent function is selected as the S-type functional element, as illustrated in Fig. 1. Later, we shall show that the specific form of a factor function actually matters less provided that its shape is subject to the principles in citation behavior.

The principles for factor function $F_1(x)$ are:

(i) $F_1(x)$ is increasing monotonically in the definitional domain $[0,+\infty)$;

(ii) $F_1(x) > 0$;

(iii) $\lim_{x\to+\infty} F_1(x) = 1$.

Due to the principles, the function with analytical expression below is applied in experiment

$$F_1(x) = \frac{1}{2}[\tanh(\frac{x}{\varepsilon} - \theta) + 1] \tag{2}$$

where x is the key citation index of journal and $\varepsilon, \theta > 0$ are the parameters shaping the curve.

The principles for factor function $F_2(n_c)$ are:

(i) $F_2(n_c)$ is increasing monotonically in the definitional domain $(0,+\infty)$;

(ii) $F_2(n_c) > 0$;

(iii) $\lim_{n_c\to+\infty} F_2(n_c) = 1$.

thus, the analytical expression of $F_2(x)$ is chosen as:

$$F_2(n_c) = \frac{1}{2}[\tanh(\frac{n_c}{\gamma} - \lambda) + 1] \tag{3}$$

where n_c is the citation number of article and $\gamma, \lambda > 0$ are the parameters shaping the curve.

With the maximum rank of article quality normalized into a prescribed value Q, the principles for factor function $F_3(\eta)$ are:

(i) $F_3(\eta)$ increases monotonically over the interval $(0, Q]$;

(ii) $\lim_{x\to 0} F_3(\eta) = 0$;

(iii) $\lim_{x \to Q} F_3(\eta) = 1$.

Linear relationships are generally observed and applied in the literature [21], [39]-[40], accordingly, the analytical expression of $F_3(\eta)$ is:

$$F_3(\eta) = \frac{\eta}{Q} \tag{4}$$

where η is the quantitative rank of article quality, i.e. the fitness.

Function $F_4(t)$ $(t \in [0, +\infty))$ serves as a factor to evaluate the correlation between the citation probability and article age, denoted by t. Its basic principles are:

(i) $F_4(t)$ is decreasing monotonically in the interval $[0, +\infty)$;

(ii) $\lim_{t \to +\infty} F_4(t) = 0$;

(iii) $\lim_{t \to 0} F_4(t) = 1$.

Based on the principles, a corresponding analytical expression is selected:

$$F_4(t) = \frac{1}{2}[\tanh(\alpha - \frac{t}{\beta}) + 1] \tag{5}$$

with t being the age of article and α, β being the parameters shaping the curve. It is worth noting that the curve of (5) is also well consistent with previous empirical observations [28], [41].

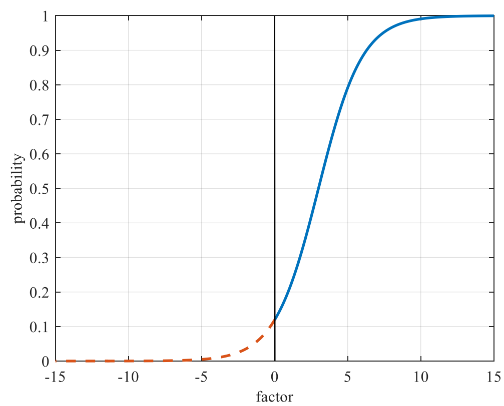

Fig.1. A curve of S-type factor function curve. Solid part depicts influence of factor on relative citation probability.

B. Article generating and publishing process

The modeling of the process mainly consists three stages:

1) Manuscript generation

As power law distribution is one of the common properties of academic social networks [23], [42], it is hypothesized that the quality of manuscripts follows power-law distribution with exponential cutoff, formulated by (6) and illustrated in Fig. 2 (a)

$$\phi(\eta) = a\eta^{-b}e^{-c\eta} \tag{6}$$

where $\phi(\eta)$ is probability density function and a, b, and c are parametric constants that determine the shape of curve.

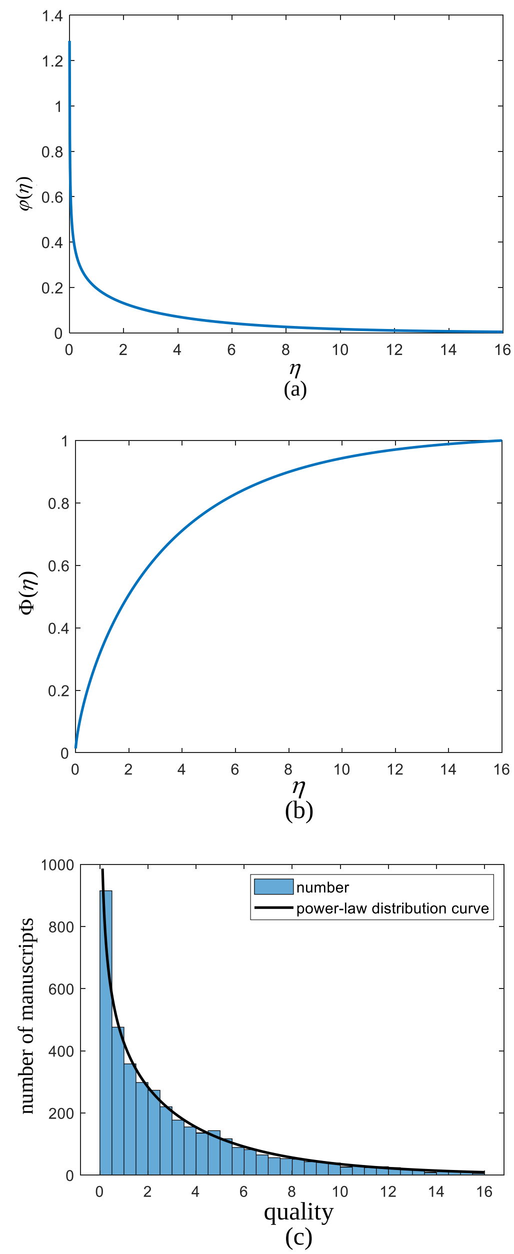

Fig. 2. (a) Probability density curve of power-law distribution with exponential cutoff. (b) Corresponding probability distribution curve. (c) 4000 samples randomly generated by Monte Carlo method.

Remark 1: To generate a random number with given probability density function $\phi(\eta)$, one needs to further obtain its probability distribution function $\Phi(\eta)$, with

$$\Phi(\eta) = \int_0^{\eta} ax^{-b}e^{-cx}dx$$

Monte Carlo method is applied here for numerical integration. Fig. 2 (b) shows the resulted probability distribution curve. For each manuscript, its quality can be generated via mapping an evenly random seed $p \in [0,1]$ on the probability distribution curve. The ultimate distribution of manuscripts is illustrated in Fig. 2 (c).

2) Manuscript submission

In this stage, a journal is selected for submission. It starts with an assessment of the quality of manuscript by the authors themselves. Subsequently, a well-matched journal will be chosen for submission. Such an activity is determined by two joint factors:

(i) according to the self-assessment of manuscript quality, authors tend to select a journal that matches better;
(ii) journals with higher JIF will be preferred.

