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Papers on the Main Paths are Associated with Lower Disruption in Scientometrics

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Abstract

We integrate two bibliometric frameworks—the Disruption Index (DI) and Main Path Analysis (MPA)—to examine how scientific papers shape knowledge flows in scientometrics. The DI measures a paper's capacity to shift citation patterns: a positive DI indicates the paper "diminishes" its predecessors (disruptive impact), while a negative DI suggests it reinforces prior work (consolidative impact). The MPA identifies dominant knowledge trajectories by extracting the most frequently traversed citation paths within a field, highlighting papers critical for sustained knowledge transmission. Analyzing 36,523 scientometrics publications, we find papers on main paths exhibit lower disruption, with disruption declining further over time. It aligns with MPA's tendency to amplify consensus-driven knowledge. Disruptive papers (DI>0) are less likely to appear on main paths, suggesting alternative diffusion pathways. Besides, indirect impact metric (SPX) is positively associated with direct impact (citation counts) but negatively correlated with disruption. Our research shows that MPA may underrepresent disruptive contributions, necessitating complementary DI/SPX evaluation.

Introduction

Information scientists aim to use citation relationships to identify impactful scientific papers. Citation count is the most common evaluation metric for its simplicity and intuitiveness. However, it overlooks the complex information within citation structures (Bu, Waltman, & Huang, 2021). Recently, the disruption index (DI) proposed by Funk and Owen-Smith (2017) has garnered significant attention (Wu, Wang, & Evans, 2019; Park, Leahey, & Funk, 2023; Lin, Frey, & Wu, 2023; H. Li, Tessone, & Zeng, 2024). Unlike citation count, DI focuses on measuring the nature of a paper's impact (Leahey, Lee, & Funk, 2023). It assesses a paper's influence based on how it disrupts existing citation patterns: when subsequent papers cite a focal paper (FP) but do not acknowledge FP's references, FP disrupts its field; conversely, FP consolidates the field's development (Azoulay, 2019). In other words, the FP's brilliance captures the attention of successors and dims its predecessors. Scholars have examined DI's validity through expert evaluations (Bornmann & Tekles, 2019; Bornmann et al., 2020a, 2020b). Some researchers explored Nobel Prize-winning papers, which often have both high DI values and citation counts(Liang, Lou, & Hou, 2022). These two metrics, reflecting the nature and level of impact, provide a two-dimensional evaluation framework (Wei, Li, & Shi, 2023). In this framework, most papers contrast with Nobel Prize-winning works, exhibiting lower citation counts and DI values. The remaining papers fall into two categories. A high DI value does not equate to a significant impact, as these papers might receive fewer citations. Conversely, highly cited papers may not possess high DI values. Review articles exemplify this, as they primarily integrate existing knowledge.

These combinations capture our interest, the two with high impact levels. Citation relationships represent a form of knowledge flow, and the DI measures how FPs disrupt this flow. Papers with high citation counts often play crucial roles in knowledge flow and tend to cluster along the main paths of citation networks. Scholars have analyzed these main paths to map the development of fields (Hummon & Dereian, 1989) and identify foundational papers (Ma & Liu, 2016). However, these studies often overlook whether the knowledge flow reflects disruption or integration. Introducing DI can help us analyze how papers on the main paths contribute to knowledge flow within specific fields.

We have additional motivation for using main path analysis (MPA). While citation count reflects the direct impact of a paper, it fails to capture indirect influence. MPA offers a complementary measure (Liu, Lu, & Ho, 2019). Furthermore, both the DI and MPA consider FP's citing and cited papers, aligning them conceptually. The DI focuses on local network structures, whereas MPA utilizes global information. Integrating network information may better measure a paper's impact, allowing us to develop a three-dimensional evaluation framework. Given the rapid growth in scientific publications, using larger datasets to represent specific research fields is essential but challenging. MPA can guide us in focusing on a subset of papers that can effectively represent the core of the research field.

We select scientometrics as a case study to address the following research questions. First, do papers on the main paths exhibit higher disruption? Do the disruptive papers tend to appear on the main paths? Second, is the indirect impact measure associated with MPA consistent with other paper evaluation metrics?

Literature Review

Disruption Index (DI)

Researchers have conducted in-depth discussions on the DI. Here we only provide a brief overview of this index. We can refer to Leibel and Bornmann (2024) for a more detailed one. To facilitate subsequent elaboration, we first introduce the regular form of this index.

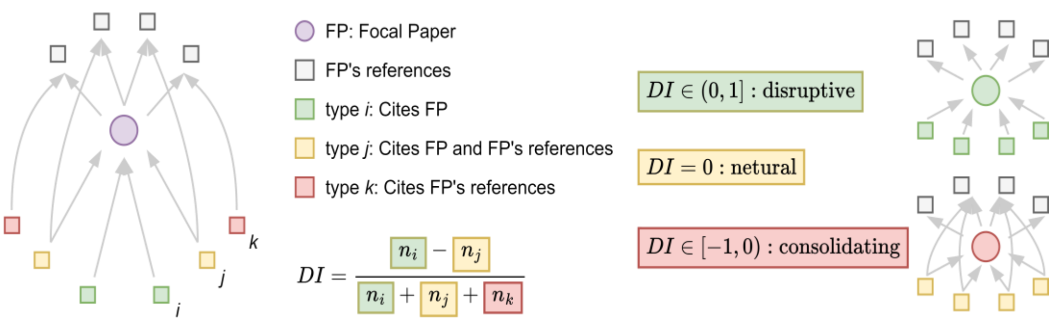

Figure 1. Illustration for DI.

In Figure 1, for an FP, we focus on its references and citing papers. It has four references (gray rectangles). The six citing papers (rectangles below) are in three parts: those citing only the FP (green, denoted as i), those citing both the FP and its references (yellow, denoted as j), and those citing only its references (red, denoted as k). The DI value for the FP is the difference in proportion between the i and j, i.e.,

$$DI = p_i - p_j = \frac{n_i - n_j}{n_i + n_j + n_k} \in [-1,1]$$

We consider $DI = 0$ as a threshold. $DI > 0$ indicates the paper is disruptive, while $DI < 0$ suggests it is consolidating. Additionally, we should determine the number of citing papers, which requires setting an appropriate citation window.

The first type of research examines the DI mechanism. Leydesdorff and Bornmann (2021) argue that the DI relies on bibliographic coupling, where the coupling of the FP and its references signifies continuity, while disruption indicates a break in continuity. Lin, Evans, and Wu (2022) suggest that disruptive papers often achieve breakthroughs in theory, methods, or discoveries compared to their references.

Further discussions on improvements are in two factions. One faction views the DI as a relative measure, considering disruption and integration as opposing concepts. The other treats it as an absolute measure, calculating disruption and integration separately (Chen, Shao, & Fan, 2021; Leydesdorff, Tekles, & Bornmann, 2021). Current research focuses more on the former approach. Since many k-type papers can skew the DI value towards zero, Bornmann et al. (2020b) propose setting a bibliographic coupling threshold to reduce the number of k-type papers. Deng and Zeng (2023) suggest severing links between citing papers and highly cited references to increase the number of i-type papers. Both methods adjust the DI value. Ruan et al. (2021) note that fewer references negatively impact the DI value and recommend focusing only on FPs with more than ten references. Yang et al. (2024) systematically review the shortcomings of the DI and offer more reasonable modifications. Yang et al. (2024) also propose disruptive citations to measure a paper's absolute disruptive impact.

