Coordinated Journals, Concentrated Networks and Citation Growth: Evidence from Finance

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Abstract

This paper introduces and tests two hypotheses: formally and openly coordinating journals boosts their impact factors; and journal coordination combined with highly-concentrated editorial and author networks augments this effect. We use Scopus and Scimago citation data and PubPeer data to proxy journals associated with highly-concentrated editorial and author networks. Focusing on the similarities and differences between twenty-six top finance journals, before and after journal coordination was arranged during 2019 among a set of Elsevier 'ecosystem' journals, we use two empirical strategies starting with difference-in-differences (DiD) analyses. The two-year impact factor model with interaction terms for different journal groups shows that ecosystem membership is associated with a modest increase in citations per document of approximately 40% for non-PubPeer ecosystem journals. However, four ecosystem journals have had an editor-in-chief who (co-)authored three or more papers that were subsequently flagged by PubPeer, and this group of journals experienced a 104% increase in citations per document. This PubPeer effect is robust to other DiD two-year model specifications, and significant at 1% – also in DiD models for three- and four-year impact factors. Machine-learning clustering independently identifies these four journals as part of a small "quickly-evolving" cluster distinguished by near-exponential growth in publication volume and extraordinary rates of self-citation and mutual citation among a small network of highly-prolific authors. The top four most-cited authors in this cluster made a total of 1,006 self-citations and 803 citations to each other's work between 2019 and 2024, compared with 90 self-citations and 53 mutual citations among the top four authors in the traditional top three journals over the same period.

Keywords: Citation stacking, Hierarchical clustering, Network centrality, Journal impact factor, Scopus metadata

JEL classification: C22, C5, E42, F31, G1, G2

1 Introduction

In June 2024, Clarivate removed seventeen journals from its impact factor list due to suspected citation stacking.[1] This is a practice whereby groups of journals inflate each other's citation counts through coordinated mutual citations. This paper documents a related phenomenon in finance publishing, using a decade of Scopus citation data to show that a small network of highly-prolific authors and editors, concentrated in a handful of Elsevier finance journals, accounts for a disproportionate share of the citation growth observed in those journals since 2019. Our analysis suggests that the structural conditions enabling this concentration were partly created, or at least amplified, by Elsevier's formal coordination of a Finance Journal Ecosystem (FJE) in 2019. But the ecosystem is context, not cause: the primary driver of the most extreme citation inflation is a tight, identifiable network of authors and editors, not ecosystem membership per se.

The traditional hierarchy of finance journals is well established. Academics have long aimed to publish in the "top three" group – the Journal of Finance (JF), the Journal of Financial Economics (JFE), and the Review of Financial Studies (RFS). A broader elite tier, recognized by the Financial Times' list of top-50 journals, adds the Journal of Financial and Quantitative Analysis (JFQA) and the Review of Finance (RF) – together with the top three, these form the FT50 group of finance journals at the time of writing. Three further journals currently hold rank 4 CABS (2021) classifications without FT50 recognition: the Journal of Money, Credit and Banking (JMCB), the Journal of Corporate Finance (JCF), and the Journal of Financial Intermediation (JFI). Together these eight journals form what we call the AJG4 group of finance journals. This hierarchy is consequential: AJG rankings are tied to UK government research funding allocation (as well as funding, tenure, and promotion among universities in other countries) making them a key determinant of faculty salaries, promotions, and institutional prestige; and publication in FT50 journals affects MBA program rankings worldwide.

This concentration of reward at the top has generated well-documented inequities. Finance journals are more likely to publish works by authors connected to editors (Brogaard et al. 2014, Colussi 2018, Heckman & Moktan 2020, Laband & Piette 1994). Editors at the top three journals are overwhelmingly US-based and male, which shapes whose work gets published and whose data gets used (Adams & Xu 2023, Berninger et al. 2024). It is against this background that Elsevier's creation of an ecosystem for finance journals can be understood: as a structural response to the perceived dominance of a very narrow set of journals, offering a coordinated network of lower-ranked journals with shared submission infrastructure, article transfer services, and editorial collaboration.

