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Reference:
Zhou Hongyu, Dong Ke, Xia Yikun.- Knowledge inheritance in disciplines : quantifying the successive and distant reuse of references
Journal of the Association for Information Science and Technology / Association for Information Science and Technology - ISSN 2330-1643 - 74:13(2023), p. 1515-1531
Full text (Publisher's DOI): https://doi.org/10.1002/ASI.24833
To cite this reference: https://hdl.handle.net/10067/1995180151162165141

KNOWLEDGE INHERITANCE IN DISCIPLINES

Quantifying the successive and distant reuse of references

Hongyu Zhou

Centre for R&D Monitoring (ECOOM), Faculty of Social Sciences, University of Antwerp, Antwerp 2020 (Belgium)

Ke Dong *

Research Institute for Data Management & Innovation, Nanjing University, Suzhou， Jiangsu 215163 (China)
School of Information Management, Nanjing University, Nanjing, Jiangsu 210023 (China)

Yikun Xia

Research Institute for Data Management & Innovation, Nanjing University, Suzhou， Jiangsu 215163 (China)
School of Information Management, Nanjing University, Nanjing, Jiangsu 210023 (China)

*: **Correspondence concerning this article should be addressed to Dr. Ke Dong,**

Email: dongke@nju.edu.cn.

The final version before accepted

Archived at the author's institution

ABSTRACT

How the knowledge base of disciplines grows, renews, and decays informs their distinct characteristics and epistemology. Here we track the evolution of knowledge bases of 19 disciplines for over 45 years. We introduce the notation of knowledge inheritance as the overlap in the set of references between years. We discuss two modes of knowledge inheritance of disciplines – successive and distant. To quantify the status and propensity of knowledge inheritance for disciplines, we propose two indicators: one descriptively describes knowledge base evolution, and one estimates the propensity of knowledge inheritance. When observing the continuity in knowledge bases for disciplines, we show distinct patterns for STEM and SSH disciplines: the former inherits knowledge bases more successively, yet the latter inherits significantly from distant knowledge bases. We further discover stagnation or revival in knowledge base evolution where older knowledge base ceases to decay after ten years (e.g. Physics and Mathematics) and are increasingly reused (e.g. Philosophy). Regarding the propensity of inheriting prior knowledge bases, we observe unanimous rises in both successive and distant knowledge inheritance. We show that knowledge inheritance could reveal disciplinary characteristics regarding the trajectory of knowledge base evolution and interesting insights into the metabolism and maturity of scholarly communication.

1. INTRODUCTION

1.1 Background

Science progresses by "standing on the shoulders of giants" and exploits prior established knowledge as a foundation, inspiration, and examination of future research. In practice, researchers cite previous studies to acknowledge intellectual debts (Garfield, 1996; Merton, 1988), link concept symbols (Small, 1978), persuade audiences through attachment to established wisdom (Gilbert, 1977), or perform specific functions such as active/passive support or criticism (Erikson & Erlandson, 2014; Tahamtan & Bornmann, 2019). From the view of social constructivists (Cetina, 1991), the citing behaviors may also be manipulated by complex political and sociological elements, which render citations less attributed to cognitive content but to social factors such as fame, authority, pleading, conformity, or citation bartering (Tahamtan & Bornmann, 2019). Deviant scholarly practices such as coercive citations (Wilhite & Fong, 2012) or citation cartels (Franck, 1999) emerge and further complicate the connotation and evaluation of citations. Nonetheless, references in scholarly publications provide useful indications on what was read, studied, utilized, or paid attention to at the time of publishing and constitutes the knowledge base of research.

From the temporal perspective, references are choices/judgments made by the authors that both link to the past and envision the future. Leydesdorff et al. (2022) point out that "citing is active and performative in the construction of possible futures, whereas being cited is the passive" (p. 5). On the one hand, cited articles in the past are selected to engage in the current research; on the other hand, researchers combine various references to contribute to future research their choice of knowledge combination, perhaps leading to new directions of research. References can therefore be recognized as recursive selections of what is relevant to future research and unveil the historical trajectories of scholarly communication (Leydesdorff, 1998; Leydesdorff et al., 2022; Leydesdorff & Milojević, 2015).

The study of references, i.e., knowledge bases, constitutes an important topic in quantitative science studies. Among others, a thread of research investigates the composition of references of specific knowledge clusters and explores their disciplinarity or interdisciplinarity, e.g. for economics (Angrist et al., 2020; Truc et al., 2020), sociology (Broadus, 1952), or social sciences in general (Zhou et al., 2022). The rationale behind these studies is to take a fixed snapshot of all the references made by a discipline during a set period and examine their interactions with itself and other disciplines, which entails the relative openness/diversity of research paradigms as traces of disciplinarity or interdisciplinarity. However, from an evolutionary perspective, how disciplines grow or evolve over time also informs their unique identities. Sugimoto and Weingart (2015) review five notions of understanding disciplinarity, i.e. what makes disciplines become disciplines, namely, cognitive coherence, social grouping, communication, separateness, tradition, and institutionalization. Regarding tradition in disciplines, the concept of *continuity* (Dascal & Dutz, 2008) is stressed that disciplines must have a "generally accepted intellectual tradition" or a "generalized cultural tradition" (Valenza, 2009, pp. 5–6). Disciplines may engage in different research topics over time and employ different methods accordingly; but to be regarded as an established discipline rather than a passing trend, disciplines should enjoy some cognitive continuity between adjacent periods and along the historical trajectory. That is to say, one could expect a certain level of continuity in the evolution of the knowledge base of disciplines.

Nonetheless, disciplines are still bounded by the research topics they are dedicated to and exhibit different levels of continuity and mutation. Some research subjects, e.g., the study of social activities, may be more subjective to historical changes, than others, e.g., the study of the universe. The knowledge bases of various disciplines may therefore evolve by different models. In 1978, Garfield et al. discussed three possible models of knowledge base evolution, or in their words, "how clusters of cited documents change over time" (p. 594). The knowledge base for a certain discipline (cluster) could "continue and maintain a constant configuration", whereas a second model expects sudden change associated with "very little overlap" between succeeding years. In the third model, one could observe a "continuing revolution … evidenced by a large and continuous turnover of highly-cited documents in the cluster". One may also find distinctions in modes of knowledge accumulation between branches of science. A significant distinction in research traditions between STEM and SS&H is whether one could enjoy the conditions of cumulativeness in knowledge production (Bonaccorsi, 2022). Natural sciences, operating under the explanation epistemic model, produce knowledge in strong regularities, for instance, in the format of mathematical formulations, and thus are more capable of transmitting knowledge for future reference. SS&H, however, tries to interpret the social and cultural endeavors of humans at a certain historic moment, which is more dynamic and complex to be formulated and shared across generations.

On the other hand, how researchers assemble their knowledge bases is also determined by their individual characteristics and the current academic climate. For instance, Wu et al. (2019) discovered that small teams are more likely to build their research on older ideas and knowledge. Chu and Evans (2021) discuss the phenomenon that already well-cited papers, usually published a while back, are receiving even more citations and attention which may cause slowed canonical progress and stagnation in science. In addition, advancements in digital infrastructures for scholarly communication (De Silva & K. Vance, 2017), e.g. online repositories and dissemination venues, can make knowledge more accessible and thus lead to a higher probability of transmission.

Examining how disciplines employ inherent knowledge over time can not only shed light on the status and evolution of the research paradigm of disparate knowledge clusters but also reveal historical shifts in the overall climate of scholarly communication. In this study, we put forward the concept of *knowledge inheritance* in discipline as reusing (inheriting) references that had been utilized in previous years by the same discipline itself. We hope to study the reference reuse patterns and how such behaviors change over time for disciplines and try to understand how *knowledge inheritance* informs disciplinarity.

1.2 Related literature

The notion of reference reuse is not often referred to as such, except for Wang et al. (2022) who claimed to find universal patterns that researchers frequently reuse a few references throughout their careers as an indication of cognitive continuity. A more commonly employed name is “re-citation” (White, 2001), suggesting the usage of the same references in multiple papers (Milojević, 2012, p. 1). White (2001) studied re-citation for individual researchers and categorized different citing identities such as “scientific-paper style”, “bibliographic-essay style”, and “literature-review style”. Analyses on re-citation were further expanded to the author level, publication level (Ajiferuke et al., 2011), and researcher cohorts (Milojević, 2012). The quantification of re-citation takes two forms: the number of re-citations (Ajiferuke et al., 2011), and the fraction of re-citations in all references of entities (Milojević, 2012). We find our employed term “reference reuse” is more intuitive and easy to understand and therefore will stick to this expression in the paper.

The study of reference reuse often involves temporal dynamics of the behavior which further links to concepts such as literature aging (Egghe & Ravichandran Rao, 1992; Egghe & Rousseau, 2000; Glänzel & Schoepflin, 1995; Gupta et al., 2002) or attention decay (Parolo et al., 2015) in research. If certain papers are decreasingly cited over years (re-used as references), one possible assumption is that they perhaps have become obsolete and are not deemed relevant or helpful to the current research. Various indicators are proposed to capture the speed/process of aging, such as citation half-life (Burton & Kebler, 1960; Tsay, 1998), Price index (Egghe, 1997; Moed, 1989; Price, 1970), reference age (Egghe, 1997), and its modified variants (Milojević, 2012), etc.