Remark 2: The ultimate selection is up to a probability P_{ij}, being positively correlated with JIF and negatively correlated with the quality discrepancy estimated between the manuscript and the journal, where subscript *i* denotes the journal number and *j* the manuscript number. According to the above principles, the following formula naturally yields:

$$P_{ij} = \tanh(\frac{x_i}{\zeta\left|\hat{\eta}_j - q_i\right|}) \tag{7}$$

where x_i is the impact factor of journal *i*; $\hat{\eta}_j$ is the self-assessment of manuscript quality by the author; q_i is the quality of journal *i*; and ζ is the parameter shaping the functional curve.

3) Article publication

All submissions will undergo peer review in this stage. This is the process of assessing the quality of manuscripts by reviewers, which is formulated as follows:

$$\tilde{\eta}_j = \eta_j(1+\Delta_i) \tag{8}$$

where $\tilde{\eta}_j$ is the review score of manuscript *j*; η_j is the intrinsic quality, and $\Delta_i \in R$ denotes the multiplicative deviation of peer review, with its magnitude being negatively correlated with the expertise of reviewer, who is invited by particular journal and willing to review for the journal.

Remark 3: The level of expertise of an appropriate reviewer should be positively correlated with JIF. In the experimental system, Δ_i follows normal distribution with expectation 0 and variance v / x_i^{κ}, where x_i is the JIF and $v, \kappa \in R^+$ are parameters shaping the distribution. For more detail of the peer review mechanism, please refer to [43].

Subsequently, as the selection criterion, each journal accepts a prescribed number of manuscripts for publishing, which have obtained relatively high scores. After that, the system can calculate the average quality of articles in each journal.

C. Merits of relative citation probability

There are two fundamental merits to adopting relative citation probability in the experimental model. In this subsection, both merits will be elaborated semi-analytically. However, the technical details are not crucial for grasping the overall concepts. For readers conducting a rapid review, it is advisable to bypass the semi-analytical details and concentrate solely on the straightforward textual descriptions of the merits.

As the first merit, citation indices are merely dependent of the relative values of P_c between journals. It is unnecessary to compute the absolute citation probability of any particular article.

Consider the collective absolute probability. For any trial in program, the probability for journal *i* to be cited is

$$P_{c(i)} = \frac{1}{N}(\frac{\sum_{j=1}^{K} P_{c(i,j)}}{K}) \tag{9}$$

where *K* is the total number of articles already published in one journal, and $P_{c(i,j)}$ denotes the relative probability for article *j* of journal *i*. Thus, the actual absolute citation probabilities are

$$P_i = \frac{P_{c(i)}}{\sum_{i=1}^{N} P_{c(i)}} = \frac{\sum_{j=1}^{K} P_{c(i,j)}}{\sum_{i=1}^{N}\sum_{j=1}^{K} P_{c(i,j)}} \quad (i = 1, 2, \ldots, N) \tag{10}$$

From the above equations, one can see that the absolute citation probability is independent of the scale of relative probabilities.

The second merit is naturally yielded from the first. The relative probability is advantageous in extendability. Since the citation behaviors are complex, accurately computing absolute citation probability by exhaustively considering all influential factors is difficult. However, due to the extendability of relative probability, it is feasible to consider only some of the prime factors with regarding the remaining as noises in model, which is compatible to later extension if needed.

With the unknown influential factors into consideration, the refined version of (9) is

$$P_{c(i)} = \frac{1}{N}(\frac{\sum_{j=1}^{K} P_{c(i,j)}\delta_{(i,j)}}{K})$$

where $\delta_{(i,j)}$ is the random noise synthesized by the influential factors other than those already integrated in $P_{c(i,j)}$, e.g. the influence of article subject, the influence of journal reputation, or the influence of author scholarship. As a result, the expectation is

$$E(P_{c(i)}) = \frac{1}{N}[\frac{\sum_{j=1}^{K} P_{c(i,j)}E(\delta_{(i,j)})}{K}]$$

Since $\delta_{(i,j)}$ (j = 1, 2, …, K) are random numbers representing probabilities, there is no reason to presuppose the existence of any fixed mode of fluctuation within a journal. Thus, it can be assumed that

$$E(\delta_{(i,1)}) = E(\delta_{(i,2)}) = \cdots = E(\delta_{(i,K)}) = E(\overline{\delta}_{(i)})$$

III. Experimental Results and Analysis

A. Polarization phenomenon

Experiments are conducted on the virtual system. As general result, Fig. 3 illustrates the JIF variation curves of ten journals.

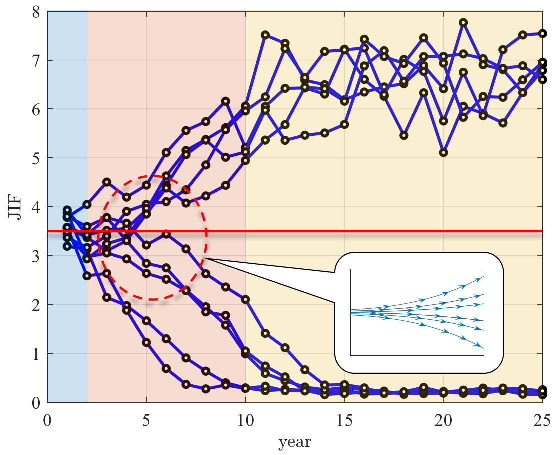

Fig. 3. Variation curves of JIF. Curves are derived under condition: $\gamma = 3$, $\lambda = 0.5$, $\varepsilon = 3$, $\theta = 1$, $Q = 10$, $\alpha = 2.5$, and $\beta = 8$. Three phases are differentiated by background colors. Horizontal thick red line indicates initial median level. Dotted circle highlights jointly diverging motions.

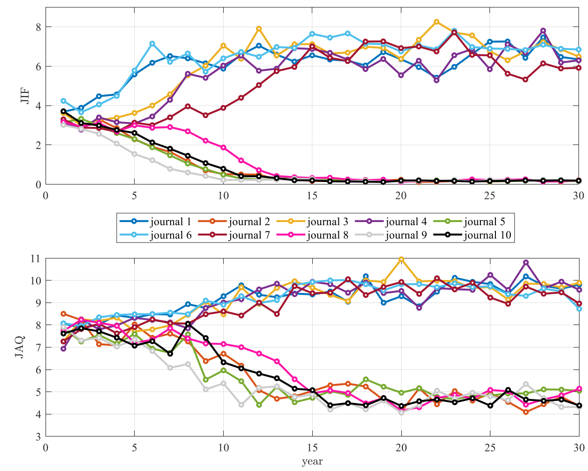

Fig. 4. Variation curves of JIF and JAQ with aligned time axes. Curves are derived under condition: $\gamma = 3$, $\lambda = 0.5$, $\varepsilon = 3$, $\theta = 1$, $Q = 10$, $\alpha = 2.5$, and $\beta = 8$.

From Fig. 3, one sees that typically the collective dynamics of JIF include three main phases. Initially, the JIFs are randomly distributed and vary around a median level, with no evident differentiation. Then, differentiation emerges in the second phase. Matthew effect is mostly intense in this phase. Every time series diverges from each other, forming the formation portrait marked by the dotted circle in Fig. 3. In the third phase, the divergence is rectified, with the collective dynamics tending to form two polarized clusters: higher and lower-ranking. Besides, it can also be observed that the curves generally become steadier while approaching the clusters.