The FJE was conceived in 2019 and formalised in 2020. Its founding members included International Review of Financial Analysis (IRFA), Finance Research Letters (FRL), Research in International Business and Finance (RIBAF), Emerging Markets Review (EMR), Journal of International Financial Markets, Institutions and Money (JIFMIM), International Review of Economics and Finance (IREF), Journal of Behavioural and Experimental Finance (JBEF), Journal of Economics and Business (JEB), and Journal of International Money and Finance (JIMF). The ecosystem has since expanded to thirteen journals at the time of writing. Its stated purpose is to offer authors a smoother submission process through coordinated editorial review and a shared article transfer service (ATS), allowing rejected papers to move between ecosystem journals without new submission fees.[2]

[1] https://retractionwatch.com/2024/06/27/seventeen-journals-lose-impact-factors-for-suspected-citation-manipulat

[2] https://www.elsevier.com/finance-ecosystem-journals

There is a legitimate case for such coordination. For many years, finance academics have noted the need for more outlets capable of rewarding rigorous work that falls outside the narrow scope or methodological preferences of the top three. The ecosystem responded to a real demand. But formal coordination also creates structural conditions under which editorial networks can become self-reinforcing. When a group of journals shares editors, conferences, and a transfer pipeline through which authors have incentives to cite journals they have submitted to or been rejected by, then these editors have greater visibility of – and familiarity with – work published in partner journals, and the boundaries between legitimate mutual citation and citation inflation can become difficult to police. Section 2 formalizes these into four structural mechanisms that underpin our two hypotheses.

Our paper investigates what happened to citation patterns following the ecosystem's formation. We use two complementary empirical strategies. First, we employ difference-in-differences (DiD) regressions on Scimago citation data from 2014 to 2024, comparing citation trajectories across twenty-six finance journals before and after the ecosystem's formation, controlling for publication volume, journal fixed effects, year fixed effects, and research topic. Second, we apply machine-learning hierarchical clustering to the full Scopus citation network of 65,876 papers published in these journals between 2014 and 2024, identifying clusters of journals and authors exhibiting statistically similar citation behaviour, and then we examine the citation patterns of the most highly-prolific and most highly-cited authors within each cluster.

The DiD results tell a nuanced story. For ecosystem journals overall, we find mixed results: the full model (with several interaction terms, one per journal group) indicates a significant 40% increase in citations per document associated with ecosystem membership, but this finding is not robust across different model specifications. The picture changes sharply when we separate ecosystem journals which have had at least one editor-in-chief who authored (or co-authored) at least three papers that are commented on by PubPeer. We label the four journals identified this way as the "PubPeer" ecosystem journals. For this group of journals the full model estimates a 104% increase in citations per document, which is significant at the 1% level, and this is robust to other model specifications. The estimated magnitude of citation increases is very different, comparing the larger group of FJE journals (40%) with the group of four PubPeer journals (104%). We investigated whether this could be explained by topic concentration, because the ecosystem journals do publish more papers on fast-moving themes such as COVID-19, cryptocurrency and sustainable finance. However, controlling for these topics did not materially reduce the estimated effect for PubPeer journals, in any model.

The machine-learning analysis provides deeper insights to the factors which drive these diverse results. Hierarchical clustering of journal-level citation metrics identifies three stable clusters: a "highly-influential" (HI) cluster comprising the traditional top three journals; a small "quickly-evolving" (QE) cluster of eight journals showing near-exponential growth in both publication volume and citations since 2019; and a "remaining" (RE) cluster of fourteen journals whose metrics have been comparatively stable. The QE cluster is dominated by FJE journals, and in particular by the four PubPeer ecosystem journals. But the cluster analysis also points to something the DiD regressions cannot directly capture: the role of individual authors.