Upon the very first proposal, they were designed to “describe and compare the differences among the sciences in their processes of knowledge growth” (Moed, 1989, p. 474), i.e. disciplinarity. By looking into researchers’ selective attention to the immediate past (e.g., references to 0 to 4 years old publications), one could find disciplinary differences in such referencing patterns which further reveals the epistemological features of disciplines. The Price index was proposed to capture the “immediacy effect” of disciplines which helps to differentiate hard and soft science (Cozzens, 1985; Price, 1970). Glänzel and Schoepflin (1999) discovered that disciplines with historical components, as summarized by Zhang and Glänzel (2017), such as parasitology, zoology, botany, and entomology exhibits higher reference age, whereas literature from life science, physics, and chemistry obsolete faster. Zhang and Glänzel (2017) took a more granulized perspective on subfields and found subfields related to *Chemistry* and *energy and fuels* tend to draw on recent literature, and subfields relating to physics and astronomy prefer a combination of older and more recent references. More related studies are summarized by Glänzel (2004) and Dorta-González & Gómez-Déniz (2022).

In this study, we expand the conceptualization and operationalization of reference reuse with a new perspective focusing on the continuity of the knowledge base and examine the continuous evolution of knowledge bases for 19 main fields over time. We hope to contribute novel indicators on tracing the process of knowledge base evolution and new insights on understanding disciplinarity.

The rest of the paper is organized as follows: In section 2, we propose the concept and indicators of knowledge inheritance. Section 3 introduces the data we utilized and the conducted analyses. We present the empirical results and discussions in Section 4 and the last section concludes.

2. THE MEASUREMENT

To operationalize the concept of knowledge inheritance, we put forward two indicators one takes a descriptive perspective and observes the level of inherited knowledge (the percentage of reused reference), while the other one quantifies knowledge inheritance as a property of disciplines (the relative reference reuse propensity). We introduce them one by one.

2.1 The percentage of inherited knowledge

Suppose two different periods, in our case, years, we define the percentage of inherited knowledge (KI_{perc}) of the latter year t_j from the prior year t_i for a certain discipline d as follows:

$$KI_{perc}(d, t_i, t_j) = \frac{\left|\{b \mid M_{ab}>0, a \in Pub_{d,t_i}\} \cap \{b \mid M_{ab}>0, a \in Pub_{d,t_j}\}\right|}{\left|\{b \mid M_{ab}>0, a \in Pub_{d,t_i}\}\right|}, (t_i < t_j) \tag{1}$$

For a matrix M describing citations between publications, M_{ab} equals 1 if publication a cites publication b, and 0 otherwise. For any entity d, e.g., disciplines in this study, we denote all the publications that are classified under it and published at time t as $Pub_{d,t}$. We then retrieve all references cited by publications in $Pub_{d,t}$ as the knowledge base of d at time t, yielding $\{b \mid M_{ab} > 0,\ a \in Pub_{d,t}\}$. The percentage of inherited knowledge by t_j from t_i for d is therefore defined as the percentage of $d's$ knowledge base at t_i overlapped with that at t_j.

The measurement is designed as a fraction so that the notion of inherited knowledge can be compared between disciplines and traced over time under the same scale. We also specifically set the denominator as the number of references from the prior year (t_i), not later years (t_j), for three reasons. First, it carries the connotation we want to explore in this study which is the magnitude of inherited prior knowledge. Having this chosen denominator can directly lead to the percentage of the prior knowledge base that is inherited. Second, the number of references from the prior year is fixed in time (already happened) so that a change in the value of our measurement can only come from the numerator. Since we aim to trace the temporal evolution of knowledge inheritance, this helps us provide a better interpretation of the results. Third, it also assists us in investigating the decay of the knowledge base from a certain prior year by tracing the percentage of its references inherited by upcoming years. Another design of this measurement is that we count the number of cited documents, not the frequency of citing behaviors. So, references are treated equally whether they are highly cited or not. In this way, we hope to avoid confounding effects of other temporal dynamics such as increasing citation inequality (Nielsen & Andersen, 2021). For these reasons, we believe the current measurement design suits this study.

This employed indicator can also be regarded as a form of bibliographic coupling (Kessler, 1963), taking disciplinary publication sets from different years as coupled entities and the number of shared references as the coupling strength. We normalize the coupling strength between two years by dividing it by the number of referenced articles for the earlier year of the two, yielding a normalized coupling strength with empirical implication, that is the degree of overlap in a phased knowledge base. In previous studies, bibliographic coupling is frequently utilized to quantify the relationships (e.g., cognitive convergence) between scientific entities to arrive at local or global maps (networks) of science. These maps serve various scientometric research, from overall science mapping (Ahlgren & Colliander, 2009; Boyack & Klavans, 2010; Jarneving, 2007), knowledge domain mapping (Ferreira, 2018; Valenzuela et al., 2017), research evaluation (Cancino et al., 2017; Glänzel & Czerwon, 1996; King, 1987), and interdisciplinarity measurements (Chang & Huang, 2012; Rafols & Meyer, 2010; Thijs et al., 2021). Nonetheless, our defined parameter is distinct from the existing forms of bibliographic coupling in two ways. First, it can be recognized as a form of self-coupling since the coupled publication sets are classified under the same discipline and represent a continuum of scientific ideas and practices. In addition, we observe the coupling strength between publication sets from different periods, i.e., temporal coupling. Put together, our defined KI_{perc} is the temporal self-coupling of disciplines which sheds light on the continuity and change of knowledge bases for disciplines. This variant of bibliographic coupling is seldomly used, except for Zeng et al. (2019) who studies the bibliographic coupling within researchers' own publication portfolios.

Under our operationalization of the percentage of inherited knowledge, we recognize its two different forms, namely *successively inherited knowledge* ($t_j - t_i = 1$) and *distantly inherited knowledge* ($t_j - t_i > 1$). The first depicts whether the knowledge base is successively inherited or re-used by the next adjacent year. By focusing on the adjacent overlap in the knowledge base and its evolutions, we aim to explore whether disciplines always situate on a continuous knowledge base or experience high turnover. The second form focuses on the re-use of distant knowledge bases from earlier years; in our later analysis, they are more than a decade old. We try to see if older references are still in fashion for disciplines and which discipline relies strongly on old classics. We would also like to stress that the distinguishment between *successive* and *distant* is not definitive. We use the threshold of one in this study to distinguish the knowledge inheriting behavior for the most adjacent year and other following years. One could also adopt different thresholds to depict *successive* and *distant* knowledge inheritance considering the characteristics of the studied entities. For instance, one could consider reusing references after two years still as successive knowledge inheritance for a study of researchers or disciplines with a longer publishing cycle. In this study, we focus on collective patterns in large corpora so that individual-level discrepancies should be negligible.

2.2 The property of knowledge inheritance

For a certain discipline or other scholarly entities, to what extent their knowledge bases overlapped between years may also be affected by many factors, for instance, the discipline size. For a large discipline, with numerous researchers working within it, one may expect greater cognitive continuity since there are more people actively choosing what knowledge is currently available and what can be passed on. Empirically, we tested the correlation between discipline size and the percentage of successively inherited knowledge in 2014 and confirmed the positive linear relationship, as shown in Figure 1a. As an attempt to remove the effect of size dependence, we constructed null models for each discipline and each year by creating publication sets with randomly assigned discipline labels. Put differently, for a discipline d at year t with N publications, we randomly select N papers published in year t as a replicate of this discipline while keeping the discipline size. The random assignments were repeated 10 times so that for each discipline d at year t we created 10 samples that capture the expected knowledge inheriting behavior for a discipline with similar size. In Figure 1b, we show again the relationship between discipline size and the percentage of inherited knowledge in the null models we created. A clear monotonic relationship is obtained which describes the size dependence issue. The average KI_{perc} for null models of all disciplines are lower than the observed value in real cases.

To further quantify the relative propensity of knowledge inheritance as a property by excluding the inherent impact of discipline size, we calculate the degree of deviation of KI_{perc} from the list of simulative KI_{perc}' in null models using a z-score format metric, which is derived as the difference between the observed value KI_{perc} and mean value of the simulated KI_{perc}', divided by the standard deviation of KI_{perc}'. The idea is to estimate to what extent the observed level of knowledge inheritance of disciplines deviates (is greater) than a scholarly entity of the same size. With this method, we hope to explore the relative knowledge inheriting propensity of disciplines while maximumly reducing the impact of discipline size.

$$KI_{prop}(d, t_i, t_j) = \frac{KI_{perc}(d,t_i,t_j) - \text{Mean}(KI_{perc}')}{\text{SD}(KI_{perc}')} \quad ,(t_i < t_j) \tag{2}$$

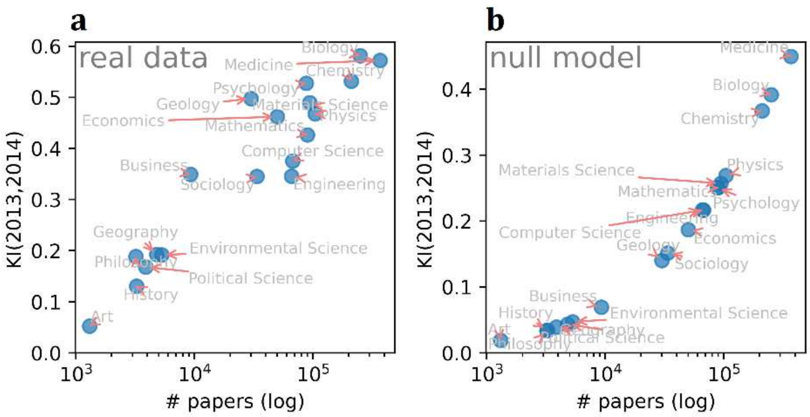

Figure 1. Discipline size and the percentage of inherited knowledge. a. the percentage of successively inherited knowledge for all disciplines in 2014; b. the average percentage of successively inherited knowledge for publication sets with the same size of each discipline.