Validation work relies on specific datasets, including milestone paper lists published by *Physical Review Letters* in physics (Bornmann & Tekles, 2021) and peer review results from F1000Prime in biology and medicine (Bornmann et al., 2020b). A notable validation effort is Macher, Rutzer, and Weder's rebuttal (2024) of Park, Leahey, and Funk's conclusions (2023), highlighting that truncating the citation window can lead to biased results.

The second type of research examines how research activities impact the papers' disruption. Lyu et al. (2021) show that team size and international collaboration negatively correlate with the papers' DI value. Zeng et al. (2021) report a positive correlation between new teams and the papers' disruption. Wang et al. (2023) reveal that scientists in structural holes within collaboration networks are more likely to publish disruptive papers. Zhao et al. (2024) note that teams with more thought leaders produce less disruptive ideas. Another set of studies investigates the impact of interdisciplinary collaboration on paper disruption. Liu et al.'s empirical results (2024) indicate that collaboration within the same discipline is more likely to produce disruptive outcomes, while Chen et al. (2024) present research with opposite conclusions. Other influencing factors include funding types (Yang & Kim, 2023) and prior knowledge (Sheng et al., 2023).

The third type of research expands the DI application scenarios. Scholars use it for scientific evaluation, applying it to papers (Zhou et al., 2022; Wang et al., 2024; Yan & Fan, 2024a), scientists (Wang, Zhou & Zeng, 2023; Yang et al., 2023), and journals (Jiang & Liu, 2023).

Overall, researchers primarily focus on the first type of research. Future research may explore using textual information to measure paper's disruption and enhance the utilization of this index.

Main Path Analysis (MPA)

MPA is a classical network method that considers citation relationships as knowledge flows, tracing the most significant dissemination paths within a field. It involves two steps: calculating the traversal weights of links and extracting the paths with the highest weights. Current research focuses on methodological improvements to achieve more interpretable results.

Early explorations focus on network topology. Hummon and Dereian (1989) establish the foundation for MPA by proposing three traversal weight methods: Node Pair Projection Count (NPPC), Search Path Link Count (SPLC), and Search Path Node Pair (SPNP). Batagelj (2003) introduces the Search Path Count (SPC), which balances inflow and outflow traversal weights. Although SPC was initially popular, Liu, Lu, and Ho (2020) conclude that SPLC better suits the knowledge dissemination context after comparing the four methods. In path searching, Liu and Lu (2012) propose the main paths: local, global, and key-route. Additionally, Pajek (Everton et al., 2018) significantly contributes to disseminating MPA, offering researchers convenience. Researchers also explore other perspectives. For instance, Liu and Kuan (2016) examine the decay of knowledge during the flow process, Jiang, Zhu, and Chen (2020) address MPA's limitations in self-loop networks, Ho, Liu, and Chang (2017) investigate the impact of review papers on generating main paths, and Kuan analyzes MPA's tendency toward long path results (2023), proposing quantitative methods to evaluate main paths (Kuan & Liao, 2024).

Subsequent studies emphasize the integration of semantic information. For example, Chen et al. (2022) introduce link semantic weights to improve paths thematic coherence. Yan and Fan (2024b) incorporates knowledge graphs to enhance the knowledge proximity of path nodes. Additionally, Liu, Lu, and Ho (2019) suggest using link traversal weights to measure the indirect influence of papers within a field, although this idea has received limited attention.

Methods

Data Collection and Network Construction

Constructing a citation network includes two steps: determine the paper set in scientometrics and obtain citation relationships (their references and citing papers). We have two accessible data sources: Web of Science (WoS) and OpenAlex (Priem, Piwowar, & Orr, 2022).

For the first step, Bornmann and Tekles (2019b) select papers from *Scientometrics* to represent this field. Both WoS and OpenAlex offer a retrieval tool that uses the

Leiden algorithm (Traag, Waltman, & Van Eck, 2019) to cluster papers and assign category labels, which facilitates our research. Therefore, we obtain data separately and compare them. The strategy is in Table 1.

Table 1. Retrieval strategy for papers in scientometrics.

Source		*Strategy*
WoS	Query	TMSO= (6.238 Bibliometrics, Scientometrics & Research Integrity)
	Index	SCI & SSCI
	Document	Article & Review
	Date	2024-12-18
	Records	40,500
OpenAlex	Query	Topic is "scientometrics and bibliometrics research"
	Document	Article & Review
	Records	51,690

The results show that OpenAlex provides more data, and only 8,029 entries overlap, indicating significant differences. Merging the two datasets is feasible, but we are concerned that it could introduce more noise. Therefore, we manually check some classic papers in scientometrics. For instance, in "An index to quantify an individual's scientific research output," Hirsch proposed the famous h-index (2005). However, OpenAlex categorizes this paper under "Cognitive Science and Mapping." Clustering algorithm may bring noise especially when the data is large and complex. Considering the data quality, we prefer the WoS data. We also acknowledge the limitation of the manual review, conducting experiments separately may be a better choice.

For the second step, we choose the OpenAlex data. First, early papers often have limited references, and WoS does not index them. It may affect the DI value of papers. Additionally, WoS does not provide bulk access to forward citations, making it challenging to construct a complete network when the FP set is large. However, OpenAlex assigns universal identifiers (OpenAlex ID) and provides powerful APIs, overcoming the shortcomings abovementioned.

Overall, we finally adopt a mixed strategy: WoS provides focal paper set and OpenAlex offers citation relationships.

The comparison between WoS and OpenAlex data is in Table 2. For the 40,500 records, OpenAlex indexes most of them. Besides, OpenAlex covers 70% of the reference data for WoS and provides more references.

Table 2. Data Comparison between WoS and OpenAlex.

	WoS	*OpenAlex*	*Shared*
Records	40,500	40,182	40,182
Reference Items	267,803*	384,627	187,398
References	757,379	1,171,004	553,012

* Only 258,580 items exist in OpenAlex.

We have two citation networks in this study. First, we utilize complete data to construct a full network. Here, we select a portion of the 40,182 original records with at least one reference for the FP set. It covers 676,140 nodes and 6,568,462 edges. We also build a close network which only retains citations where both sides belong to the FP set (Li & Chen, 2022). The illustration is in Figure 2. Such an approach reflects knowledge flow within scientometrics, aligning with the strategy used in MPA studies. Table 3 shows the minor differences between the two close networks.

Table 3. Close network comparison between WoS and OpenAlex version.

	WoS	*OpenAlex*	*Shared*
Nodes	35,319	36,523	33,438
Edges	388,588	376,958	349,561

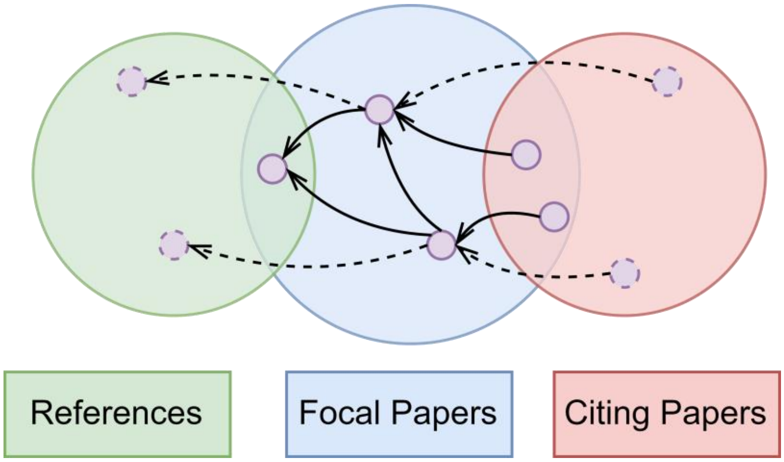

Figure 2. Illustration for close network construction.