Whether a citation index can accurately reflect the quality of journals is a crucial issue, especially in a dynamical perspective. In practice, direct measurability of journal quality is normally low, whereas it is quite convenient to measure journal quality via computation experiments. As an experimental result, a time-aligned comparison between the temporal variation of JIF and JAQ (Journal Average Quality) for ten journals is illustrated by Fig. 4. One sees a strong dynamic correlation between JIF and JAQ, both in numeric value and in variation trend. Although the system is autonomous without any external interventions, the dynamics of JAQ still noticeably lag behind JIF. Besides, a noteworthy phenomenon is that the ratio of high to low limits of JIF is much higher than the ratio of JAQ, despite the similar formation shape in the two sub-figures.

In order to dynamically measure the volatility of time series, the index CV (Coefficient of Variation) is employed, which is computed as:

$$CV(t,s) = \sqrt{\sum_{i=t-s+1}^{t} [(x(i) - \bar{x}(t)) / x(i)]^2 / s} \tag{11}$$

where t denotes time, s denotes the width of local time span concerned, $x(i)$ denotes the value of data in year i, and $\bar{x}(t)$ is the local average

$$\bar{x}(t) = \sum_{i=t-s+1}^{t} x_i / s$$

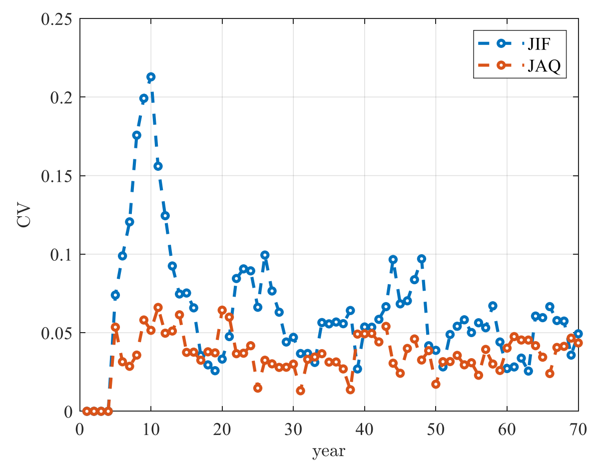

Fig. 5. Volatility of JIF and JAQ time series. Data are derived under condition: $\gamma = 3$, $\lambda = 0.5$, $\varepsilon = 3$, $\theta = 1$, $Q = 10$, $\alpha = 2.5$, and $\beta = 8$.

As experimental result, the temporal variation of $CV(t, 5)$ for JIF and JAQ of journal falling within the higher-ranking cluster is illustrated in Fig. 5. One sees a common tendency of decreasing volatility for both JIF and JAQ, whilst the volatility for JIF is generally more intense than JAQ. This verifies the visual intuition conveyed in Fig. 4, reflecting a steadiness or "inertia" in the dynamics of journal quality.

B. Robustness

The steadiness of the collective dynamics of a journal community is already examined in the previous subsection. Now the focus of this subsection shifts to the robustness. We shall examine the reaction of the system dynamics to external interventions.

To this end, experiments are conducted, involving the falsification of JIF for one specific year of a selected journal, followed by the observation of subsequent variations. Such a deliberate manipulation can be seen as an abrupt interference directly imposed on the JIF value. The findings and corresponding results are presented in Fig. 6.

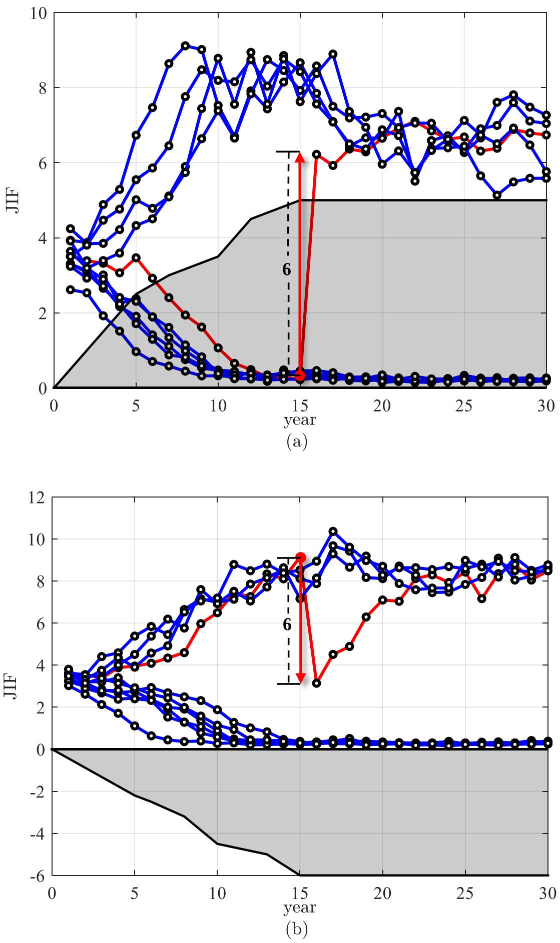

Fig. 6. Temporal variation of JIF response to deliberate falsification: (a) One journal in lower-ranking cluster is imposed positive falsification; (b) One journal in higher-ranking cluster is imposed negative falsification. Curves are derived under condition: $\gamma = 3$, $\lambda = 0.5$, $\varepsilon = 3$, $\theta = 1$, $Q = 10$, $\alpha = 2.5$, and $\beta = 8$. In each sub-figure, red curve represents interfered journal; red vertical arrow marks amplitude, direction, and time of falsification; edge curve of shaded area denotes temporal variation of threshold for interference resulting transition to opposite cluster.

As Fig. 6 displays, JIF indeed holds robustness. After being imposed a relatively minor interference, the journal returns to its original state within a short period. But if the magnitude of interference exceeds a certain threshold, there would be a different result--the journal will jump into the opposite cluster and stay there. This indicates that the robustness of JIF is limited and will be broken if it is seriously interfered with.

Moreover, it can be seen by Fig. 7 that, the variation of JAQ is always strongly correlated with JIF, even when JIF is abruptly perturbed, and regardless of the magnitude of perturbation.

A common operation in reality to manipulate JIF is inducing the articles to be published to cite more articles in the same journal. Here, experiments are conducted to study whether deliberately increasing SCR (Self-Citation Rate) will affect the robustness of JIF. Starting from one specific year, an individual journal with low JIF is picked out and mounted a constant level of SCR for the subsequent years. The result is illustrated in Fig. 8.