3. DATA AND ANALYSES

In the empirical study, we examine the knowledge inheritance of scientific disciplines for a 45-year time span (1970-2014). We harness data from Microsoft Academic Graph (MAG) and retrieve 23 million publications and their 589 million references (K. Wang et al., 2020). 19 major disciplines of science are investigated in this study, which is recognized by MAG through paper-level classifications at the most aggregated level (Level 0). We manually set two criteria for the inclusion of publications. First, only publications that are assigned to one discipline are included, and thus avoid problems relating to multi-assignment; In addition, only publications that are cited at least once are included, hoping to partially filter out non-scholarly publications collected by MAG (Visser et al., 2021) and achieve publication sets that are visible and impactful to at least one citing paper. We replicate the analyses using two journal-based classification systems, namely the American Physics Society (APS) journal list and the EconLit journal lists, as robustness tests.

We recognize the significance of discipline delineation in our research design that most of the calculations rely on publication sets embodying disciplines. A sensitive and unstable classification scheme may come with a sudden change in disciplinary publication sets that will eventually distort our metrics. To partially avoid this problem in this study, we choose the broadest discipline classification to achieve somewhat stable disciplinary publication sets over time. In Figure 1, we discuss three descriptive statistics of the defined disciplines and get a nuanced understanding of the temporal patterns of these publication sets. The total number of publications (Figure 1a) for each discipline kept growing for the last 45 years, except for some humanities disciplines such as history, philosophy, and art which experienced drops in recent years. The total number of references that appeared in disciplinary publication sets has also increased since 1970 for almost all disciplines, with similar drops or slowdowns for the humanities disciplines in the 2010s. The third statistic describes the total number of cited publications, i.e., unique references, for each discipline, which appears in the denominator of our defined metrics. Similar patterns can be found also for these statistics which show the relative stability of the defined disciplines and our calculation. Given that disciplines exhibit relative stability and similar growth patterns in the volume of scientific outputs and knowledge base, it is reasonable to assume that the discrepancies in the level of knowledge inheritance, if any, can be attributed to the distinct characteristics of the disciplines themselves, that is to say, disciplinarity.

To understand the status and propensity of knowledge inheritance of disciplines, we organize our analyses in two groups, with the first group utilizing KI_{perc} to observe the evolution of the percentage of inherited knowledge within disciplines. We start by presenting a panoramic view of the evolution of knowledge base and knowledge inheriting for disciplines over 45 years and hope to give a birds-eye view of how the continuity of disciplinary knowledge bases evolve. We further quantitatively distinguish typologies of knowledge inheriting behavior of disciplines by applying hierarchical clustering on the resulted matrices following methods by Yan and Ding (2012). We examine the obtained hierarchies/clusters and discuss the implied connotations of disciplinarity. In addition, we articulate the concept of knowledge base decay by focusing on how the knowledge base of a certain year is reused in the next 20 years and further discuss some empirical changes in recent years. For the second group of analyses, we employed the KI_{prop} indicator, the relative propensity of knowledge inheritance, and conducted comparisons among disciplines over the investigated time span. The idea is to discover which disciplines are more likely to inherit from their prior knowledge bases and how such propensities change over time. Two aspects of knowledge inheritance will be examined, namely, successive and distant knowledge inheritance, as introduced in the *Measurement* section. For the second one, we set the "distant" time difference as 10 years and present the results on how disciplines inherent knowledge bases from 10 years ago.

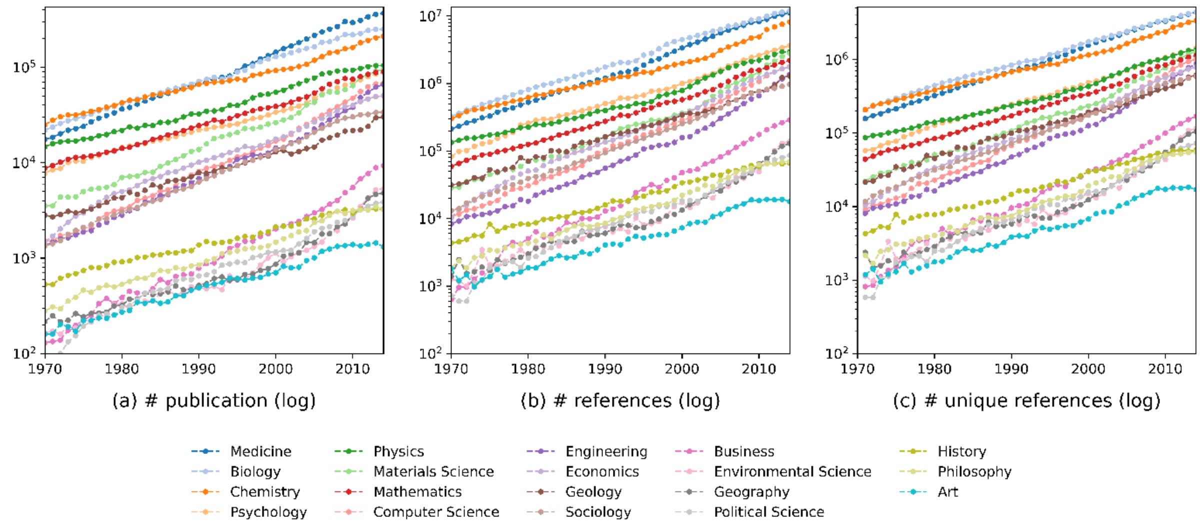

Figure 2. Temporal statistics for the defined 19 disciplines. (a) the number of publications for each discipline; (b) the total number of references cited by the publications of each discipline; (c) the total number of unique references cited by the publications of each discipline. Discipline labels in legend are arranged by the descending order of value in (c).

Table 1. Indicator and parameter settings for the four conducted analyses

Analysis	Indicator	Parameter setting
4.1 A panorama on the evolution of knowledge inheriting	KI_{perc}	$t_i < t_j$
4.2 The decay of the knowledge base	KI_{perc}	$t_j \in [t_i..t_i + 20]$

4.3 The propensity of successive knowledge inheritance	$\boldsymbol{KI_{prop}}$	$\boldsymbol{t_j = t_i + 1}$
4.4 The propensity of distant knowledge inheritance	$\boldsymbol{KI_{prop}}$	$\boldsymbol{t_j = t_i + 10}$

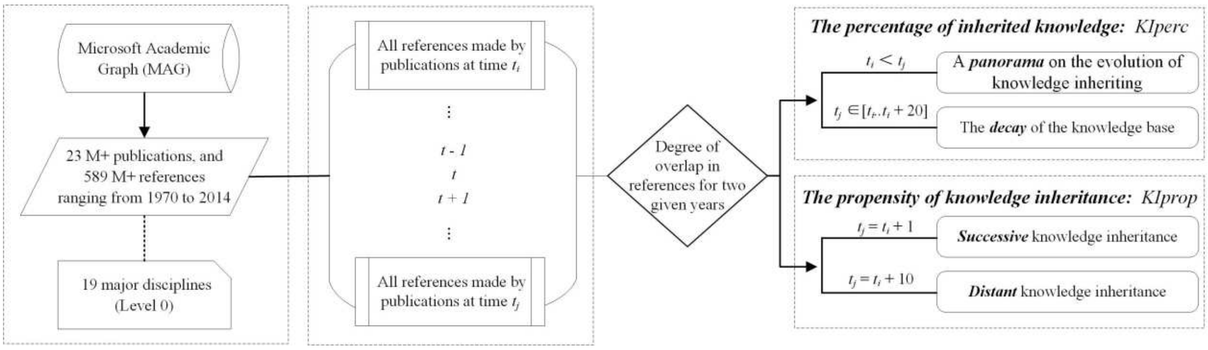

Figure 3. Outline of the data and analyses in this study

4. RESULTS AND DISCUSSION

4.1 A panorama view on the evolution of knowledge base and knowledge inheriting

We start by showing a holistic view of the evolution of knowledge inheriting practices for all disciplines during the studied period. As suggested in the *Measurements* section, the defined knowledge inheritance can be operationalized as a triangular matrix (Figure 4). We further investigate the characteristics of the disciplinarity of these disciplines by applying hierarchical clustering on vectors (concatenated from matrices) representing the knowledge inheritance of disciplines and examine latent structures of disciplines for this attribute. The retrieved hierarchy/clusters are shown in Figure 5.

We start with Figure 4 to provide a holistic understanding of the knowledge base evolution of disciplines. The first observation that can be drawn from Figure 4 is that the knowledge bases of disciplines are much more similar between adjacent years, the diagonal, than other distant years. For all disciplines, we find higher values in the diagonals and adjacent years, evidenced by the dense red clusters. Some disciplines exhibit a stronger and clearer diagonal, mostly STEM fields, which indicates a greater degree of overlap in the knowledge bases of adjacent years, whereas some relatively nascent disciplines, such as Material Science and Environmental Science started to have greater overlap in knowledge bases since the new century. In general, the differences in the evolution of knowledge inheriting between STEM and SS&H are more visually discernable that many STEM fields are associated with strong and clear diagonals signaling high successive knowledge inheritance and strong decays. On the other hand, many SS&H disciplines exhibit a lower percentage of successively inherited knowledge and a weak decay process, the latter may even lead to a stable percentage of references reused constantly as indicated by the red triangles in the lower half of the matrices of Political Science, Business, Economics, etc. As robustness checks, we applied the same analyses on two discipline-specific journal indexes, namely EconLit for Economics, and APS for Physics, and arrived at similar patterns in their knowledge base evolution (in Appendix).