Within the QE cluster, a small number of highly-prolific and most-cited authors account for a striking share of total citation activity. One author published 134 papers across our twenty-six journals in six years: nearly one every two weeks. Between 2019 and 2024 the top four most-cited authors in the QE cluster made 1,006 self-citations in total, and 803 citations to each other's work. By contrast, the top four most-cited authors in the traditional top three journals made 90 self-citations and 53 citations to each other over the same period. When we remove papers authored by or citing the thirty most-cited authors in any cluster, of course citation counts will fall for some journals in that cluster. However, the noticeable difference for the QE cluster compared with the HI and RE clusters is the scale of such falls, which are very dramatic especially for certain QE journals. The removal of most-cited authors in the HI or RE cluster has a much more modest effect on mutual citations within the respective cluster. It therefore appears that this concentration of a small, tightly networked group of thirty authors publishing prolifically, citing each other intensively, and co-authoring frequently is the primary proximate driver of the citation inflation we document.

We are careful about causal inference throughout. We do not claim that the ecosystem caused individual editors or authors to behave as they did. What we document is that the ecosystem created structural conditions – overlapping editorial roles, shared transfer pipelines, publisher-supported conferences – that reduced the expected cost and increased the expected benefit of concentrated citation networks. Whether individual actors exploited these conditions deliberately or whether citation inflation emerged as an inadvertent by-product of legitimate collaboration is not something our data can resolve. What the data do show, clearly and consistently, is that the citation growth in the most affected journals is concentrated in a small author network and is not associated with improvements in conventional quality indicators. In fact, in 2024 the average submission-to-acceptance times in the QE cluster was only 205 days, compared with 311 days in the RE cluster. Publication volumes in the QE journals also grew, near-exponentially, while quality-adjusted metrics such as the Scimago Journal Rank showed no comparable increase.

Our findings have implications beyond the specific case analysed in this paper. Citation-based metrics have become deeply embedded in academic evaluation; they influence tenure decisions, journal rankings, funding allocations, and MBA program prestige. Our results illustrate how concentrated author-editor networks, operating within a formally coordinated publishing infrastructure, can systematically distort these metrics in ways that are difficult to detect from any single metric alone. The San Francisco Declaration on Research Assessment (DORA) provides relevant guidance here; our findings offer concrete empirical support, in the context of finance publishing, for its recommendation that journal-level citation metrics should not be used as proxies for individual research quality.

The paper is organized as follows: Section 2 sets out our hypotheses; Section 3 analyses the determinants of journal citation counts using DiD regressions; Section 4 analyses citation patterns within and between journal groups before and after the ecosystem's formation; Section 5 presents the machine-learning clustering analysis and the author-level citation network analysis, which together constitute the paper's central empirical contribution; and Section 6 concludes. Appendices provide additional details on data, network, and citation metrics, as well as supplementary empirical results. Table A.1 in the Appendix includes a complete list of all journal acronyms with their full names.

2 Hypotheses

Understanding how journal coordination affects citation patterns requires distinguishing between two types of mechanisms: structural mechanisms that operate at the level of the publishing system, and behavioural mechanisms that operate at the level of individual editors and authors. Previous analyses of citation patterns in finance have focused primarily on the former: the role of journal rankings, submission fees, and editorial overlap in shaping what gets published and where (Brogaard et al. 2014, Colussi 2018, Heckman & Moktan 2020). Our analysis adds a second layer: the possibility that formally coordinated publishing structures create conditions under which individual citation behaviour can diverge substantially from what quality-based citation norms would predict.

First we identify four structural features of the FJE that, individually and in combination, can be expected to increase citations among ecosystem journals, independently of any change in the quality of the papers published.