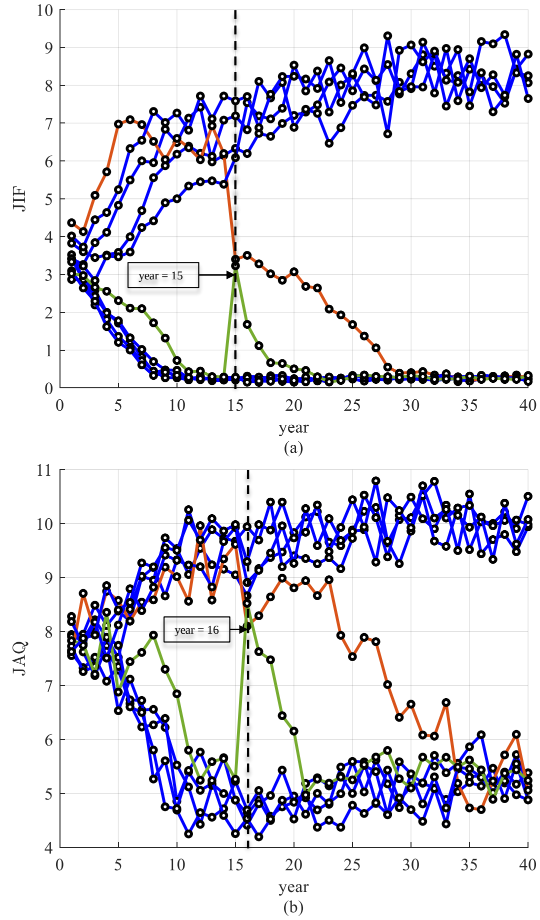

Fig. 7. Variation of JIF and JAQ with aligned time axes, in response to JIF deliberate falsification.: (a) Temporal variation of JIF, and (b) Corresponding variation of JAQ. Curves are derived under condition: $\gamma = 3$, $\lambda = 0.5$, $\varepsilon = 3$, $\theta = 1$, $Q = 10$, $\alpha = 2.5$, and $\beta = 8$. One journal in higher-ranking cluster is falsified negatively, while one journal in lower-ranking cluster is falsified positively. In each sub-figure, red & green curves represent interfered journals; dotted vertical line indicates year with abrupt change.

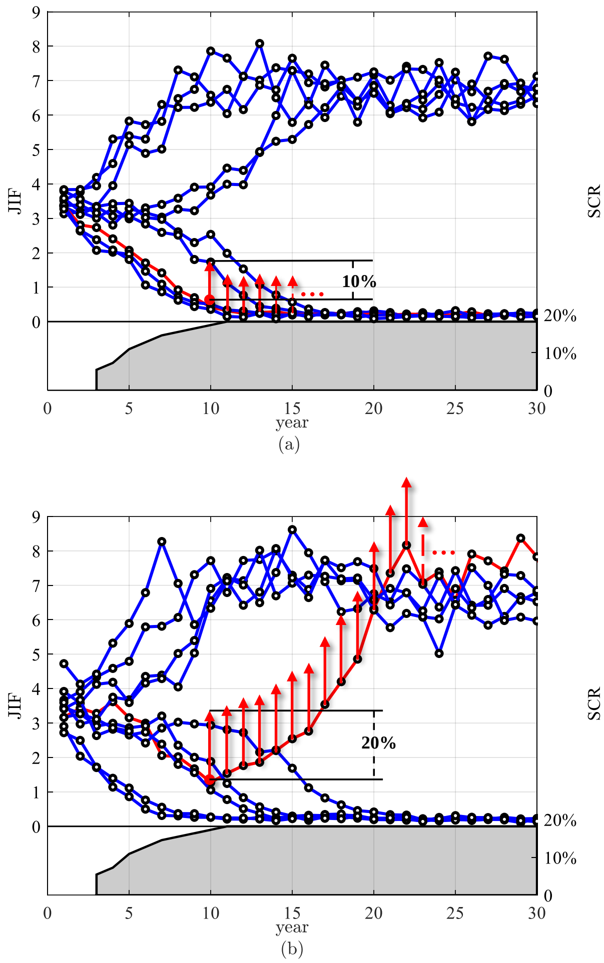

Fig. 8. Temporal variation of JIF subject to different SCR: (a) For selected journal, SCR = 10%; (b) For selected journal, SCR = 20%. Curves are derived under condition: $\gamma = 3$, $\lambda = 0.5$, $\varepsilon = 3$, $\theta = 1$, $Q = 10$, $\alpha = 2.5$, and $\beta = 8$. In each sub-figure, red curve represents one journal with deliberately increased SCR; red vertical arrows mark amplitude, direction, and time of SCR; edge curve of shaded area denotes temporal variation of threshold for SCR resulting transition to higher-ranking cluster.

As can be seen from Figs. 8 (a) and (b), the journal with a deliberately increased SCR will have advantage in competition with other journals, admittedly. However, such an advantage is quite minor under relatively low level of SCR, e.g., 10%, due to the robustness of JIF. Nevertheless, if SCR is sufficiently large to surpass certain threshold, e.g., 20% as in experiment, the robustness will still be broken and there may be a gradual transition of the journal into the higher-ranking cluster.

IV. Semi-Analytical Study

In this section, the cause of the emerging patterns observed in experiments will be explained through a semi-analytical study.

Suppose there are N journals, each publishes n articles per year. For each article, the average number of references published in the past two years is ω, with a refined decomposition:

$$\omega = \omega_1 + \omega_2 + \cdots + \omega_N$$

where $\omega_1, \omega_2, \cdots, \omega_N$ denote the average numbers of references published on different journals, respectively. The citation probabilities of journals, which refer to the probability of a specific journal being cited as the publication source of any reference, are denoted by $p_1, p_2, \ldots, p_N$. Due to the closedness of the journal community, the following identical equation holds:

$$\sum_{i=1}^{N} p_i \equiv 1 \tag{12}$$

The computation of JIF can naturally be inferred from the above definitions:

$$x_i = \frac{Nn\omega_i}{2n} = \frac{N\omega_i}{2} \quad (i = 1,2,\ldots,N)$$

Since $\omega_i = p_i\omega$ $(i = 1,2,\ldots,N)$, $x_i \propto p_i$ through the equation:

$$x_i = \frac{N\omega p_i}{2} \quad (i = 1,2,\ldots,N) \tag{13}$$

In what follows, we mainly address the dynamics of $p_i(t)$.

The sequence chart clearly reveals that

$$p_i(t+1) \sim \{x_i(t), \bar{n}_{ci}(t), \bar{\eta}_i(t-1,t-2), *\} \tag{14}$$

where $\bar{n}_{ci}(t)$ denotes the average accumulated citations during year t for articles published in journal i in the past two years, $\bar{\eta}_i(t-1,t-2)$ denotes JAQ of journal i in years t-1 and t-2, and '$*$' denotes other influence factors.

For $\bar{n}_{ci}(t)$ in (14),

$$\bar{n}_{ci}(t) \sim \{x_i(t), x_i(t-1), x_i(t-2), \bar{\eta}_i(t-1), \bar{\eta}_i(t-2)\}$$

Since $\bar{\eta}_i(t-1) \sim x_i(t-1)$ and $\bar{\eta}_i(t-2) \sim x_i(t-2)$, we have

$$\bar{n}_{ci}(t) \sim \{x_i(t), x_i(t-1), x_i(t-2)\} \tag{15}$$

and

$$\bar{\eta}_i(t-1,t-2) \sim \{x_i(t-1), x_i(t-2)\} \tag{16}$$

Substituting (15) and (16) into (14) yields

$$p_i(t+1) \sim \{x_i(t), x_i(t-1), x_i(t-2), *\} \tag{17}$$

which corresponds to a third-order difference equation as the dynamical model. Let $\bar{p}_i(t)$ denote the convoluted version of $p_i(t)$ and $\bar{x}_i(t)$ the convoluted version of $x_i(t)$, which are the convolution results through any one filter with window width of 3, respectively. Then in view of the steadiness of the system dynamics, we derive

$$\bar{p}_i(t+1) = \varphi_i(\bar{p}_i(t), t) \quad (i = 1,2,\ldots,N)$$

and

$$p_i(t+1) = \hat{\varphi}_i(\bar{p}_i(t), t) \quad (i = 1,2,\ldots,N)$$

via synthesizing (13) and (17), where the idiosyncratic influence factors denoted by '$*$' are integrated into particular functional expressions. It is worthy remarking that despite the distinctions, the functions hold fundamental homogeneity.