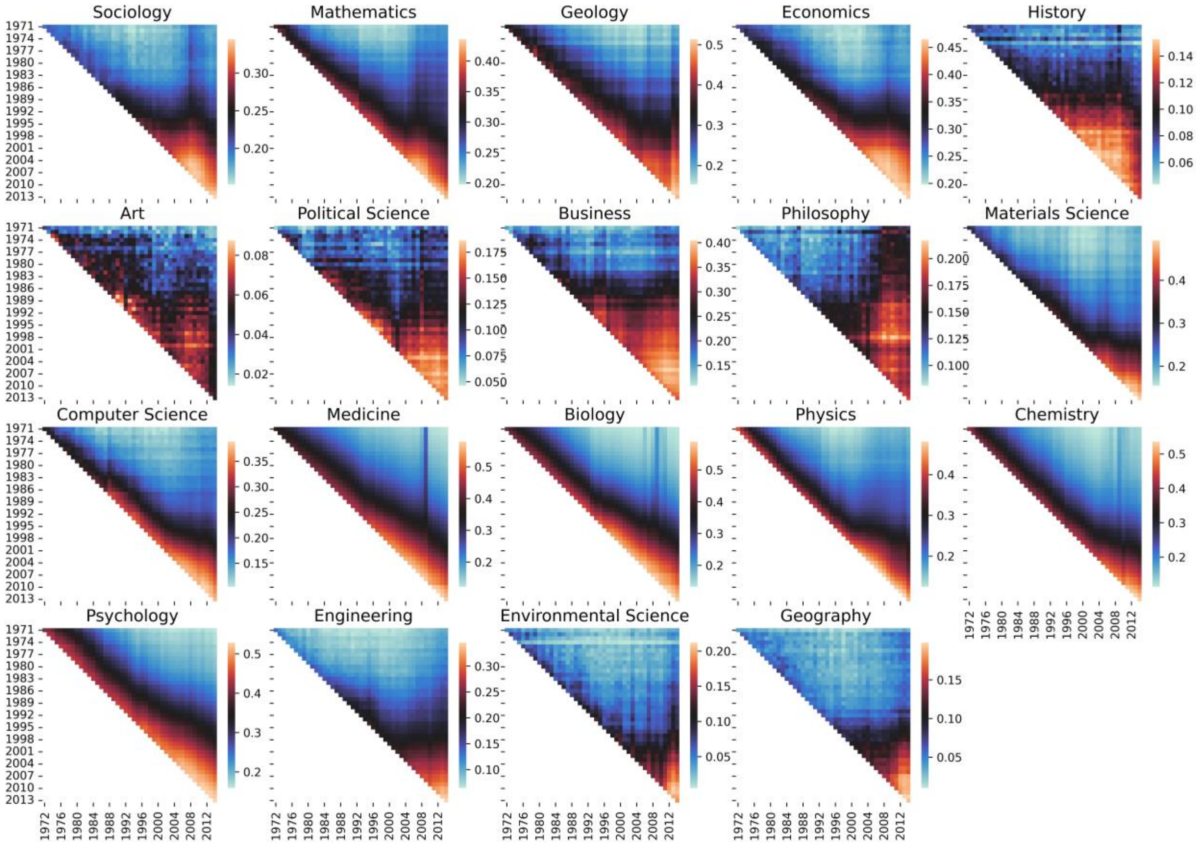

Figure 4. Overview of the knowledge base evolution of disciplines. The x-axis denotes the later year that inherits knowledge from the prior year indicated in the y-axis. The colors denote the percentage of the inherited knowledge base. The color bar in each subplot shows the scale of values, cells with lighter red indicate greater values, whereas lighter blue indicates smaller values.

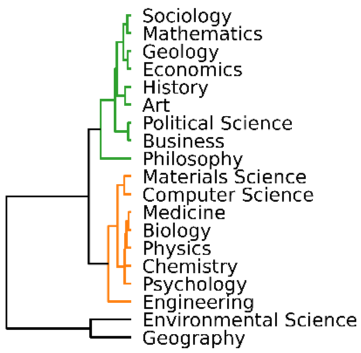

Figure 5. Hierarchical structures of knowledge base evolution

In addition to reiterating findings from previous sections, we also hope to detect shared patterns among disciplines and shed light on the discrepancies in knowledge inheritance to inform their disciplinarity. We result in a hierarchical clustering in Figure 5 that illustrates the difference between STEM and SS&H in terms of knowledge inheritance by assigning most disciplines from the two to separate clusters. In the first cluster, we find most SS&H disciplines, accompanied by Mathematics which shares a similar enthusiasm for older knowledge bases (high distant knowledge inheritance as found in Section 4.2) with SS&H disciplines. In the second cluster, most STEM disciplines are assigned to this group, along with Psychology which is cognitively and methodologically adjacent to many Life science disciplines such as Biology and Medicine. In the third cluster, two relatively nascent disciplines (as independent institutionalized disciplines), namely Geography and Environmental Science, are found here with both low successive knowledge inheritance and weak decays. The two disciplines involve elements from both STEM and SS&H which makes them hard to be categorized as purely one of them. Environmental Science is still regarded as an interdisciplinary science (Oberg, 2011) that integrates knowledge from various disciplines and therefore is still trying to gain independence in research paradigm and discourse, hence less continuity and inheritance in the knowledge base.

Overall, we can observe that increasing percentages of prior knowledge bases were inherited by the disciplines themselves in recent years, evidenced by thicker diagonals along the x-axis and growing bottom triangles. Can the observed pattern be explained by the growth of disciplines over time that each discipline publishes more publications in recent years and therefore yielding more actors to inherit prior knowledge? Do the observed disciplinary differences in the evolution of their knowledge base inheriting practice not relate to their disciplinarity but only to the change in discipline size? We further test this hypothesis by comparing the successive and distant (10-year) KI_{perc} with the growth rate of disciplines, as shown in Figure 6. The purple dashed lines and red lines show the growth rate of publications for disciplines, while the green and blue lines denote the percentage of inherited knowledge for successive and distant KI_{perc}. The green lines are *de facto* the diagonal in Figure 4. We see that many disciplines experienced rather steady publication growth over the four decades, yet exhibit a steep rise in KI_{perc} in recent years. For instance, in Biology, Physics, Chemistry, and Medicine, their publications increased at a steady rate, yet their knowledge inheriting behavior, for both successive and distant, showed an accelerated increase since the 1990s. It shows that these disciplines are inheriting a greater percentage of prior knowledge bases and the observed change is not attributed to the growth of their publications.

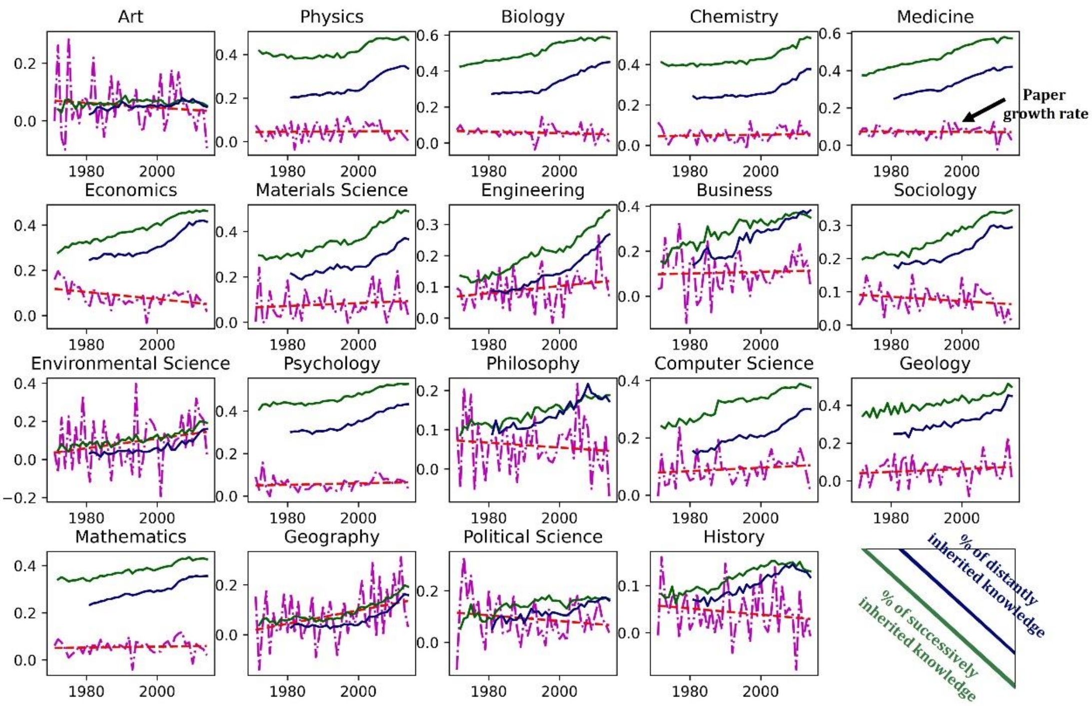

Figure 6. Publication growth rate and the percentage of knowledge that is successively or distantly inherited. The dashed purple line denotes the publication growth and the red dashed line provides the linear fit. The green solid line presents the percentage of knowledge that the year in the x-axis successively inherited from the previous adjacent year. The blue solid line presents the percentage of knowledge that

the year in the x-axis distantly inherited from the knowledge base of ten years ago.

In summary, we show that tracing the knowledge inheriting practices and knowledge base evolution of disciplines provides direct intuitions in inferring their characteristics in disciplinarity and the maturity of disciplines.

4.2 The decay of the knowledge base

While examining the change in the percentage of inherited knowledge, we notice that the references of disciplines for disciplines in a certain year seem to be increasingly less inherited over time, as shown by the decreasing value from the diagonals to the top-left corner for all disciplines in Figure 4. For instance, the knowledge base of Biology in 1970 was reused for 43.6% in 1971, 28.8% in 1980, 18.7% in 1990, and 15.0% in 2000. How does the re-usage of disciplines decay over time? Do disciplines exhibit different decay patterns? What does it tell the characteristics of disciplinarity? Could we find temporal changes in decay patterns that signal shifts or evolutions in the scientific enterprise? To explore these questions, we study how each year's knowledge base is inherited in the next 20 years and compare differences in the decay patterns among years and disciplines.