1. *Overlapping editorial roles:* When editors serve simultaneously or sequentially across multiple journals in the same network, authors submitting to those journals have incentives to cite work published in the other journals in the network. This may reflect direct editorial encouragement, but it could also be a rational response to perceived editorial preferences, or familiarity effects among editors and referees who have read and handled papers in partner journals. None of these mechanisms requires bad intent: familiarity with a body of work is a legitimate reason to cite it. But the structural condition creates a systematic tendency toward increased mutual citations that is independent of paper quality.

2. *Submission fees and transfer incentives:* Publishers charge substantial submission fees for finance journals and typically will not refund authors in the case of a desk rejection, preferring to partially compensate authors by allowing rejected papers to transfer to another of their finance journals without incurring another fee. Through direct emails to authors, finance publishers actively suggest journals for authors to consider after their paper has been rejected and this way, if authors agree to transfer, the submission stays within the same publishing house. Because non-diligent authors tend to retain citations to journals where their paper has been previously considered, papers that travel through the transfer pipeline may accumulate citations to multiple journals over successive rounds of revision. This is an unintended but predictable consequence of the design of an article transfer scheme, not a product of editorial misconduct.

3. *Publisher-supported conferences:* Many publishers have financially-supported conferences that bring together editors from different journals in the same academic area. Such events strengthen co-authorship networks, increase editors' familiarity with work published in partner journals, and reinforce the professional ties that make mutual citations more likely. This is a structural effect operating through legitimate channels.

4. *Editorial network concentration:* By promoting a coordinated network of journals, publishers signal to editors and authors that they are serving a shared professional interest by supporting those journals, including by citing them. Where a small number of editors and authors are highly central to the network, the potential for following this signal – resulting in concentrated citation activity – is correspondingly high. Critically, this mechanism need not be uniformly distributed across all journals in the same network: it is most likely to be pronounced where editorial networks are densest and where individual authors are most prolific.

These four mechanisms motivate our two hypotheses. We state them precisely to reflect what our data can and cannot establish:

Hypothesis 1. *The formal coordination of the Finance Journal Ecosystem in 2019 was associated with an increase in citations per document for ecosystem journals relative to non-ecosystem journals, driven primarily by the structural mechanisms of editorial overlap, transfer incentives, publisher-supported conference and editorial network concentration.*

Hypothesis 1 concerns the ecosystem as a whole. It predicts a positive but moderate citation effect for ecosystem membership, operating through the four structural mechanisms described above. It does not predict that all ecosystem journals will be equally affected, nor that the effect will be large enough to close the citation gap with the traditional top-tier journals. Crucially, it does not hypothesise any misconduct by any editor. The predicted effect follows from the structural design of the ecosystem alone.

Hypothesis 2. *Within the FJE, journals associated with highly-concentrated editorial and author networks exhibit citation growth substantially larger than that predicted by Hypothesis 1 alone, driven by the concentration of self-citation and mutual citation within a small author network.*

Hypothesis 2 concerns variation within the ecosystem, not the ecosystem as a whole. It predicts that the citation effect documented in Hypothesis 1 will be substantially amplified in journals where editorial and author networks are densest. Our first analysis uses PubPeer commentary on papers co-authored by editors-in-chief as a proxy for network concentration and elevated post-publication scrutiny. We are explicit that PubPeer commentary is not a finding of misconduct: it is a signal of post-publication concern that we treat as an indicator of elevated network concentration risk. Our second analysis uses a machine-learning analysis to identify the journals with unusually rapid growth in citation indices. The hypothesis does not claim that the ecosystem caused concentrated editorial behaviour; it claims that the ecosystem created structural conditions under which such concentration, where it pre-existed or developed, could produce larger citation effects.

These framings have important implications. The two hypotheses are nested: Hypothesis 2 is a conditional amplification of Hypothesis 1. A finding that supports Hypothesis 2 but shows mixed support for Hypothesis 1 would be internally consistent, not contradictory. It means that the structural mechanisms in Hypothesis 1 are not, by themselves, sufficient to produce large citation effects; what matters additionally is the concentration of individual author and editorial networks within the ecosystem.