The function $\varphi_i(\bullet)$ follows the essential principles below:

(i) $\varphi_i(\bullet)$ is monotonically increasing with respect to $\bar{p}_i(t)$;

(ii) $\varphi_i(\bullet)$ is both upper and lower bounded;

(iii) Due to the criterion that $\sum_{i=1}^{N} p_i(t) \equiv 1$, it is impossible for all elements in

$$\{p_1(t), p_2(t), \cdots, p_N(t)\}$$

to increase or decrease simultaneously.

For convenience of expression, we refer to the straight line depicted by equation

$$\bar{p}_i(t+1) = \bar{p}_i(t)$$

as the baseline in the $\bar{p}_i(t)$ -- $\bar{p}_i(t+1)$ plane.

Principle (ii) implies two fixed-points of $\varphi_i(\bullet)$ as the limits at the boundary of its effective domain. Principle (iii) implicates that in the effective domain, the curve of $\varphi_i(\bullet)$ cannot be exclusively above or beneath the baseline, i.e., there must exist a crossing point in the middle, which is the third fixed-point. According to these inferences, $\varphi_i(\bullet)$ possesses the basic features illustrated in Fig. 9. $\Delta\varphi_i$ is exhibited in (a) of Fig. 9, which is a simplified denotation of the discrete derivative in equation $\bar{p}_i(t+1) = \varphi_i(\bar{p}_i(t), t)$:

$$\Delta\varphi_i(\bar{p}_i(t), t) = \bar{p}_i(t+1) - \bar{p}_i(t) = \varphi_i(\bar{p}_i(t), t) - \bar{p}_i(t)$$

In (b) of Fig. 9, the effective domain is divided into four regions by three vertical lines, namely lines A, B, and C. These regions correspond to the different dynamical patterns emerging from experimental observations, respectively, e.g., those in Fig. 3. Line B designates the boundary for the phase transition between decreasing and increasing. The region to the left of line A corresponds to the clustering with low level JIF, whereas the region to the right of line C corresponds to the high-level clustering. Finally, the region between lines A and C corresponds to the differentiation phase manifesting intense Mattew effect.

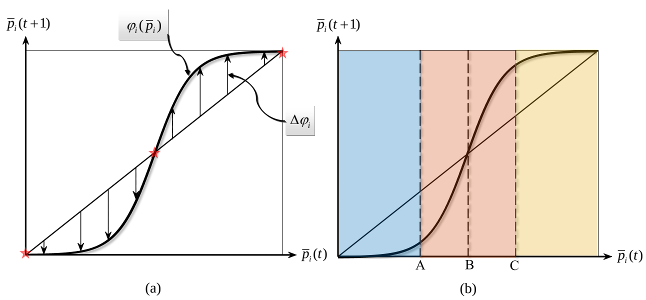

Fig. 9. Graphic representation for basic features of function φ_i. Diagonal denotes the baseline. (a) Red asterisks mark fixed-points. Vertical arrows represent $\Delta\varphi_i$. (b) Four regions of effective domain, differentiated by dotted lines A, B, and C.

For a more comprehensive elaboration, let us examine the region to the right of line C in (b) of Fig. 9 as a survey example.

Theorem 1: Suppose that $\bar{p}_2(t_0)$ locates at this specific region. Then $\exists\theta(\bar{p}_2(t_0)) > \bar{p}_2(t_0)$, such that $\forall t > t_0$ and $\forall \bar{p}_1(t)$,

$$\bar{p}_1(t+1) - \bar{p}_2(t+1) < \bar{p}_1(t) - \bar{p}_2(t)$$

provided $\bar{p}_1(t_0) > \theta$.

Proof: Without loss of generality, suppose that the curves of $\varphi_1(\bullet)$ and $\varphi_2(\bullet)$ do not intercept each other and demonstrate no noticeable fluctuations as $\bar{p} > \bar{p}_2(t_0)$. The situation consists of two cases.

Case 1: $\varphi_1 < \varphi_2$

$\Delta\varphi_1(t) < \Delta\varphi_2(t)$, provided that $\bar{p}_1(t) > \bar{p}_2(t)$.

$$\begin{aligned} &\bar{p}_1(t+1) - \bar{p}_2(t+1) \\ &= [\bar{p}_1(t) + \Delta\varphi_1(t)] - [\bar{p}_2(t) + \Delta\varphi_2(t)] \\ &= [\bar{p}_1(t) - \bar{p}_2(t)] + [\Delta\varphi_1(t) - \Delta\varphi_2(t)] \\ &< [\bar{p}_1(t) - \bar{p}_2(t)] \end{aligned}$$

See (a) of Fig. 10.

Case 2: $\varphi_1 > \varphi_2$

$\exists\theta$ satisfying that $\Delta\varphi_1(\theta, t_0) = \Delta\varphi_2(\bar{p}_2(t_0), t_0)$. Then,

$$\Delta\varphi_1(\bar{p}_1(t_0), t_0) \le \Delta\varphi_2(\bar{p}_2(t_0), t_0)$$

when $\bar{p}_1(t_0) \ge \theta$.

Referring to (b) of Fig. 10, one knows that

$$\Delta\varphi_1(t_0+1) = \Delta\varphi_1(t_0) \cdot \xi_1(t_0)$$

where $\xi_1(t_0) \in (\dot{\varphi}_1(\bar{p}_1(t_0), t_0), \dot{\varphi}_1(\bar{p}_1(t_0+1), t_0+1))$, and

$$\Delta\varphi_2(t_0+1) = \Delta\varphi_2(t_0) \cdot \xi_2(t_0)$$

where $\xi_2(t_0) \in (\dot{\varphi}_2(\bar{p}_2(t_0), t_0), \dot{\varphi}_2(\bar{p}_2(t_0+1), t_0+1))$. Evidently, $\xi_1(t_0) < \xi_2(t_0)$ and therefore,

$$\Delta\varphi_1(t_0+1) < \Delta\varphi_2(t_0+1)$$

The above analysis is also valid for any $t > t_0$.□

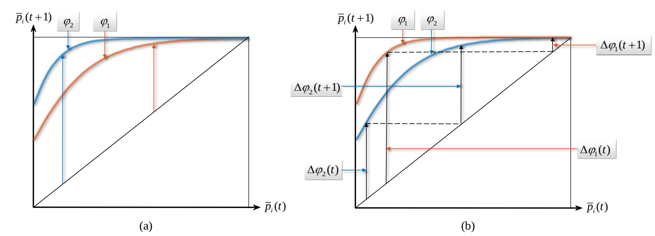

Fig. 10. Graphic representation corresponding to theoretical analysis for Theorem 1: (a) Case 1, and (b) Case 2. Upward arrows indicate $\Delta\varphi_1$ and $\Delta\varphi_2$.

Remark 4: Normally, in steady state the overall scale of JIF is generally constant, regardless of minor fluctuations. This implies the fact that the value of ω does not drift over time. See Fig. 11, which illustrates corresponding experimental confirmation.