Evaluation Metrics

The metrics we select to evaluate paper's impact are in Table 4.

Table 4. Evaluation metrics.

Dimension	*Metrics*	*Illustration*
Level	I_{10}	Citation counts within a 10-year citation window.
	I_{2024y}	Citation count received until 2024.
Nature	DI_{10}	DI within 10-year citation window.
	DI_{2024y}	DI values in 2024.

Main Path Analysis with Indirect Impact Metrics

We choose SPLC to calculate citation traversal count because this is more consistent with the representation of knowledge flow (Liu, Lu, & Ho 2019). We use multiple methods integrated in Pajek to extract the main paths for comprehensive results (Liu & Lu, 2012). We accomplish the task only on the close network to reduce bias (Filippin, 2021).

We also refer to the method provided by Liu, Lu, and Ho (2019) to measure the paper's indirect impact. Each FP has n citation links whose sum of citation traversal counts is s, and its indirect impact is $SPX = \frac{s}{n}$. The illustration is in Figure 3.

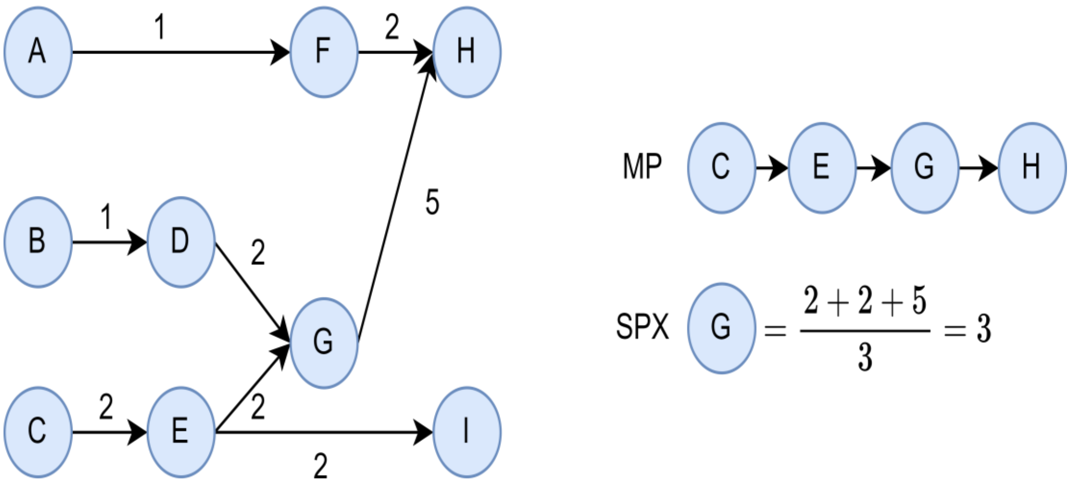

Figure 3. Illustration for MPA and SPX metrics.

Results

Network Description

In the citation network, the in-degree represents the citation count, and the out-degree represents the number of references. Figure 4 illustrates the logarithmic distribution of the FPs in the two networks.

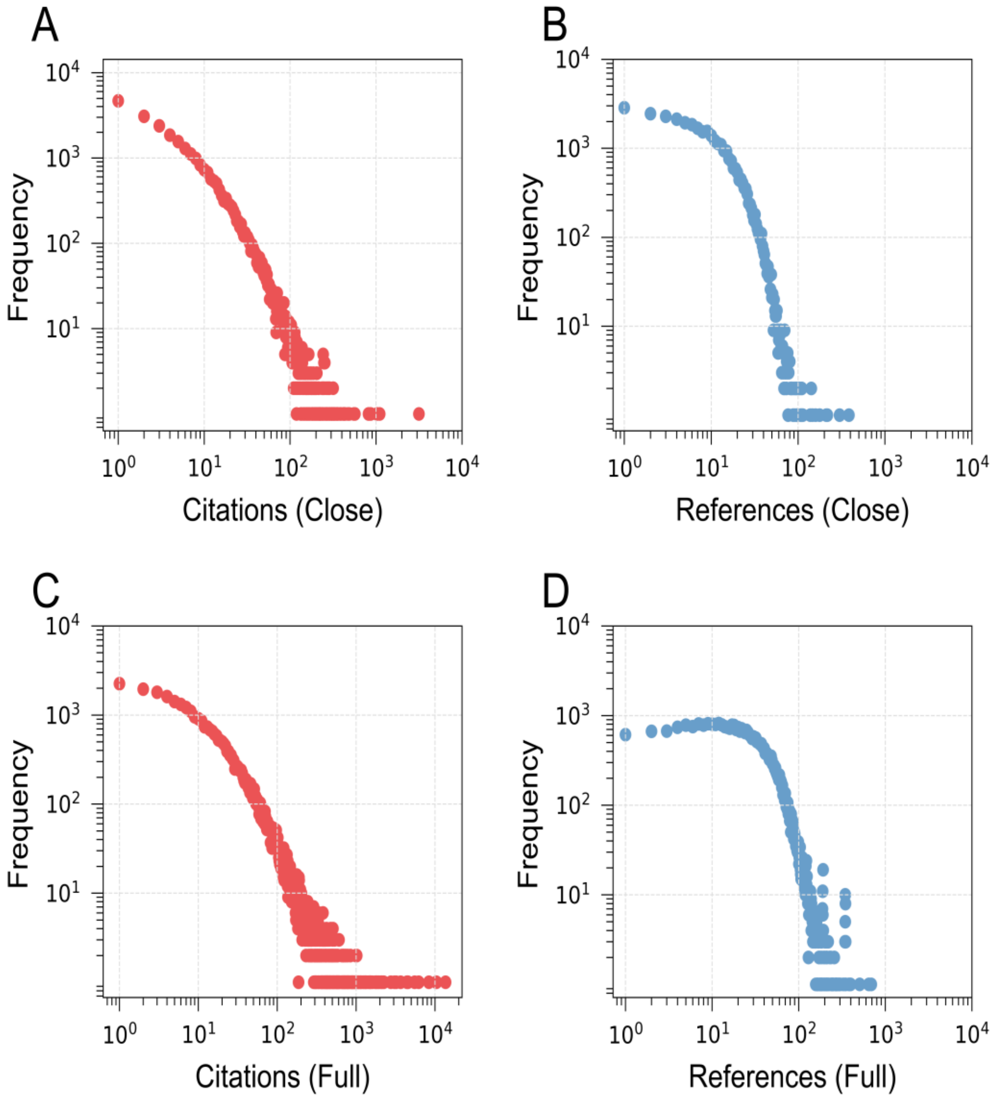

Figure 4. Citation and reference distribution in the two networks.