3 Determinants of Citation Counts

This section investigates the determinants of impact factors measured as citations per document using two-year metrics obtained from Scimago Journal & Country Rank. We also use PubPeer data to identify journals associated with highly-concentrated editorial and author networks. For these data we searched the PubPeer website, using Google and Gemini, for the journal Editors-in-Chief (EiCs) of all twenty-six journals in our October 2025 dataset who had served between 2014 and 2024.[3] It is important to note that we entered the resulting names of hundreds of EiCs into the PubPeer.com search engine in October 2025. Shortly after this, Elsevier retracted several papers from its finance

[3] If there was no obvious EiC, such as in the case of JFQA, we selected all editors who were mentioned in our Google searches. Additionally, we visited each of the journal's webpages individually to verify the identities of the editors, but several journals do not report historical records of all prior EiCs over 2014-2024, and in those cases we relied on our Google searches.

journals. Although they were subsequently documented in PubPeer, these comments were not in our search results.

If an EiC had three or more papers mentioned on PubPeer.com in October 2025 then we recorded the journal as a "PubPeer" journal. We used the criteria of three or more, based on the market manipulation literature, which typically identifies cases from repeat behaviour patterns rather than one-off outliers (Financial Markets Standards Board 2022, Commodity Futures Trading Commission 2025). Our search revealed that four FJE journals had editors who had co-authored papers that were the subject of comments on PubPeer and from henceforth we refer to these as the "PubPeer" group.

We emphasise three points regarding our classification and use of external groupings. PubPeer is a post-publication peer review platform rather than an adjudicative body, so its commentary reflects community concern rather than established misconduct, and we use it solely as a proxy for network concentration risk without drawing any conclusions about the intent of any individual editor or author. The PubPeer commentary on the editors considered here predates the first public version of this paper, posted on SSRN in December 2024, and the authors had no knowledge of PubPeer in any form until February 2025, ruling out both the possibility that our analysis prompted the commentary and that PubPeer data were selected to confirm a prior hypothesis. More broadly, all journal groupings employed in our analysis are exogenous, including the FT50 and AJG4 lists, in whose construction we had no involvement. Likewise, PubPeer constitutes an exogenous source for identifying potential citation concerns because its content is peer-reviewed rather than informal rumour, is generated independently of this study, and was established prior to both our dissemination of this work.

With this classification, our analysis can distinguish between different classes of journals. Specifically, we consider five groups: (1) PubPeer – these are the ecosystem journals whose editors have authored papers that are the subject of PubPeer comments; (2) FJE, Not PubPeer – the other ecosystem journals; (3) FT50 journals; (4) AJG4 journals, excluding the FT50; and (5) the remaining journals.

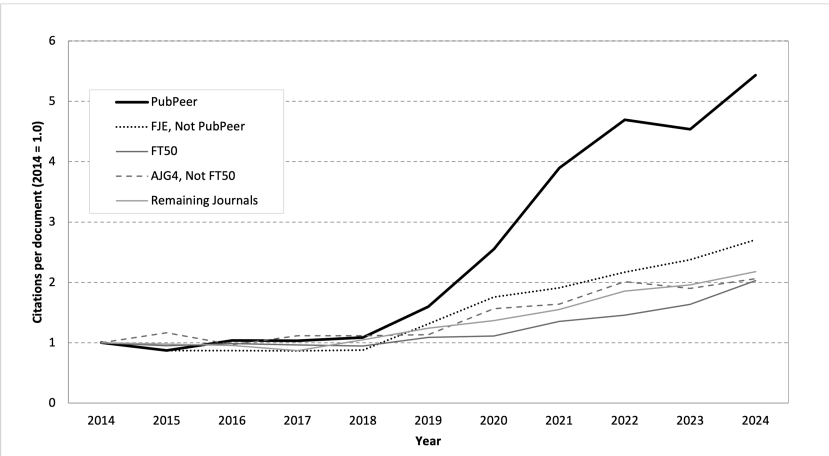


Figure 1: Evolution of Two-Year Finance Journal Impact Factors. Source: Scimago. Citations per document are normalised to one in 2014 for each journal grouping in order to show parallel trends pre-ecosystem.