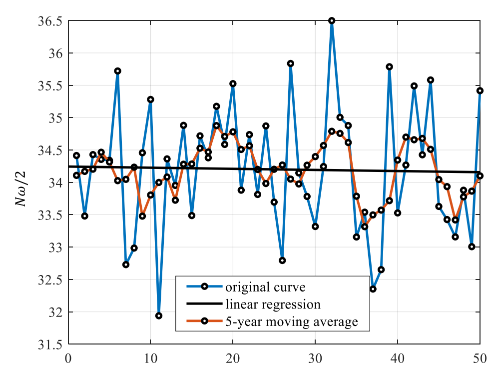

Fig. 11. Time series of JIF sum of all journals based on experimental data.

Remark 5: The pattern in relationship between journal citation probability and JIF, derived through experiments, also exhibits sound consistency with the theory. See Fig. 12.

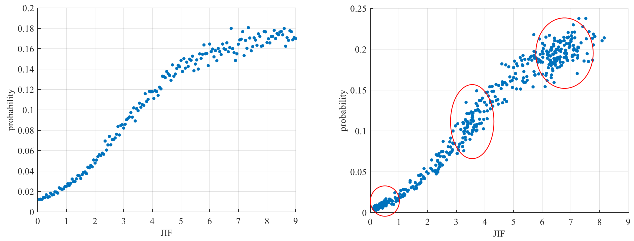

Fig. 12. Relationship between journal citation probability and JIF. (a) Scatter diagram of citation probability of one journal versus its JIF, with JIF of other journals held constant. (b) Scatter diagram of citation probability of journals versus JIF values. Data is collected in free experiments without additional constraints. Red circles mark potential regions that may contain fixed-points of corresponding pattern.

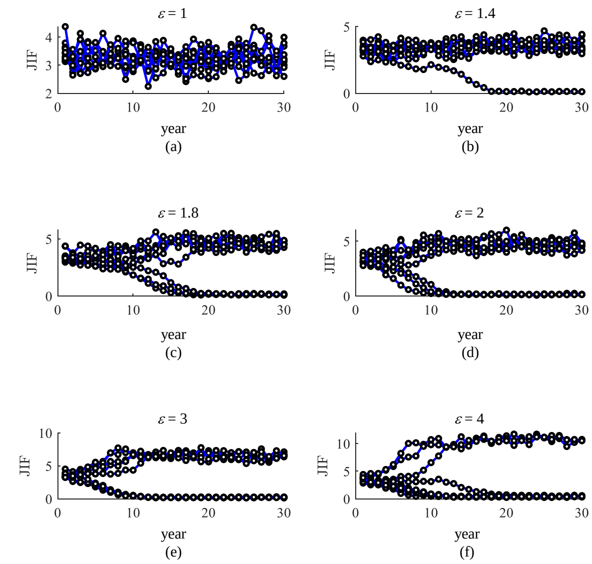

Fig. 14. Varying patterns in collective dynamics of JIF with changes in ε.

V. Sensitivity Analysis

In this section, one will witness the expansive generality of the phenomena observed, laws discovered, and discussions engaged throughout this paper. Actually, they are widely prevalent provided the elementary behavioral principles only, without relying on any specific form of model settings.

The ε is a key parameter that shapes the factor function $F_1(x)$ (4) and determines the sensitivity of the system to the change of JIF. Within its feasible range, a greater value of ε indicates a higher sensitivity of the system. The parameter can be regarded as a reflection of the weight of JIF influence. Fig. 13 illustrates the varying shapes of the curves of function $F_1(x)$ with changes in ε. Correspondingly, Fig. 14 exhibits the transition of patterns in collective dynamics of JIF with changes in ε.

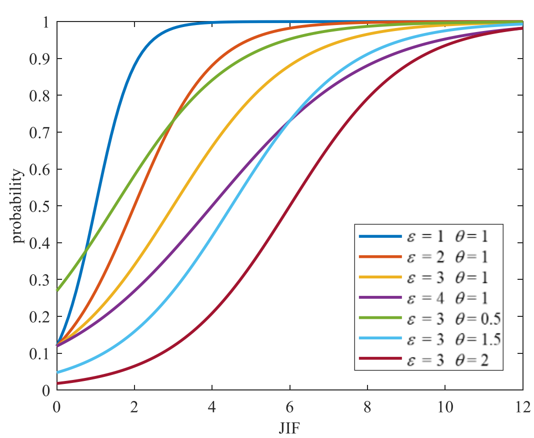

Fig. 13. Varying curve shapes of function $F_1(x)$ with changes in ε and θ.

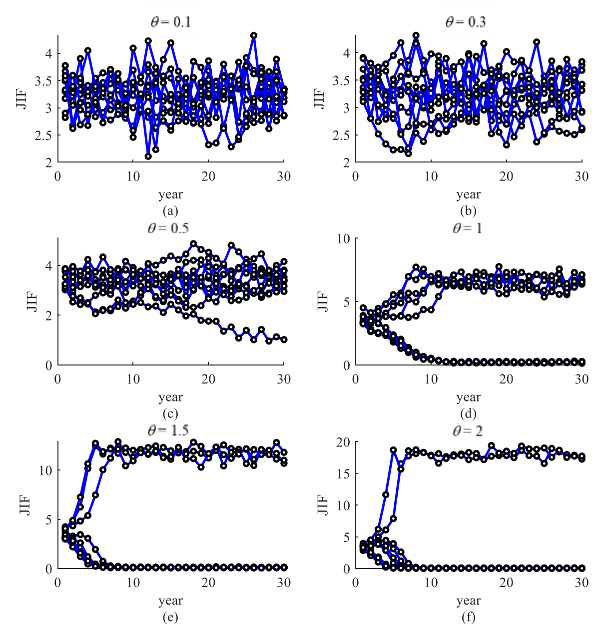

Fig. 15. Varying patterns in collective dynamics of JIF with changes in θ.

According to Fig. 14, when ε is small, there is no visible Mattew effect. But when ε increases to cross certain threshold, Mattew effect emerges. Afterwards, with greater ε, Matthew effect will become more intensive. A notable fact is that the ratio between the upper and lower rank journal clusters in steady state will also change accordingly. With a greater value of ε, the portion of high rank journals becomes smaller. In a sense, such a ratio of upper versus lower rank journals can be regarded as an indicator reflecting the intensity of Matthew effect. A more intensive Matthew effect may implicate intense competitions and fewer number of winners, meanwhile, with amplified gap between the winners and others. Similarly, the pattern of the collective dynamics of JIF undergoes a comparable transition with variations in the parameter θ, see Fig. 15.

Next, we consider the variants of the factor function $F_1(x)$. In this regard, three types of variants of the basic form (2) are addressed, namely,

$$F_1(x) = \tanh(\frac{x^p}{\varepsilon}) \;\; (p > 1)$$

$$F_1(x) = \tanh(\frac{x^p}{\varepsilon}) \;\; (1 > p > 0)$$

$$F_1(x) = \tanh(\frac{x}{\varepsilon}) + \delta \sin(\frac{x}{r}) \;\; (\delta , r > 0)$$

In the above list of variants, the first two are derived via replacing the independent variable x by the power function of x, with the power p being greater and smaller than 1, respectively. The third variant is derived via mounting an additive smooth noise. Fig. 16 exhibits the typical simulation results corresponding to different types of variants. Fig. 17 illustrates the distinctions in curve shapes of different variants of function $F_1(x)$. One sees that, despite the variation in model setting, the common features keep on persisting. Besides, a greater power p generally arouses more intense Matthew effect, and a relatively minor fluctuating noise in factor function does not affect the collective trend of dynamics.