In Figure 5, we show that the decay of knowledge inheritance is rather common in many disciplines, mostly from STEM, and less clear in some SS&H disciplines. The knowledge bases of Chemistry, Biology, Medicine, and Physics decay most significantly. For their references made in 1970, around 40% of them were reused in 1971 (successively inherited knowledge) and only 15% remained employed after 45 years (distantly inherited knowledge). We can characterize them as disciplines with greater adjacently inherited knowledge and strong decays of the knowledge base. On the other hand, we also see many SS&H disciplines exhibit less successively inherited knowledge and weak decays. For instance, Sociology in 1971 reused 19.6% of references from 1970, 17.5% of which remained in the knowledge base of Sociology 2014. In some SS&H disciplines, we even observe that a prior knowledge base is increasingly inherited in the upcoming years, for instance, in Philosophy, or inherited for a constant percentage, for instance, in Political Science, History, and Business.

Regarding historical shifts, we find a rise in the percentage of inherited knowledge for all disciplines over the past 45 years for both successive and distant. Disciplines from STEM and SS&H in recent years, regardless of their own patterns in knowledge inheritance and decays, are all re-using a larger proportion of references from the adjacent prior year and previous years than 45 years ago, as shown in the upward-moving from lower purple lines to upper green lines. As the scientific enterprise continues to grow and prosper, one could certainly anticipate increasing continuity in knowledge inheritance, presumably brought by more well-developed scholarly infrastructures such as journals, conferences, programs, and institutions. Nonetheless, two special findings warrant further discussions. First, Physics and Chemistry, unlike the other disciplines, did not gain a substantial increase in successive knowledge inheritance, which maintained at around 40% for more than four decades. They, on the other hand, both experienced growth in distant knowledge inheritance. Put together, the decay process of knowledge inheritance for the two disciplines shrank significantly. In empirical terms, a great proportion of their knowledge was reused in the next year and continued to be re-used in the upcoming years. The second finding is observed in many disciplines such as Mathematics, Economics, Material Science, Computer Science, Physics, and Chemistry. Their knowledge base in the 1970s used to follow a continuous decay pattern for 20 years. Yet the knowledge base of the 1990s decayed only for the first following ten years and plateaued during the second decade (2000s and 2010s). Around 20% of references made by publications from Computer Science in 1994 had remained employed since 2004, which seems to have become a fixture (or classics) in the knowledge base of Computer Science.

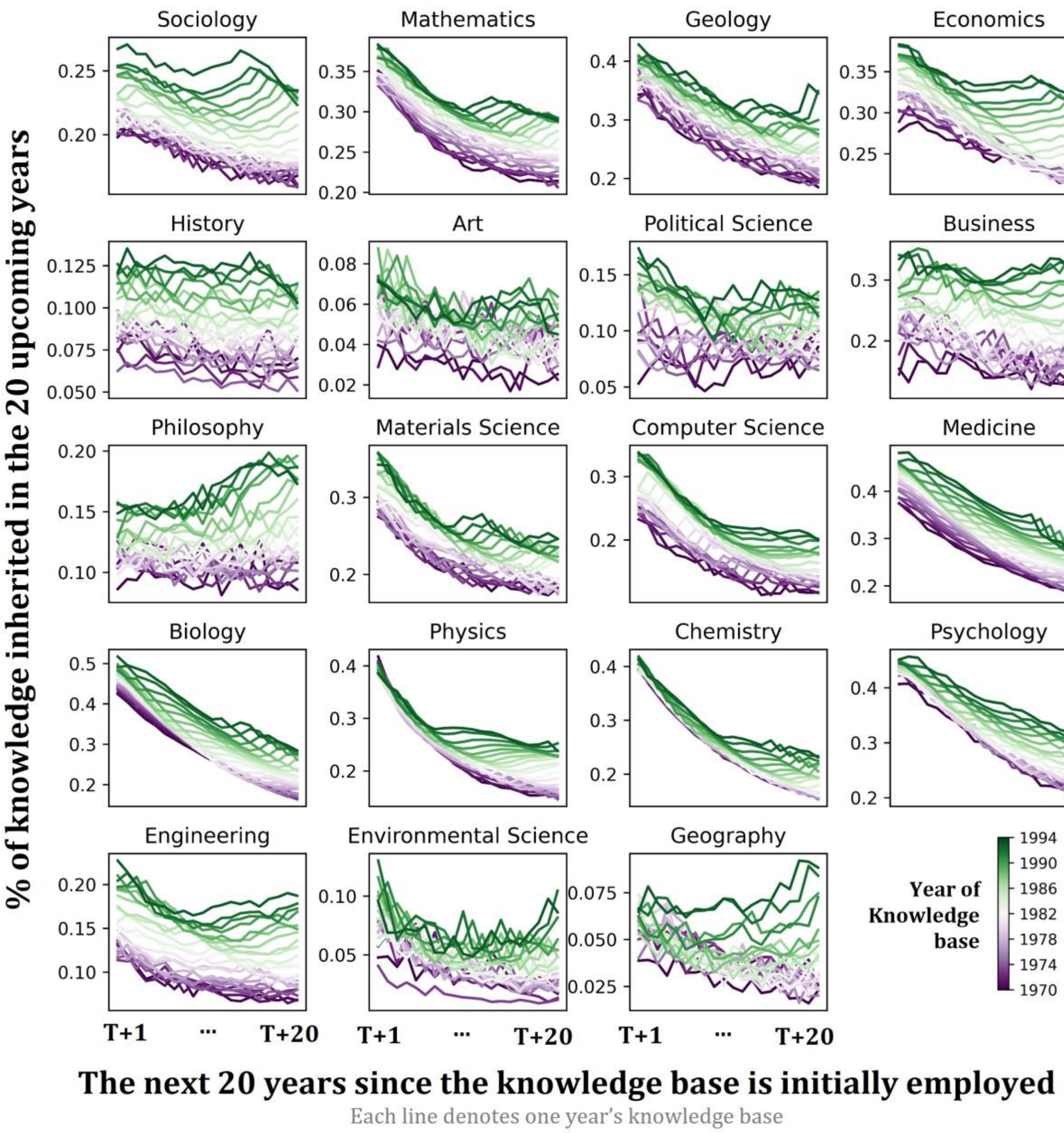

Figure 7. The decay of knowledge inheritance in 20 years. Each line denotes the level of inheritance of a certain year's knowledge base over the following 20 years, as annotated by colors for which green represents recent years (until 1994) and purple for the older years (from 1970). The y-axis shows the level of knowledge inheritance while the x-axis shows the decay period of 20 years. For a knowledge base employed in 1994 the decay period is then 1995-2014, and for that of 1970 is 1971-1990.

4.3 Successive knowledge inheritance

In previous sections, we see each discipline as an autonomous and distinct habitat and try to observe the evolutionary trajectory and the knowledge inheriting practices of their knowledge bases. In this section, we further move on to estimate and compare the relative propensity of knowledge inheritance among various disciplines. In addition to the above-discussed descriptive view, we hope to answer which disciplines may exhibit a greater propensity of knowledge inheritance and relatively higher cognitive continuity and how it changes over time.

By looking at results from 2014, we found that the majority of Natural Science disciplines, such as Biology, Geology, Physics, Mathematics, and Material Science exhibit the greatest level of successive knowledge inheritance. Three disciplines from the Social Sciences are also associated with a higher level of successive knowledge inheritance, namely Psychology, Business, and Economics, as compared to relatively lower values for the rest of the Social Science disciplines. For at least two of them, their separated pattern from the rest of the Social Sciences is not unexpected. Psychology, especially under recent developments in clinical psychology, neuropsychology, etc., shares a significant portion of knowledge and methods with biomedical sciences, which renders similar patterns in knowledge inheritance and accumulation. Economics, at least for some of its subfields, is known to have embraced mathematization early since the later 19th century (Bonaccorsi, 2022) and therefore build knowledge more mathematically and cumulatively, with greater resemblance to Natural Science disciplines. On the other hand, two application-oriented disciplines, such as Engineering and Computer Science rank at the second echelon, among Philosophy and Sociology. Political Science, History, and Art exhibit the lowest level of successive knowledge inheritance.