Most papers have less than 10 citations, while a few obtain extremely high impact. Hirsch's proposal on the h-index receives significant attention in the close network. In the full version, Van Eck and Waltman (2010) have the highest impact with the introduction of VOSviewer. One likely reason is that VOSviewer has become fundamental to scientometrics, leading researchers in the field to choose not to cite it. The distribution of reference is more concentrated in the upper range. Earlier papers tend to have fewer references, and OpenAlex may not fully index them. The paper with the most references is a 2008 review by Bar-Ilan (2008). In the full network, some nodes with numerous references, such as "Quantitative Studies of Science: A Current Bibliography" (ID "W2135332121"), appear. OpenAlex sometimes provides extensive but incorrect reference relationships for these nodes, introducing noise into the network.

Park et al. suggest that the current decline in the disruption of papers may be due to researchers bearing a heavier knowledge load (2023). Figure 5 presents a box plot showing the distribution of reference counts for FPs published from 1955 to 2024. Over time, researchers in scientometrics have consulted more literature.

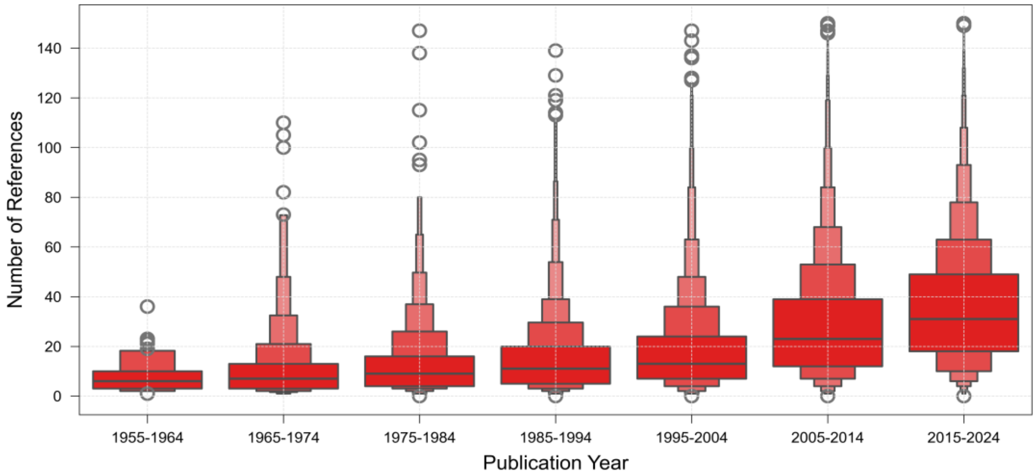

Figure 5. Reference distribution over years in the full network.

We examine the temporal distribution of citation behaviour. Figure 6 illustrates that most FPs derive insights from works published within the last decade and receive citations within ten years of publication. The citation window influences both the citation count and disruption. Thus, setting the ten-year window is more proper in this context.

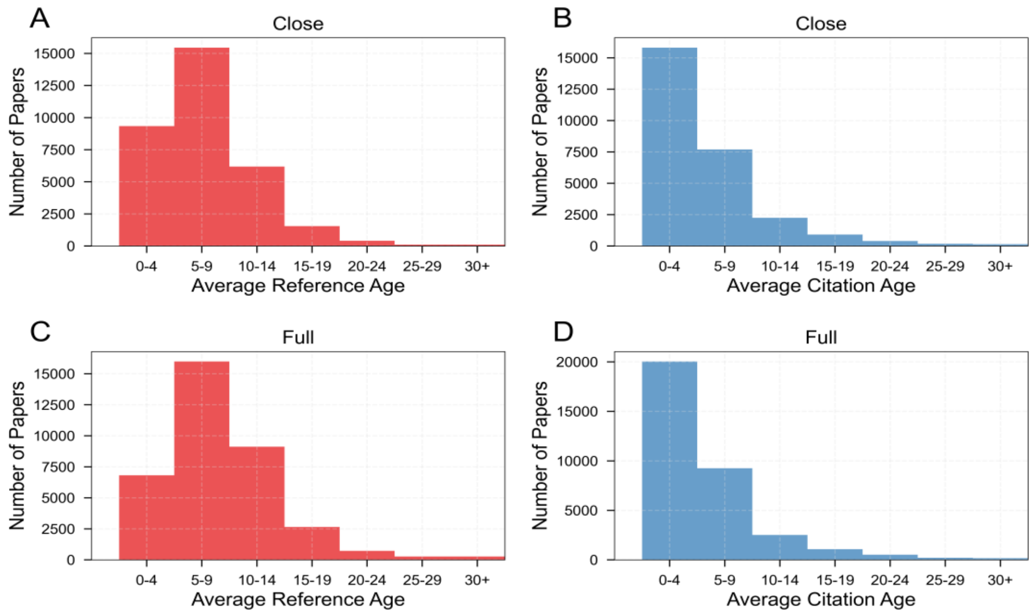

Figure 6. Average reference and citation age distribution in the two networks.

Disruption Distribution

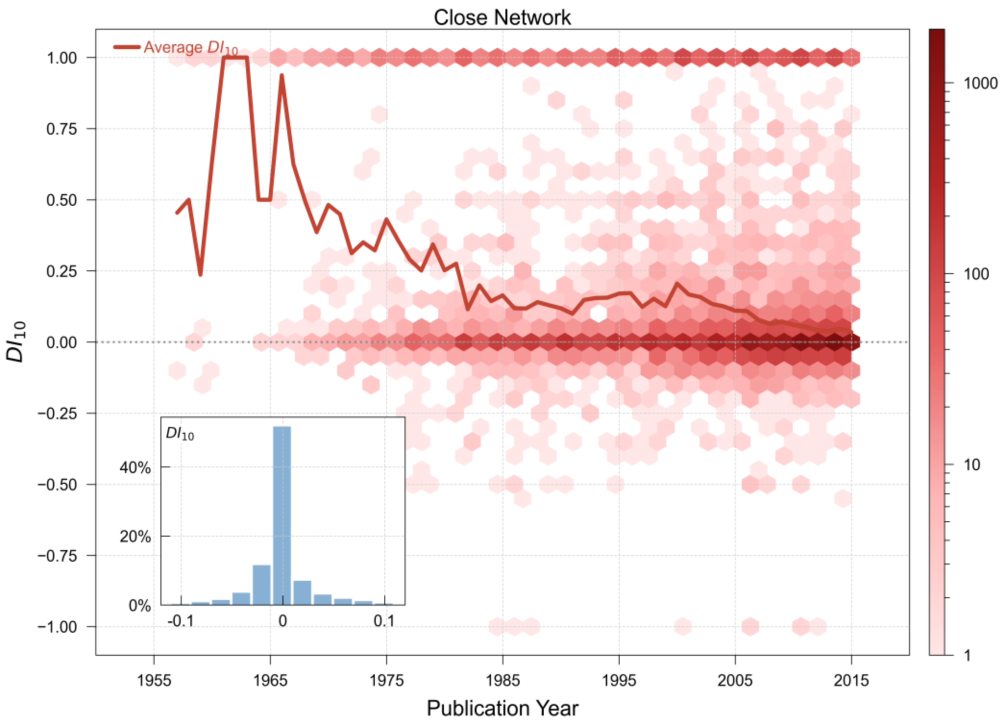

Figure 7. Distribution of DI_{10} values in the close network.