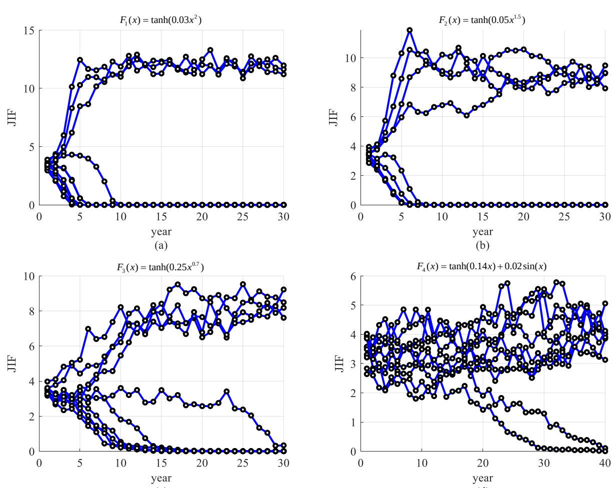

Fig. 16. Varying patterns in collective dynamics of JIF with different types of $F_1(x)$ variants.

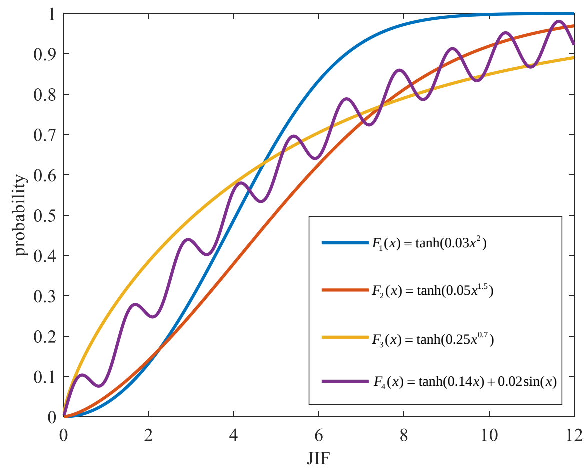

Fig. 17. Different types of variants of function $F_1(x)$.

V. Conclusion

A computational experimental model has been developed to explore the temporal dynamics of academic journals. This model integrates fundamental human behaviors inherent to the academic publication cycle, including manuscript submission, peer review, publication, and citation, creating a dynamic citation network, where each article is represented as a vertex, embedded with bibliographic data such as publication title, release date, and article quality score. The emergent citation map is then decoded by examining the topological connections between these article vertices. Studies with this model have revealed fundamental dynamic features of academic journals, particularly in terms of steadiness, inertia, and their differentiation across various journals.

The variation of journal quality is strongly correlated with citation index, suggesting a tandem in indicators as proxies for academic influence and recognition. There is Matthew effect in the collective dynamics and the initial gap could be amplified over time. More specifically, such a process may also demonstrate polarization, i.e., the dynamics tend to form two clusters, with one rising and the other declining. In addition, both the rise and decline trends would slow down and become ultimately bounded. The volatility of time series is also generally weakening over years. Besides, theoretical explanation for the observed laws is revealed through semi-analytical deduction.

The dynamics is robust against external disturbances. This implies that even certain incidental events may arouse timely distortion, the overall secular trend would still remain unaltered, unless the perturbation is too serious. In particular, it is worth noting that, deliberate self-citation could hardly lead to observable effect so long as the self-citation rate is moderate.

The practical implications of the research are multifaceted, including but not limited to the following. The experimental model facilitates testing the collective evolution of journal performance across various scenarios. Insights into robustness enable policymakers and journal managers to develop strategies that promote long-term stability and prioritize sustained quality over instant fluctuations. Researchers may leverage the findings to make strategic decisions about publication venues, maximizing the enduring impact of their work. Furthermore, the dynamic lens on journal performance underscores the necessity of adopting temporal and longitudinal frameworks for evaluation, in place of reliance on short-term metrics. The approach also holds the potential to guide the development of more sophisticated and equitable evaluation systems for academic institutions, journals, and researchers, fostering fairness and comprehensiveness.

The current research is an endeavor to extract common laws from the complexity of social behaviors. Beyond enhancing journal management, we trust that the perspectives will deepen our understanding of the temporal variations within academic journal communities, clarify the causality of significant phenomena, and offer actionable insights for similar challenges in broader domains. Along this route, extended studies can be carried out addressing diverse issues concerned in practice.

REFERENCES

[1] H. I. Okagbue, J. A. Teixeira da Silva, "Correlation between the CiteScore and Journal Impact Factor of top-ranked library and information science journals", *Scientometrics*, vol. 124, pp. 797-801, 2020.

[2] M. Villaseñor-Almaraz, J. Islas-Serrano, C. Murata, *et al.*, "Impact factor correlations with Scimago Journal Rank, Source Normalized Impact per Paper, Eigenfactor Score, and the CiteScore in Radiology, Nuclear Medicine & Medical Imaging journals", *Radiol. Med.*, vol. 124, pp. 495-504, 2019.

[3] M. F. Ali, "Evaluating the correlation between different impact indicators for library and information science journals: Comparing the Journal Citation Reports and Scopus", *Learn. Publ.*, vol. 34, no. 3, pp. 315-330, 2021.

[4] A.-L. Barabási, R. Albert, "Emergence of scaling in random networks", *Science*, vol. 286, no. 5439, pp. 509-512, 1999.

[5] Z. Wu, P. Holme, "Modeling scientific-citation patterns and other triangle-rich acyclic networks", *Phys. Rev. E*, vol. 80, no. 3, 037101, 2009.

[6] P. L. Krapivsky, S. Redner, F. Leyvraz, "Connectivity of growing random networks", *Phys. Rev. Lett.*, vol. 85, no. 21, pp. 4629-4632, 2000.

[7] S. N. Dorogovtsev, J. F. F. Mendes, A. N. Samukhin, "Structure of growing networks with preferential linking", *Phys. Rev. Lett.*, vol. 85, no. 21, pp. 4633-4636, 2000.

[8] F. Papadopoulos, M. Kitsak, M. Á. Serrano, *et al.*, "Popularity versus similarity in growing networks", *Nature*, vol. 489, no. 7417, pp. 537-540, 2012.

[9] Z. Xie, Z. Ouyang, Q. Liu, *et al.*, "A geometric graph model for citation networks of exponentially growing scientific papers", *Physica A*, vol. 456, pp. 167-175, 2016.

[10] M. Wang, G. Yu, D. Yu, "Effect of the age of papers on the preferential attachment in citation networks", *Physica A*, vol. 388, no. 19, pp. 4273-4276, 2009.

[11] X. Geng, Y. Wang, "Degree correlations in citation networks model with aging", *EPL*, vol. 88, no. 3, 38002, 2009.

[12] G. Bianconi, A.-L. Barabási, "Bose-Einstein condensation in complex networks", *Phys. Rev. Lett.*, vol. 86, no. 24, pp. 5632-5635, 2001.

[13] Z. Wu, P. Holme, "Modeling scientific-citation patterns and other triangle-rich acyclic networks", *Phys. Rev. E*, vol. 80, no. 3, 037101, 2009.