Based on data from Scimago, Figure 1 presents the evolution of annual averages of two-year citations per document. We normalize the cites per doc for each group of journals to 1.0 in the year 2014 in order to show parallel trends; Table 1 provides the raw data before normalization. The

Table 1: Average Citations per Document, 2014–2024. Source: Scimago. For each journal we calculate the average number of citations per document, and then we average these over all the journals in each group.

Year	PubPeer Ecosystem	Ecosystem Not PubPeer	FT50 Finance	AJG4 Not FT50	Remaining Journals
2014	1.58	1.87	4.30	2.04	1.78
2015	1.38	1.63	4.09	2.38	1.75
2016	1.64	1.63	4.24	1.98	1.71
2017	1.63	1.62	4.14	2.29	1.56
2018	1.72	1.65	4.08	2.28	1.87
2019	2.52	2.45	4.69	2.32	2.21
2020	4.03	3.29	4.78	3.20	2.44
2021	6.15	3.57	5.83	3.35	2.77
2022	7.40	4.06	6.26	4.11	3.31
2023	7.16	4.44	7.04	3.88	3.50
2024	8.58	5.06	8.73	4.22	3.89

idea for the ecosystem was conceived in 2019 and formalised in 2020. In Figure 1 a clear change began in 2019 and became pronounced in 2020, growing over time. Within five years, the PubPeer ecosystem journal impact factors had risen to levels between two and three times higher than those of non-ecosystem journals. The non-PubPeer ecosystem journals grew faster than their non-ecosystem counterparts too, but the growth is notably less pronounced. Pre-ecosystem the two-year impact factors for all groups were broadly stable, with no group exhibiting sustained upward or downward trends comparable to the post-2019 divergence. This supports the use of difference-in-differences (DiD) regressions to further analyse the data, with the 'treatment' event occurring in 2019.

The DiD panel regression analysis presented in Table 2 examines the determinants of journal impact factors for different journal groups. The dependent variable in each model is a journal's two-year average citations per document. Explanatory variables include journal and year fixed effects, a dummy variable for 'after' the introduction of the ecosystem (which becomes one in 2020 and is zero before), interaction variables for 'treatment $\times$ after' in the standard DiD specifications, a variable for the total number of papers published in the journal per year, and variables for the numbers of papers published in the journal on popular 'trendy topics', namely ESG & CSR, Crisis, COVID-19, Crypto & DeFi, FinTech, AI, and Safe Haven. See Appendix C.2 for further details on these topics, and subsequent network analysis.

There are six different model specifications in Table 2: the first five models use different individual interaction terms and then Model 6 employs all possible interaction terms.[4] The control variables show that the size of a journal, in terms of number of papers published, is negatively associated with its impact factors,[5] but that journals that published more articles on COVID-19 and Crypto & DeFi had higher impact factors. Examining the interaction terms in each model reveals that being

[4]All the interaction terms cannot be estimated jointly, due to collinearity. Results not reported here, but available on request, include DiD regressions without the controls. These show that the significance of the interaction terms is barely affected by either number of publications or any topic-related control variable.

[5]The result could be interpreted as: holding the quality and number of submissions constant, publishing more papers may lower the average quality of the papers in the journals. We also excluded this variable from the regression, which increased the economic significance of the PubPeer ecosystem interaction variable, while the statistical significance remains at 1%. We keep the variable in the regressions to show robustness, and to show the more conservative effect.