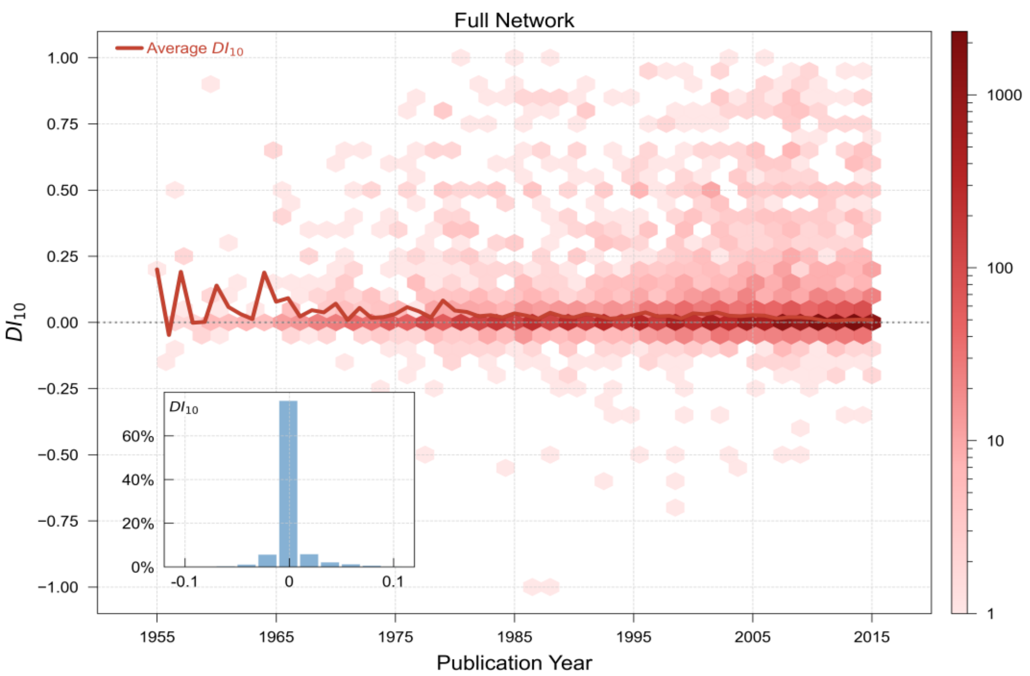

Figure 8. Distribution of DI_{10} values in the full network.

Figure 7 illustrates the distribution of DI_{10} for papers published in the close network from 1955 to 2014. A total of 1088 nodes are absent due to a denominator of zero. The main part is a hexbin plot, where each hexagonal area corresponds to a specific publication year and DI_{10} value, with colour indicating the density of papers. Most papers have DI_{10} values concentrated around zero. The histogram in the lower left corner reflects a similar trend, with over 40% of papers having a DI_{10} value of zero. The line graph depicts the average DI_{10} value per year, suggesting that the field of scientometrics is experiencing a decline in disruption. Figure 8 presents a similar picture, showing even lower annual average DI_{10} values and a more extreme distribution.

In the close network, we see variations in DI_{10} values. Figure 9 illustrates this dynamic. Red nodes have higher DI_{10} values in the full network, while blue nodes appear more disruptive in the close network. Blue nodes in the grey area show extremely high DI_{10} values, indicating that the structure of the close network significantly impacts these measurements.

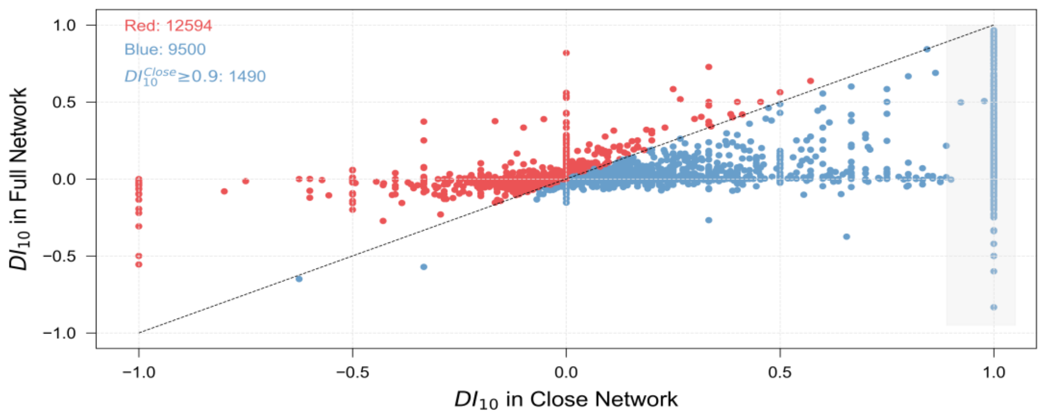

Figure 9. Distribution of DI_{10} difference between the two networks.

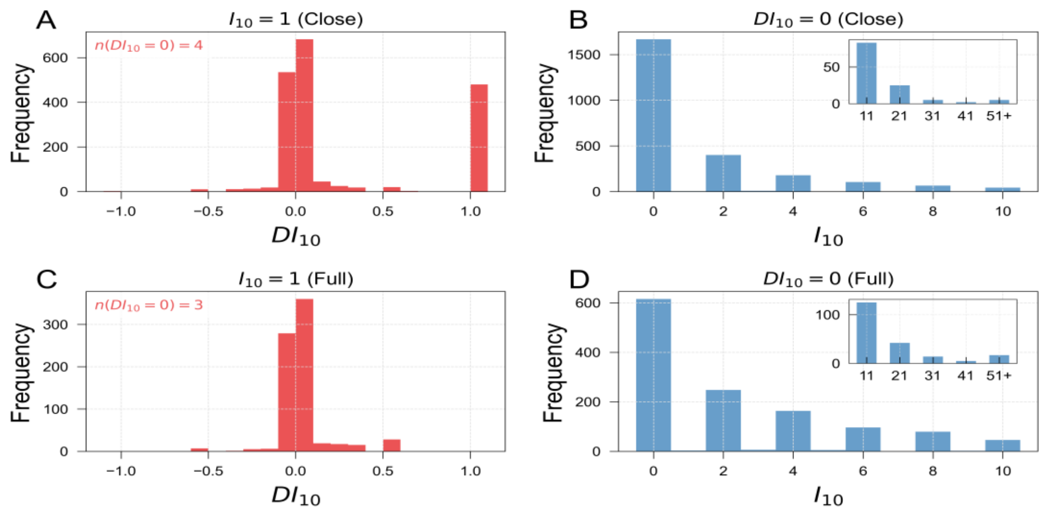

Figure 10. Distribution of DI_{10} and I_{10} values for papers with $I_{10}=1$ or $DI_{10}=0$.

We combine I_{10} and DI_{10} metrics to analyze paper impact. Previous results indicate that many papers receive few citations or exhibit low disruption. We select papers with only one citation or a DI_{10} of zero. In Figure 10, the red histogram shows that most papers with a single citation have DI_{10} values near zero. However, over four hundred papers exhibit extremely high DI_{10} values in the close network. Similarly, the blue histogram indicates that many papers have an I_{10} less than 5, with the rest being outliers.