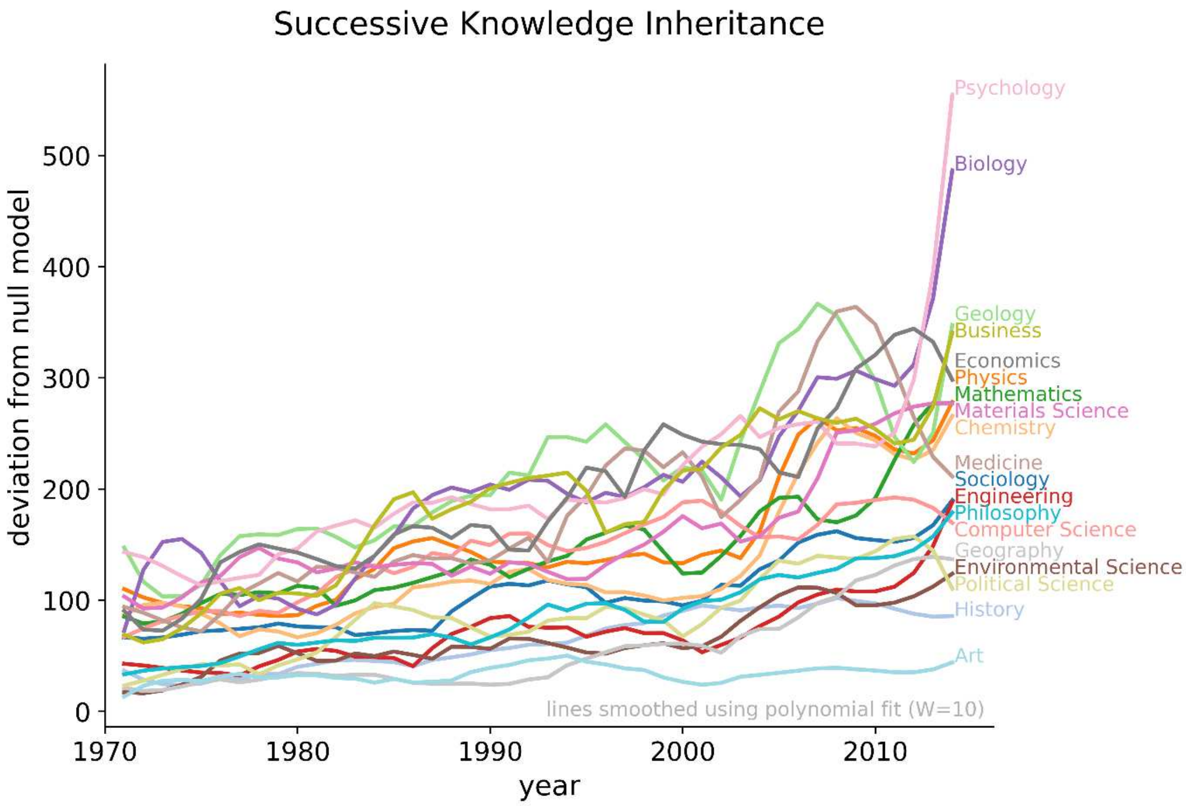

Figure 8. Successive knowledge inheritance of scientific disciplines: the relative propensity of inheriting knowledge base from the adjacent year compared to the null model. Results for disciplines are annotated with the same color as the text and their labels are ranked according to their corresponding value around 2014.

Following the temporal evolution of successive knowledge inheritance, we discover a unanimous rise in the propensity of reusing the last adjacent knowledge base for almost all disciplines. Such an increase is more prominent in Business which climbed from 12th in the 1970s to 4th in the 2010s. Engineering also grew faster than the others in inheriting successive knowledge. On the contrary, History and Arts are associated with mild increases and fluctuations over the five decades and may even experience slight downward trends in recent years. Overall, the increase in the propensity of successive knowledge inheritance indicates that disciplines are more likely to reuse the adjacent knowledge base and evolve with greater adjacent cognitive continuity.

4.4 Distant knowledge inheritance

We then move on to explore patterns in distant knowledge inheritance of disciplines. We set the time difference as ten years so that we are looking at the behaviors of reusing references that were used ten years ago. For example, for the distant knowledge inheritance in 2014 for Geology, we quantify the propensity of inheriting the knowledge base of 2004 for the same discipline.

The rankings of disciplines for distance knowledge inheritance remain similar for some of the disciplines such as Psychology, Biology, and Mathematics, which still exhibit the highest level. On the other hand, some disciplines, such as Geology and Economics, are found to be more inclined to reuse older references than others. They are all located in higher rankings for distant knowledge inheritance than that for successive knowledge inheritance. In Economics, such enthusiasm in older literature is also found in previous studies. For instance, Card and DellaVigna (2013) discovered that older papers (pre-1990) in *Econometrics and Theory* are more cited than recent ones in top journals from Economics (opposite pattern in *Development and International Economics*). Another study on dissertations and thesis in *Mathematics and Statistics* reported that their cited materials are on average 19.9 years old and therefore suggest librarians not be afraid to purchase older materials (Flynn, 2020). Disciplines' behavior in distant knowledge inheritance is deeply embedded in their research traditions and informs the characteristics of their disciplinarity.

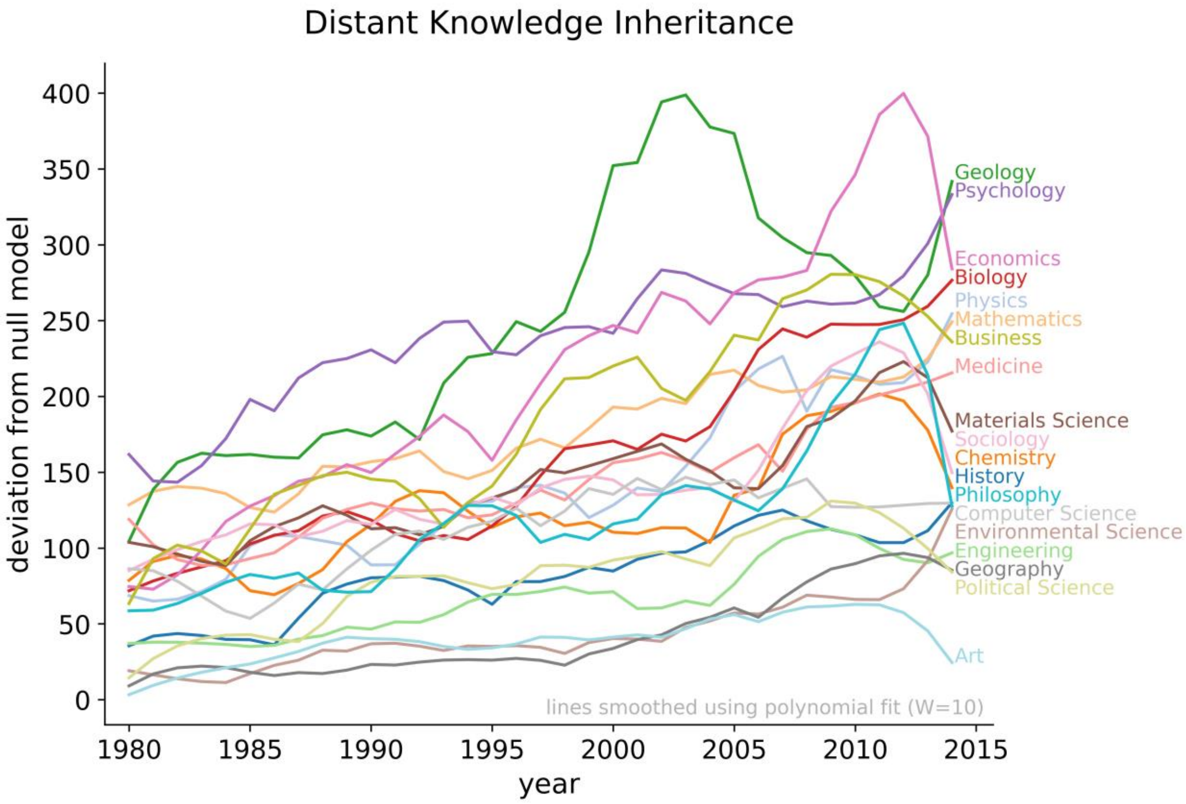

Figure 9. Distant knowledge inheritance of scientific disciplines: the relative propensity of inheriting the knowledge base from 10 years ago compared to the null model. Results for disciplines are annotated with the same color as the text and their labels are ranked according to their corresponding value around 2014.

Similar to what is observed in successive knowledge inheritance, an increasing trend over time is also found in all disciplines, with fluctuations for some. Geology, Psychology, and Economics continued their leading role in distant knowledge inheritance throughout the four decades, while Biology, Physics, and Medicine experienced a greater increase and have become disciplines that are most likely to reuse decade-old knowledge bases. The increase is less obvious, if any, in Computer Science, Engineering, and Art. We also want to mention that, for many disciplines, their remote knowledge inheritance seems to have achieved faster growth since the new century, evidenced by steeper lines since around 2005. It is possible that more older references have been made available through more openly available and comprehensive electronic reference resources such as Google Scholar since 2004 (Adlington & Benda, 2005) and the pervasive adoption of electronic publishing since the 1990s (De Silva & K. Vance, 2017).

5 CONCLUSION

This study proposes a new perspective on understanding the connotation of disciplinarity by investigating the modes of knowledge base evolution of scientific disciplines. We put forward the notion of knowledge inheritance to unveil how disciplines recursively assemble their knowledge base and how such selections from different periods may overlap with each other. We propose two methods to quantify both the status of knowledge inheriting from a descriptive view and the propensity of knowledge inheritance from a relative view with comparisons with null models. From the descriptive perspective, we define reusing references from a certain year as inheriting the knowledge base from that year and quantify the percentage of inherited references as an indication of the cognitive continuity between that year and a current year. Reusing knowledge bases from the last adjacent year is referred to as successive and reusing knowledge bases from, for instance, 10-, 20, and 30- years ago are therefore distant. To estimate the relative propensity of knowledge inheritance for disciplines, we compared the observed overlap in knowledge bases with that of randomized publication sets with the same number of publications and estimated the degree of deviation as a proxy for their relative propensity of knowledge inheritance. We examine this new concept and the indicators on 19 major disciplines for 45 years (1970-2014) using data from MAG. Below we summarize some major findings.

When observing the evolutions of the continuity of knowledge base for disciplines, we find distinct patterns for disciplines, which can be categorized into three groups, the STEM group (include also Psychology), the SS&H group (include also Mathematics), and the third group with Geography and Environmental Science. The STEM disciplines show a consistent and clearer pattern in inheriting the successive and recent knowledge bases, whereas the knowledge base of SS&H disciplines often maintains great overlap with older knowledge bases. From successive to distant, the percentage of the knowledge base from a prior year that is reused by the following years decays over time: the knowledge base of STEM disciplines decays most significantly and less for SS&H disciplines. We even observe that a prior knowledge base is increasingly inherited in the upcoming years, for instance, in Philosophy, or inherited for a constant percentage, for instance, in Political Science, History, and Business. On the other hand, we also observe historical shifts in knowledge inheritance that the decay process stops earlier to plateau in recent years for some disciplines such as Mathematics, Economics, Material Science, Computer Science, Physics, and Chemistry. Around 20% of references made by publications from Computer Science in 1994 became a fixture in the knowledge base of Computer Science. When comparing the percentage of knowledge bases disciplines reused successively with null models, we see that STEM disciplines are associated with a greater level of successive knowledge inheritance than SS&H disciplines, except for Psychology, Business, and Economics. For the propensity of distant knowledge inheritance, we find that Geology and Economics are more inclined to reuse older references than others. Overall, we observe a unanimous increase over the 45 years in both successive and distant knowledge inheritance in the majority of disciplines, which signals that disciplines are more likely to reuse prior knowledge bases.