[14] F.-X. Ren, H.-W. Shen, X.-Q. Cheng, "Modeling the clustering in citation networks", *Physica A*, vol. 391, no. 12, pp. 3533-3539, 2012.

[15] M. C. V. Medo, G. Cimini, S. Gualdi, "Temporal effects in the growth of networks", *Phys. Rev. Lett.*, vol. 107, no. 23, 238701, 2011.

[16] G. Peterson, S. Pressé, K. A. Dill, "Nonuniversal power law scaling in the probability distribution of scientific citations", *Proc. Natl. Acad. Sci. USA*, vol. 107, no. 37, pp. 16023-16027, 2010.

[17] Y. Eom, S. Fortunato, "Characterizing and modeling citation dynamics", *PLoS ONE*, vol. 6, no. 9, e24926, 2011.

[18] A. M. Petersen, S. Fortunato, R. K. Pan, *et al.*, "Reputation and impact in academic careers", *Proc. Natl. Acad. Sci. USA*, vol. 111, no. 43, pp. 15316-15321, 2014.

[19] M. Golosovsky, S. Solomon, "Stochastic dynamical model of a growing citation network based on a self-exciting point process", *Phys. Rev. Lett.*, vol. 109, no. 9, 098701, 2012.

[20] M. Golosovsky, "Mechanisms of complex network growth: Synthesis of the preferential attachment and fitness models", *Phys. Rev. E*, vol. 97, no. 6, 062310, 2018.

[21] D.-S. Wang, C.-M. Song, A.-L. Barabási, "Quantifying long-term scientific impact", *Science*, vol. 342, no. 6154, pp. 127-132, 2013.

[22] J. Wang, Y. Mei, D. Hicks, "Comment on 'Quantifying long-term scientific impact'", *Science*, vol. 345, no. 6193, 149-b, 2014.

[23] M. Perc, "Self-organization of progress across the century of physics", *Sci. Rep.*, vol. 3, 1720, 2013.

[24] T. Kuhn, M. Perc, D. Helbing, "Inheritance patterns in citation networks reveal scientific memes", *Phys. Rev. X*, vol. 4, 041036, 2014.

[25] R. Sinatra, D. Wang, P. Deville, *et al.*, "Quantifying the evolution of individual scientific impact", *Science*, vol. 354, no. 6312, aaf5239, 2016.

[26] L. Liu, Y. Wang, R. Sinatra, *et al.*, "Hot streaks in artistic, cultural, and scientific careers", *Nature*, vol. 559, no. 7714, pp. 396-399, 2018.

[27] P. Lorenz-Spreen, B. M. Mønsted, P. Hövel, *et al.*, "Accelerating dynamics of collective attention", *Nat. Commun.*, vol. 10, 1759, 2019.

[28] C. Candia, C. Jara-Figueroa, C. Rodriguez-Sickert, *et al.*, "The universal decay of collective memory and attention", *Nat. Hum. Behav.*, vol. 3, no. 1, pp. 82-91, 2019.

[29] G. Abramo, C. A. D'Angelo, G. Felici, "Predicting publication long-term impact through a combination of early citations and journal impact factor", *J. Informetr.*, vol. 13, no. 1, pp. 32-49, 2019.

[30] A. S. Sunahara, M. Perc, H. V. Ribeiro, "Universal productivity patterns in research careers", *Phys. Rev. Res.*, vol. 5, 043203, 2023.

[31] V. Nanumyan, C. Gote, F. Schweitzer, "Multilayer network approach to modeling authorship influence on citation dynamics in physics journals", *Phys. Rev. E*, vol. 102, no. 3, 030303, 2020.

[32] X.-M. Bai, F.-L. Zhang, J.-Z. Li, *et al.*, "Quantifying scientific collaboration impact by exploiting collaboration-citation network", *Scientometrics*, vol. 126, no. 9, pp. 7993-8008, 2021.

[33] D. Pajić, "On the stability of citation-based journal rankings", *J. Informetr.*, vol. 9, no. 4, pp. 990-1006, 2015.

[34] X.-Z. Liu, H. Fang, "A comparison among citation-based journal indicators and their relative changes with time", *J. Informetr.*, vol. 14, no. 1, 101007, 2020.

[35] X. Wang, X.-H. Zheng, X.-Z. Zhang, *et al.*, "Analysis of cyber interactive behaviors using artificial community and computational experiments", *IEEE Trans. Syst. Man Cybernet. Syst.*, vol. 47, no. 6, pp. 995-1006, 2017.

[36] N. Cai, C. Diao, B.-H. Yan, "A social computing-based analysis on monogamous marriage puzzle of human", *IEEE Trans. Comput. Soc. Syst.*, vol. 6, no. 3, pp. 518-524, 2019.

[37] A. Clauset, D. B. Larremore, R. Sinatra, "Data-driven predictions in the science of science", *Science*, vol. 355, no. 6324, pp. 477-480, 2017.

[38] S. N. Groesser, "Dynamics of journal impact factors", *Syst. Res. Behav. Sci.*, vol. 29, no. 6, pp. 624-644, 2012.

[39] M. E. J. Newman, "Clustering and preferential attachment in growing networks", *Phys. Rev. E*, vol. 64, no. 2, 025102, 2001.

[40] M.-H. Li, J.-S. Wu, D.-H. Wang, *et al.*, "Evolving model of weighted networks inspired by scientific collaboration networks", *Physica A*, vol. 375, no. 1, pp. 355-364, 2007.

[41] R. K. Pan, A. M. Petersen, F. Pammolli, *et al.*, "The memory of science: Inflation, myopia, and the knowledge network", *J. Informetr.*, vol. 12, no. 3, pp. 656-678, 2018.

[42] X.-J. Kong, Y.-J. Shi, S. Yu, *et al.*, "Academic social networks: Modeling, analysis, mining and applications", *J. Netw. Comput. Appl.*, vol. 132, pp. 86-103, 2019.

[43] L. Liu, Q. Wang, Z.-Y. Tan, *et al.*, "On novel peer review system for academic journals: Analysis based on social computing", *Nonlin. Dyn.*, vol. 111, pp. 11613-11627, 2023.

Ning Cai received the B.E. degree in control engineering from Tsinghua University, Beijing, China, in 1996, the M.S. degree in computer science from the Chinese Academy of Sciences, Beijing, in 1999, and the Ph.D. degree in control theory from Tsinghua University in 2010. He is currently the Director of the Department of Automation, Beijing University of Posts and Telecommunications, Beijing, China. He is a Section Editor of *PLoS ONE* and an editorial board member of *PLoS Complex Systems*. His research interests include robust control, simulation, and analysis of dynamical complex systems.

Li Liu received the B.E. degree in control engineering from Beijing University of Posts and Telecommunications, Beijing, China, in 2020, where he is currently pursuing the Ph.D. degree. His research interest focuses on simulation and analysis of dynamical social systems.

Jun-Wei Cao received the B.E. degree in control engineering and M.S. degree in systems engineering from Tsinghua University, Beijing, China, in 1996 and 1998, respectively, and Ph.D. degree in computer science from the University of Warwick, Coventry, United Kingdom, in 2001. He is currently a Full Professor and Vice Dean of the Research Institute of Information Technology, Tsinghua University. Prior to joining Tsinghua University in 2006, he had been a Research Scientist with MIT LIGO Laboratory and NEC Laboratory Europe for about five years. His research interests include distributed computing technology and cyber-physical social systems.