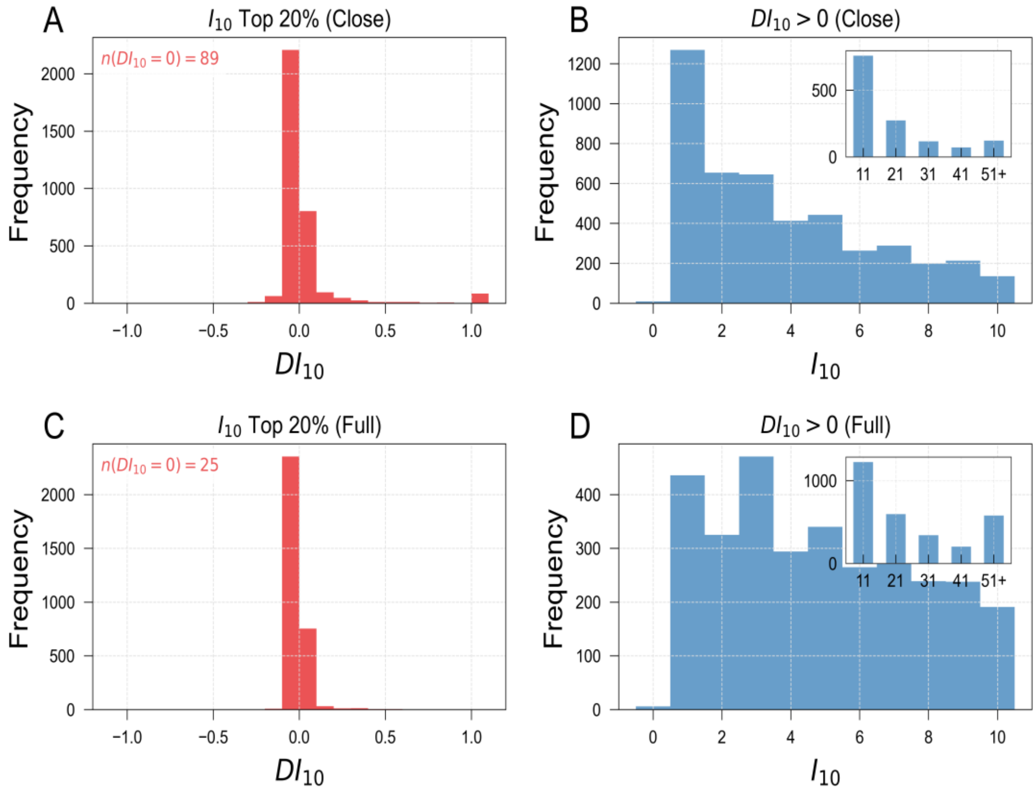

Figure 11. Distribution of DI_{10} and I_{10} values for papers with I_{10} in the top 20% or $DI_{10} > 0$.

We then examine papers with high impact. The red plot illustrates the DI_{10} distribution for papers in the top 20% of the I_{10} (thresholds: close = 14, full = 40). Most papers have DI_{10} values clustered around zero, with a sizable proportion below 0. We also analyze the papers with $DI_{10} > 0$, which typically rank in the lower 80% of the I_{10}. Table 5 further demonstrates this negative correlation. It is insignificant when the threshold is Top 1% and 5%. Figure 12 shows that a few outliers have both high impact and disruption.

Table 5. Negative correlation between I_{10} and DI_{10}.

Network	*Range (Top %)*	*Threshold*	*Sample*	*Correlation*	*p-value*
Close	1%	89	159	-0.162	p=.041
	5%	39	809	-0.115	p<.01
	10%	25	1653	-0.155	p<.001
	20%	14	3375	-0.170	p<.001
	100%	0	15701	-0.04	p<.001
Full	1%	255	159	-0.105	p=.187
	5%	107	800	-0.067	p=.059
	10%	69	1587	-0.12	p<.001
	20%	40	3195	-0.16	p<.001
	100%	0	15701	-0.298	p<.001

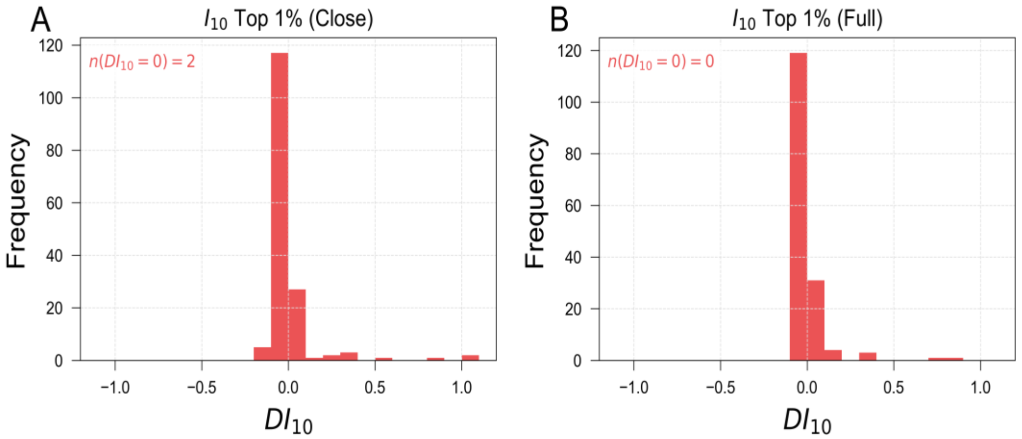

Figure 12. Distribution of DI_{10} values for papers with I_{10} in the top 1%.

Main Paths

We utilize Pajek to obtain five main paths with SPLC as the traversal count indicator and different selection methods. The main paths overlap and include 147 papers in total. Table 6 provides an overview. Diversity appears in the local forward path.

Table 6. Overview to main paths.

Main Paths	*Parameter*	*Nodes*	*Unique*
Global Standard	/	79	0
Local Backward	Tolerance=0.2	83	0
Local Forward	Tolerance=0.2	100	10
Local Key-route	Paths=1-20	130	3
Global Key-route	Paths=1-20	93	2

We merge the main paths for analysis. Table 7 shows the topics in different periods. From 1961 to 1983, early studies explored scientists' resistance to discoveries and

Matthew's effect on science. Co-citation analysis stood out in 1973 and ignited subsequent research in the 1980s. In 1991-2007, scholars discussed the journal's impact and research trends in the specific discipline. The third period enriched the knowledge in evaluating citation and journal impact. New indicators like success index and t-factor introduced new informetrics models. In the next period, scientists turned to bibliographic databases. They compared Scopus and WoS to analyze the data quality. Discussions on open platforms like Microsoft Academic Graph and Open Citations were also remarkable. We do not mention the last period because the relevant papers are not representative. In other words, they may not reflect the leading development of scientometrics in the last two years. A probable reason is the limitation of the MPA method itself. It relies on a sufficient citation window to determine the appropriate papers that appear on the main paths.

Table 7. Topics in the different periods of the main paths.

Period	*Main Topic*	*Count*
1961-1987	Co-citation analysis	31
1991-2007	Empirical studies with bibliometrics methods	18
2008-2016	Evaluation metrics	43
2016-2022	Bibliographic database	38

Figure 13 presents the DI value of papers along the main paths. Since only 86 papers appeared before 2015, we include DI_5 for papers published up to 2019, enabling a more comprehensive discussion. The final dataset comprises 118 papers. DI_{2024y} represents the most recent DI value. Each color block corresponds to a single paper, arranged chronologically with ten papers per row. Red indicates $DI > 0$, blue represents $DI < 0$, white denotes $DI = 0$, and grey signifies the absence of a DI value for the paper. The results show that most papers have $DI < 0$, while papers with $DI > 0$ cluster in the earlier years.