The observed greater value in both the degree and propensity of knowledge inheritance for STEM fields provides empirical evidence of their significant cognitive continuity in the knowledge base. It could corroborate previous theoretical discussions on the differences in research tradition between STEM and SS&H. Some disciplines do not only study research subjects that are rather constant over time (e.g. the universe), but also build their research methods or tools incrementally (e.g. microscope), and are rooted in theories that are insensitive to temporal shifts in humanity (e.g. Newton's law of motion). However, the divide between STEM and SS&H cannot explain disciplinarity solely: some social science disciplines such as Economics exhibit greater cognitive continuity in the knowledge base, yet the knowledge base of Computer Science evolves quickly and vastly, yielding frequent turnover in utilized knowledge. Although focusing on economic aspects of the (changing) society, many topics in Economics gradually build their knowledge and theories on mathematical formulations and further enrich prior theories with empirical studies from more granularized and diverse data. On the other hand, the knowledge base of Computer Science, with an invariant focus on computing technologies, may also be influenced by the computing devices, supporting technologies, societal/business needs, or commercial products. The cognitive continuity of disciplines may be a sum total of the immutability of various elements in research: subjects, methods, tools, theories, venues, applications, etc.

On the other hand, the increasing knowledge inheritance, for both successive and distant, may indicate the increasing maturity of studied disciplines that their research practice is conducted on a continuously evolved knowledge base. Such knowledge continuity embodies well-developed research paradigms and methodology, widely recognized classics and canons, long-term research visions and questions, designated academic training and mentorship, and specialized research institutions and invisible colleges. Reusing a prior knowledge base may also represent a vote of confidence by a new generation of researchers who find the last adjacent knowledge and even distant prior knowledge still useful to a current research question and therefore would like to take up the torch. Disciplinary identities are gradually consolidated by cognitive continuity and stable research tradition. On the other hand, one may also concern about stagnation in knowledge base evolution that too much attention is devoted to old classics but hinders the canonical process of new works (Chu & Evans, 2021), which are found to be an important recipe for greater academic impact (Poncela-Casasnovas et al., 2019). High knowledge inheritance could, on the one hand, indicate cognitive continuity which foregrounds disciplinarity and, on the other hand, alarm deficit in new ideas. Having an optimal combination of past knowledge and new ideas could foster disciplines to achieve greater impact (Mukherjee et al., 2017) and maintain a healthy metabolism of knowledge evolution for future breakthroughs.

ACKNOWLEDGMENT

H.Z. thanks the Flemish Government for its support to the Centre for R&D Monitoring (ECOOM). The opinions in the paper are the authors' and not necessarily those of the government. K.D. would like to acknowledge support from the National Social Science Funds of China (Grant No. 21CTQ017). We thank the reviewers for their constructive and useful comments which significantly improved the paper.

REFERENCES

Adlington, J., & Benda, C. (2005). Checking under the hood: Evaluating Google Scholar for reference use. *Internet Reference Services Quarterly*, *10*(3–4), 135–148.

Ahlgren, P., & Colliander, C. (2009). Document–document similarity approaches and science mapping: Experimental comparison of five approaches. *Journal of Informetrics*, *3*(1), 49–63. https://doi.org/10.1016/j.joi.2008.11.003

Ajiferuke, I., Lu, K., & Wolfram, D. (2011). Who are the research disciples of an author? Examining publication recitation and oeuvre citation exhaustivity. *Journal of Informetrics*, *5*(2), 292–302. https://doi.org/10.1016/j.joi.2011.01.001

Angrist, J., Azoulay, P., Ellison, G., Hill, R., & Lu, S. F. (2020). Inside Job or Deep Impact? Extramural Citations and the Influence of Economic Scholarship. *Journal of Economic Literature*, *58*(1), 3–52. https://doi.org/10.1257/jel.20181508

Bonaccorsi, A. (2022). An epistemic approach to research assessment in the social sciences. In *Handbook on Research Assessment in the Social Sciences* (pp. 14–47). Edward Elgar Publishing. https://www.elgaronline.com/view/edcoll/9781800372542/9781800372542.00009.xml

Boyack, K. W., & Klavans, R. (2010). Co-citation analysis, bibliographic coupling, and direct citation: Which citation approach represents the research front most accurately? *Journal of the American Society for Information Science and Technology*, *61*(12), 2389–2404. https://doi.org/10.1002/asi.21419

Broadus, R. N. (1952). An Analysis of Literature Cited in the American Sociological Review. *American Sociological Review*, *17*(3), 355–357. https://doi.org/10.2307/2088083

Burton, R. E., & Kebler, R. W. (1960). The “half-life” of some scientific and technical literatures. *American Documentation*, *11*(1), 18–22. https://doi.org/10.1002/asi.5090110105

Cancino, C. A., Merigó, J. M., & Coronado, F. C. (2017). A bibliometric analysis of leading universities in innovation research. *Journal of Innovation & Knowledge*, *2*(3), 106–124. https://doi.org/10.1016/j.jik.2017.03.006

Card, D., & DellaVigna, S. (2013). Nine Facts about Top Journals in Economics. *Journal of Economic Literature*, *51*(1), 144–161. https://doi.org/10.1257/jel.51.1.144

Cetina, K. K. (1991). Merton’s Sociology of Science: The First and the Last Sociology of Science? *Contemporary Sociology*, *20*(4), 522–526. https://doi.org/10.2307/2071782

Chang, Y.-W., & Huang, M.-H. (2012). A study of the evolution of interdisciplinarity in library and information science: Using three bibliometric methods. *Journal of the American Society for Information Science and Technology*, *63*(1), 22–33. https://doi.org/10.1002/asi.21649

Chu, J. S. G., & Evans, J. A. (2021). Slowed canonical progress in large fields of science. *Proceedings of the National Academy of Sciences*, *118*(41). https://doi.org/10.1073/pnas.2021636118

Cozzens, S. E. (1985). Using the archive: Derek Price’s theory of differences among the sciences. *Scientometrics*, *7*(3), 431–441. https://doi.org/10.1007/BF02017159

Dascal, M., & Dutz, K. D. (2008). The beginnings of scientific semiotics. In *The beginnings of scientific semiotics* (pp. 746–762). De Gruyter Mouton. https://doi.org/10.1515/9783110095845.1.5.746

De Silva, P. U. K., & K. Vance, C. (2017). Access to Scientific Knowledge: A Historical Perspective. In P. U. K. De Silva & C. K. Vance (Eds.), *Scientific Scholarly Communication: The Changing Landscape* (pp. 17–24). Springer International Publishing. https://doi.org/10.1007/978-3-319-50627-2_2

Dorta-González, P., & Gómez-Déniz, E. (2022). Modeling the obsolescence of research literature in disciplinary journals through the age of their cited references. *Scientometrics*, *127*(6), 2901–2931. https://doi.org/10.1007/s11192-022-04359-w

Egghe, L. (1997). Price index and its relation to the mean and median reference age. *Journal of the American Society for Information Science*, *48*(6), 564–573. https://doi.org/10.1002/(SICI)1097-4571(199706)48:6<564::AID-ASI8>3.0.CO;2-S

Egghe, L., & ravichandra rao, I. K. (1992). Citation age data and the obsolescence function: Fits and explanations. *Information Processing & Management*, *28*(2), 201–217. https://doi.org/10.1016/0306-4573(92)90046-3

Egghe, L., & Rousseau, R. (2000). Aging, obsolescence, impact, growth, and utilization: Definitions and relations. *Journal of the American Society for Information Science*, *51*(11), 1004–1017. https://doi.org/10.1002/1097-4571(2000)9999:9999<::AID-ASI1003>3.0.CO;2-8

Erikson, M. G., & Erlandson, P. (2014). A taxonomy of motives to cite. *Social Studies of Science*, *44*(4), 625–637. https://doi.org/10.1177/0306312714522871

Ferreira, F. A. F. (2018). Mapping the field of arts-based management: Bibliographic coupling and co-citation analyses. *Journal of Business Research*, *85*, 348–357. https://doi.org/10.1016/j.jbusres.2017.03.026

Flynn, K. H. (2020). Citation Analysis of Mathematics and Statistics Dissertations and Theses from the University at Albany. *Science & Technology Libraries*, *39*(2), 142–154. https://doi.org/10.1080/0194262X.2020.1727396

Franck, G. (1999). Scientific Communication—A Vanity Fair? *Science*, *286*(5437), 53–55. https://doi.org/10.1126/science.286.5437.53

Garfield, E. (1996). When to Cite. *The Library Quarterly*, *66*(4), 449–458. https://doi.org/10.1086/602912

Garfield, E., Malin, M. V., & Small, H. (1978). Citation data as science indicators. In *Y. Elkana, J. Lederberg, R. Merton, A. Thackray, H. Zuckerman (Eds.), Toward a metric of science: The advent of science indicators* (pp. 179–208). John Wiley, New York.

Gilbert, G. N. (1977). Referencing as Persuasion. *Social Studies of Science*, *7*(1), 113–122.