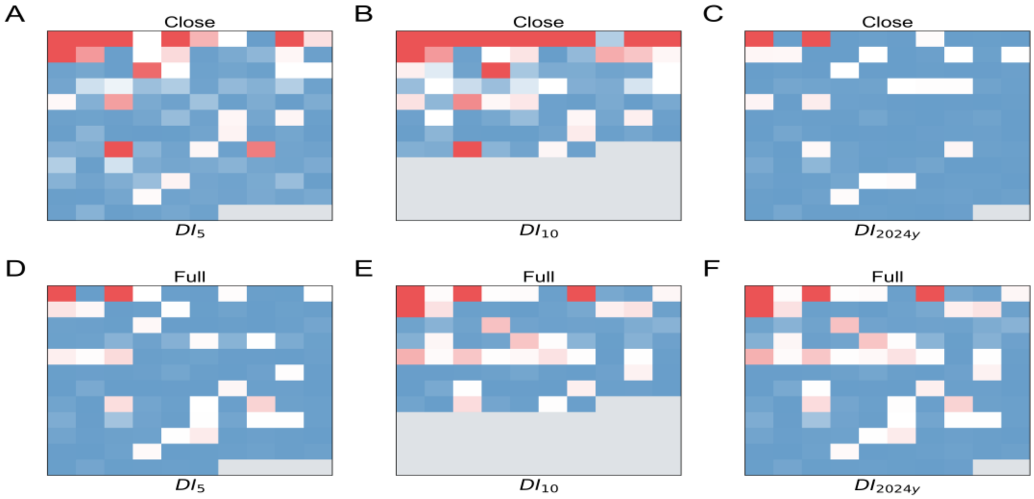

Figure 13. Distribution of DI values in different formats.

Additionally, we compare each paper with others published in the same year. Figure 14 demonstrates that all papers on the main paths exhibit DI_5 values higher than the annual average and median. However, this trend reverses significantly in DI_{10}. Regarding I_5 and I_{10}, papers on the main paths perform well within the close network but do not show a distinct advantage in the full network. One explanation is that some papers outside the main paths contribute to other fields.

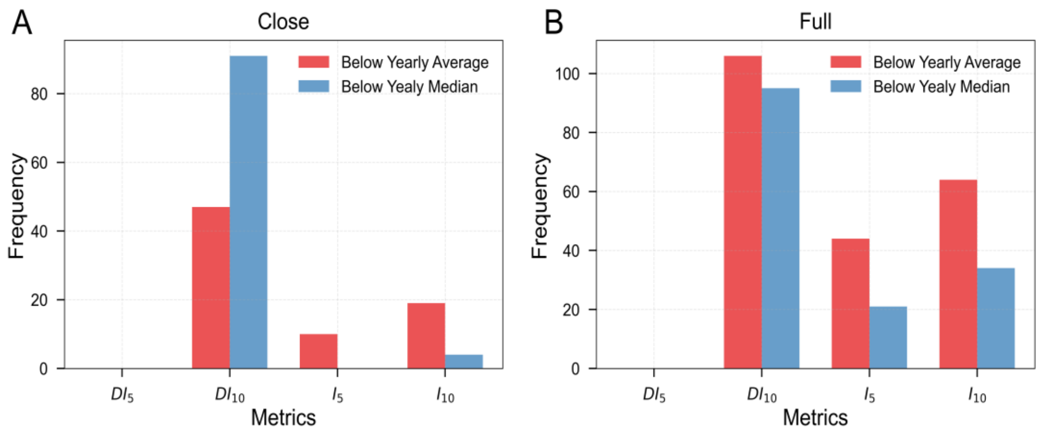

Figure 14. Comparison between papers on the main paths and others published in the same year.

The decline in values from DI_5 to DI_{10} catches further attention. Table 8 highlights this trend. Within the close network, all papers display a consistent decrease, while in the full network, some papers maintain higher DI values even 10 years after publication. The probable reason is that researchers from other fields adopt knowledge from scientometrics.

Table 8. Distribution of papers on the main paths with different relations on DI_5 and DI_{10}.

Relation	*Close*	*Full*
$DI_{10} < DI_5$	86	54
$DI_{10} = DI_5$	0	1
$DI_{10} > DI_5$	0	31

The papers on the main paths represent only a tiny fraction of the FPs. To broaden the scope of our analysis, we employ SPX, which measures a paper's contribution to knowledge flow within the citation network and reflects its indirect impact. Table 9 reports the Spearman correlation between SPX, DI, and I. To account for temporal variations, we apply different time windows, resulting in three groups of papers. The findings are significant and robust across the two networks, indicating a negative correlation between SPX and DI, while SPX shows a positive correlation with I.

Table 9. Spearman correlation between SPX, DI, and I.

Group	*Sample*	*Variable*	*Close*	*Full*
1955-2014	12,197	DI_5	-0.103***	-0.244***
		DI_{10}	-0.132***	-0.246***
		DI_{2024y}	-0.147***	-0.216***
		I_5	0.524***	0.356***
		I_{10}	0.512***	0.353***
		I_{2024y}	0.568***	0.438***
1955-2019	20,338	DI_5	-0.176***	-0.252***
		DI_{2024y}	-0.199***	-0.234***
		I_5	0.507***	0.367***
		I_{2024y}	0.540***	0.420***
1955-2024	32,042	DI_{2024y}	-0.210***	-0.223***
		I_{2024y}	0.200***	0.200***

*** $p < .001$

We further analyze papers with $DI > 0$ to explore the relationship between disruption and main path membership. Table 10 reveals that the negative correlation remains statistically significant.

Table 10. Negative correlation between SPX and DI.

Variable	*Time Span*	*Close*	*Sample*	*Full*	*Sample*
DI_5	1955-2019	-0.183***	6084	-0.144***	6901
DI_{10}	1955-2014	-0.144***	4973	-0.109***	4974
DI_{2024y}	1955-2024	-0.232***	9967	-0.190***	12511

*** $p < .001$

We employ the Monte Carlo simulation method to validate this observation, randomly assigning the “main path member” label while keeping the publication year constant. This approach allows us to simulate expected values under an unbiased condition. Figure 15 illustrates a consistent trend across all disruption metrics (DI_5, DI_{10}, and DI_{2024y}): the participation rate of highly disruptive papers in the main paths is consistently lower than the random baseline.

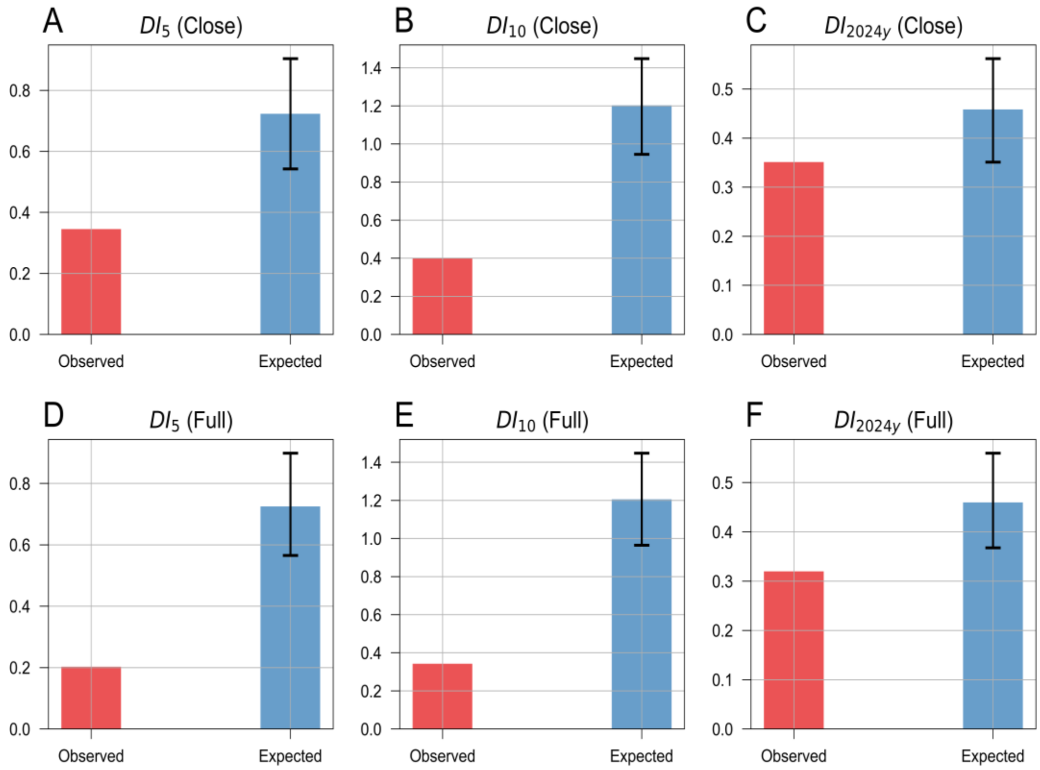

Figure 15. Participation of papers with $DI > 0$ on the main paths in the two situations.

Table 11. Statistic results for the validation experiment.

Variable	*Time Span*	*Close*	*OR (95%CI)*	*Full*	*OR (95%CI)*
DI_5	1955-2019	p<.001	0.388	p<.001	0.203
DI_{10}	1955-2014	p<.001	0.225	p<.001	0.187
DI_{2024y}	1955-2024	p<.1	0.691	p<.01	0.582

Additionally, the close and full networks exhibit similar patterns, suggesting that the observed results are independent of the citation network construction strategy. This trend demonstrates robustness across different network configurations. Table 11 provides detailed statistical evidence, showing that, except DI_{2024y} ($p = .06$ in the close network and $p = .002$ in the full network), the p-values for all other metrics are below 0.001.

In summary, we conclude that disruptive papers are significantly less likely to appear on the main paths.

Discussion and Conclusion

We analyze two metrics, I and DI, to examine papers in the scientometrics, with a particular emphasis on those situated on the main paths. Overall, papers on the main paths tend to exhibit lower disruption and demonstrate stronger consolidative tendencies over time. A comparative analysis with papers published in the same year reveals that this downward trend in disruption is significant. At the same time, these papers consistently show higher I values. However, their advantage in I diminishes when considering the attention from other fields.

Let us review the formula of the disruption:

$$DI = \frac{n_i - n_j}{n_i + n_j + n_k}$$

Here, j-type papers, which cite both the FP and the references of the FP, contribute directly to a negative impact on disruption. We hypothesize that the coupling relationships among main path members play a key role in reducing disruption. Figure 16 provides evidence for this hypothesis. For each j-type descendant of a paper, we identified b-type papers that cite both the FP and other members of the main paths. We then calculate the proportion of b-type papers within the j-type set. The results indicate that b-type papers significantly increase the number of j-type papers, thereby reducing DI values.

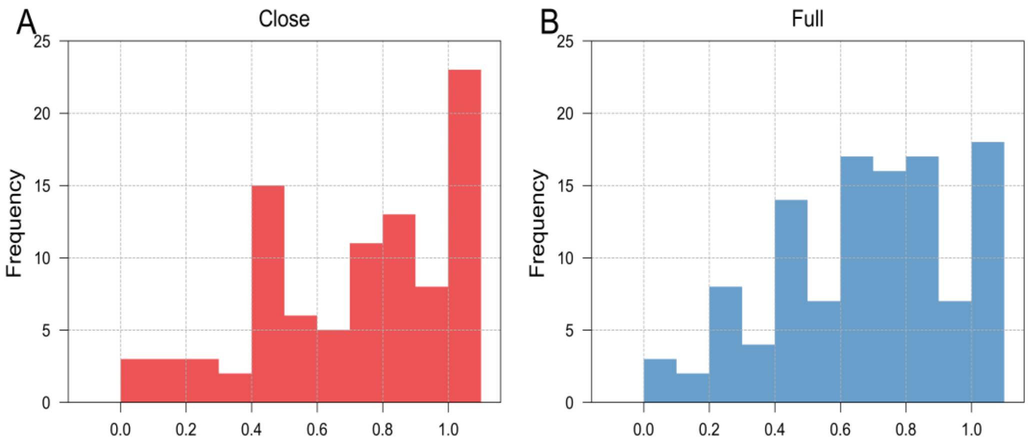

Figure 16. Proportion of b-type within j-type papers for the members of the main paths.

We introduce the SPX to examine the relationship between direct impact, indirect impact, and disruption. Our findings show that indirect impact is positively correlated with direct impact, while both negatively correlate with disruption.

The top 1% of highly influential papers form a distinct group. The sample size ($n \in (100{,}350)$, depending on the time window) influences the robustness and significance of these correlations. For example, outliers with high influence and high disruption weaken the observed negative correlation. Similarly, some papers with exceptionally high impact fail to achieve high SPX values. This discrepancy arises because network structure is critical in determining SPX values. Notably, the correlations regain statistical significance when we set the threshold from the top 1% to the top 5%. Future studies could investigate their topics and citation patterns to provide deeper insights into their unique characteristics.

On the other hand, we specifically focus on FPs with $DI > 0$, where their SPX values demonstrate a consistently stable negative correlation with DI. Statistical analyses further indicate that disruptive papers are less likely to be part of the main paths.

Our study provides a multidimensional evaluation framework. It can bring a more comprehensive understanding of how papers contribute to scientific progress. Future research could further investigate it across different disciplines.

In addition, we focus on analyzing papers along the main path. The main path mechanism prioritizes and amplifies conventional scientific achievements, creating a “highway” for knowledge diffusion. In contrast, disruptive papers are more likely to spread through smaller, less prominent paths, suggesting a divergence in the dissemination patterns of traditional and disruptive contributions.

This study also offers two practical recommendations. First, we propose giving greater attention to non-mainstream breakthroughs when assessing the impact of papers, as these contributions may represent emerging or unconventional advancements. Second, main path analysis may not be the suitable tool for identifying disruptive technological frontiers, given its inherent focus on established knowledge trajectories.

There still exist certain limitations. It is difficult to reduce noise in the dataset like incorrect citation relationships and papers that do not belongs to scientometrics, which may affect identifying the main paths. Besides, we only adopt SPLC as the link traversal algorithms, introducing advanced approaches could help optimize the results. Additionally, the SPX indicator covers only about 90% of the nodes, as calculating SPLC values in Pajek requires selecting the largest subnetwork. Future research could explore methods to address this constraint and ensure more comprehensive coverage. Finally, we do not disclose the difference in citation patterns between main path members and disruptive papers in detail. Case study may bring more insight into how the two kinds of papers contribute the scientific progress in scientometrics.

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