Glänzel, W. (2004). Towards a model for diachronous and synchronous citation analyses. *Scientometrics*, *60*(3), 511–522. https://doi.org/10.1023/B:SCIE.0000034391.06240.2a

Glänzel, W., & Czerwon, H. J. (1996). A new methodological approach to bibliographic coupling and its application to the national, regional and institutional level. *Scientometrics*, *37*(2), 195–221. https://doi.org/10.1007/BF02093621

Glänzel, W., & Schoepflin, U. (1995). A bibliometric study on ageing and reception processes of scientific literature. *Journal of Information Science*, *21*(1), 37–53. https://doi.org/10.1177/016555159502100104

Glänzel, W., & Schoepflin, U. (1999). A bibliometric study of reference literature in the sciences and social sciences1Parts of this study have been presented at the 5th International Conference on Scientometrics and Informetrics, held in River Forest, Illinois, June 7–10, 1995.1. *Information Processing & Management*, *35*(1), 31–44. https://doi.org/10.1016/S0306-4573(98)00028-4

Gupta, B. M., Kumar, S., Sangam, S. L., & Karisiddappa, C. R. (2002). Modeling the growth of world social science literature. *Scientometrics*, *53*(1), 161–164. https://doi.org/10.1023/A:1014844222898

Jarneving, B. (2007). Bibliographic coupling and its application to research-front and other core documents. *Journal of Informetrics*, *1*(4), 287–307. https://doi.org/10.1016/j.joi.2007.07.004

Kessler, M. M. (1963). Bibliographic coupling between scientific papers. *American Documentation*, *14*(1), 10–25. https://doi.org/10.1002/asi.5090140103

King, J. (1987). A review of bibliometric and other science indicators and their role in research evaluation. *Journal of Information Science*, *13*(5), 261–276. https://doi.org/10.1177/016555158701300501

Leydesdorff, L. (1998). Theories of citation? *Scientometrics*, *43*(1), 5–25. https://doi.org/10.1007/BF02458391

Leydesdorff, L., & Milojević, S. (2015). Scientometrics. In J. D. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)* (pp. 322–327). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.85030-8

Leydesdorff, L., Zhang, L., & Wouters, P. (2022). *Trajectories and Regimes in Research and Knowledge Evaluations: Contributions to an Evolutionary Theory of Citation?*

Merton, R. K. (1988). The Matthew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property. *Isis*, *79*(4), 606–623.

Milojević, S. (2012). How Are Academic Age, Productivity and Collaboration Related to Citing Behavior of Researchers? *PLOS ONE*, *7*(11), e49176. https://doi.org/10.1371/journal.pone.0049176

Moed, H. F. (1989). Bibliometric measurement of research performance and Price's theory of differences among the sciences. *Scientometrics*, *15*(5), 473–483. https://doi.org/10.1007/BF02017066

Mukherjee, S., Romero, D. M., Jones, B., & Uzzi, B. (2017). The nearly universal link between the age of past knowledge and tomorrow's breakthroughs in science and technology: The hotspot. *Science Advances*, *3*(4), e1601315. https://doi.org/10.1126/sciadv.1601315

Nielsen, M. W., & Andersen, J. P. (2021). Global citation inequality is on the rise. *Proceedings of the National Academy of Sciences*, *118*(7), e2012208118. https://doi.org/10.1073/pnas.2012208118

Oberg, G. (2011). *Interdisciplinary environmental studies: A primer*. John Wiley & Sons.

Parolo, P. D. B., Pan, R. K., Ghosh, R., Huberman, B. A., Kaski, K., & Fortunato, S. (2015). Attention decay in science. *Journal of Informetrics*, *9*(4), 734–745. https://doi.org/10.1016/j.joi.2015.07.006

Poncela-Casasnovas, J., Gerlach, M., Aguirre, N., & Amaral, L. A. N. (2019). Large-scale analysis of micro-level citation patterns reveals nuanced selection criteria. *Nature Human Behaviour*, *3*(6), Article 6. https://doi.org/10.1038/s41562-019-0585-7

Price, D. J. (1970). Citation measures of hard science, soft science, technology, and nonscience. *Communication among Scientists and Engineers*, *1*, 3r22.

Rafols, I., & Meyer, M. (2010). Diversity and network coherence as indicators of interdisciplinarity: Case studies in bionanoscience. *Scientometrics*, *82*(2), 263–287. https://doi.org/10.1007/s11192-009-0041-y

Small, H. G. (1978). Cited Documents as Concept Symbols. *Social Studies of Science*, *8*(3), 327–340.

Sugimoto, C. R., & Weingart, S. (2015). The kaleidoscope of disciplinarity. *Journal of Documentation*, *71*(4), 775–794. https://doi.org/10.1108/JD-06-2014-0082

Tahamtan, I., & Bornmann, L. (2019). What do citation counts measure? An updated review of studies on citations in scientific documents published between 2006 and 2018. *Scientometrics*, *121*(3), 1635–1684. https://doi.org/10.1007/s11192-019-03243-4

Thijs, B., Huang, Y., & Glänzel, W. (2021). Comparing different implementations of similarity for disparity measures in studies on interdisciplinarity. In *FEB Research Report MSI_2103* (pp. 1–11). FEB Research Report MSI_2103. https://lirias.kuleuven.be/retrieve/610314

Truc, A., Santerre, O., Gingras, Y., & Claveau, F. (2020). The Interdisciplinarity of Economics. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3669335

Tsay, M.-Y. (1998). Library journal use and citation half-life in medical science. *Journal of the American Society for Information Science*, *49*(14), 1283–1292. https://doi.org/10.1002/(SICI)1097-4571(1998)49:14<1283::AID-ASI6>3.0.CO;2-I

Valenza, R. (2009). *Literature, Language, and the Rise of the Intellectual Disciplines in Britain, 1680–1820*. Cambridge University Press. https://doi.org/10.1017/CBO9780511635601

Valenzuela, L. M., Merigó, J. M., Johnston, W. J., Nicolas, C., & Jaramillo, J. F. (2017). Thirty years of the Journal of Business & Industrial Marketing: A bibliometric analysis. *Journal of Business & Industrial Marketing*, *32*(1), 1–17. https://doi.org/10.1108/JBIM-04-2016-0079

Visser, M., van Eck, N. J., & Waltman, L. (2021). Large-scale comparison of bibliographic data sources: Scopus, Web of Science, Dimensions, Crossref, and Microsoft Academic. *Quantitative Science Studies*, *2*(1), 20–41. https://doi.org/10.1162/qss_a_00112

Wang, D., Huang, Y., Hu, L., Cheng, Q., & Bu, Y. (2022). Inequality of authors' reference reuse. *Journal of Information Science*, 01655515221111062. https://doi.org/10.1177/01655515221111062

Wang, K., Shen, Z., Huang, C., Wu, C.-H., Dong, Y., & Kanakia, A. (2020). Microsoft Academic Graph: When experts are not enough. *Quantitative Science Studies*, *1*(1), 396–413. https://doi.org/10.1162/qss_a_00021

White, H. D. (2001). Authors as citers over time. *Journal of the American Society for Information Science and Technology*, *52*(2), 87–108. https://doi.org/10.1002/1097-4571(2000)9999:9999<::AID-ASI1542>3.0.CO;2-T

Wilhite, A. W., & Fong, E. A. (2012). Coercive Citation in Academic Publishing. *Science*, *335*(6068), 542–543. https://doi.org/10.1126/science.1212540

Wu, L., Wang, D., & Evans, J. A. (2019). Large teams develop and small teams disrupt science and technology. *Nature*, *566*(7744), 378–382. https://doi.org/10.1038/s41586-019-0941-9

Yan, E., & Ding, Y. (2012). Scholarly network similarities: How bibliographic coupling networks, citation networks, cocitation networks, topical networks, coauthorship networks, and coword networks relate to each other. *Journal of the American Society for Information Science and Technology*, *63*(7), 1313–1326. https://doi.org/10.1002/asi.22680

Zeng, A., Shen, Z., Zhou, J., Fan, Y., Di, Z., Wang, Y., Stanley, H. E., & Havlin, S. (2019). Increasing trend of scientists to switch between topics. *Nature Communications*, *10*(1). https://doi.org/10.1038/s41467-019-11401-8

Zhang, L., & Glänzel, W. (2017). A citation-based cross-disciplinary study on literature aging: Part I—the synchronous approach. *Scientometrics*, *111*(3), 1573–1589. https://doi.org/10.1007/s11192-017-2289-y

Zhou, H., Guns, R., & Engels, T. C. E. (2022). Are social sciences becoming more interdisciplinary? Evidence from publications 1960–2014. *Journal of the Association for Information Science and Technology*. https://doi.org/10.1002/asi.24627

APPENDIX

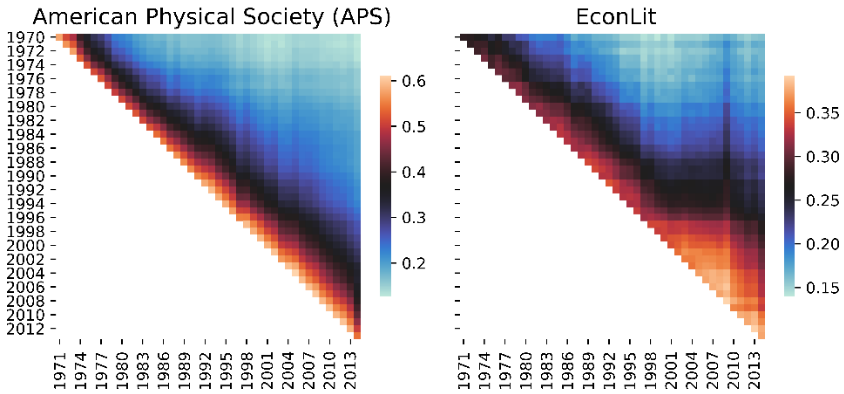

Figure A1. Robustness checks using journal lists from two discipline-dedicated datasets: American Physical Society (APS) and journals index (partial) in EconLit offered by American Economic Association (https://www.aeaweb.org/econlit/journal_list.php).