Table 2: DiD Regression Results: Determinants of Two-Year Journal Impact Factors. *The result of the difference-in-differences model where the dependent variable is the two-year average number of citations per document. All models include journal and year fixed effect dummies to allow for journal specific constant terms which are not reported in the table. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Post 2019	2.5655***	2.5100***	2.3992***	2.3729***	2.5781***	2.0634***
	(9.31)	(8.67)	(8.44)	(8.21)	(8.95)	(6.57)
PubPeer Journal × After 2019	1.3401***					1.8134***
	(3.44)					(4.39)
FJE (Excl. PubPeer) × After 2019		0.0882				0.7223**
		(0.35)				(2.52)
FJE (All) × After 2019			0.5891**			
			(2.43)			
FT50 × After 2019				0.5945**		1.0216***
				(2.16)		(3.37)
AJG4 × After 2019					-0.2670	0.3450
					(-0.79)	(0.97)
Number of Papers	-0.0047**	-0.0057***	-0.0051**	-0.0055***	-0.0058***	-0.0037*
	(-2.24)	(-2.71)	(-2.42)	(-2.64)	(-2.73)	(-1.78)
ESG & CSR	0.0042	0.0082	0.0065	0.0086	0.0083	0.0035
	(0.70)	(1.36)	(1.09)	(1.45)	(1.38)	(0.59)
Crisis	0.0043	0.0058	0.0053	0.0026	0.0065	-0.0024
	(0.31)	(0.41)	(0.38)	(0.18)	(0.45)	(-0.17)
COVID-19	0.0180**	0.0213**	0.0197**	0.0229***	0.0206**	0.0202**
	(2.11)	(2.45)	(2.28)	(2.65)	(2.36)	(2.40)
Crypto & DeFi	0.0370**	0.0471***	0.0408***	0.0478***	0.0476***	0.0313**
	(2.38)	(3.02)	(2.61)	(3.09)	(3.05)	(2.04)
FinTech	0.0535	0.0522	0.0531	0.0471	0.0535	0.0441
	(1.55)	(1.48)	(1.52)	(1.34)	(1.51)	(1.30)
AI	0.0232	0.0222	0.0212	0.0187	0.0204	0.0176
	(0.90)	(0.84)	(0.81)	(0.71)	(0.77)	(0.69)
Safe Haven	0.0138	0.0427	0.0383	0.0493	0.0408	0.0295
	(0.25)	(0.75)	(0.69)	(0.88)	(0.72)	(0.54)
Constant	2.6437***	2.6898***	2.6455***	2.7107***	2.6857***	2.6335***
	(11.49)	(11.42)	(11.34)	(11.63)	(11.42)	(11.66)
Observations	282	282	282	282	282	282
R-squared (within)	0.7693	0.7579	0.7636	0.7625	0.7584	0.7816
R-squared (between)	0.0349	0.0221	0.0156	0.0842	0.0259	0.1218
R-squared (overall)	0.4473	0.4318	0.4242	0.4796	0.4356	0.5074
F-statistic	41.59***	39.05***	40.30***	40.04***	39.16***	38.06***

in the PubPeer group has the greatest effect on two-year average impact factors and with the highest significance, at 1%, which is robust to different specifications (i.e. Model 1 vs Model 6). Being in the FT50 group is also a robustly significant factor determining increases in two-year impact factors, and though only significant at 5% in Model 4 this is significant at 1% in Model 6. By contrast, journals in the FJE (excluding PubPeer) group, and in the AJG4 group, did not experience a significant increase in their impact factor by virtue of being in those groups.

For each journal group we use these models to estimate a percentage increase in average impact factor, relative to their average during the 2014 – 2019 period.[6] Model 6 estimates a 104% increase in impact factor in the second period (1.8134) relative to the average impact factor for these journals in the pre-ecosystem period (1.7439); but Model 1 is more conservative, estimating a 1.3401/1.7439 = 77% increase. Model 6 also shows that the non-PubPeer ecosystem journal group experienced a

[6]Pre-ecosystem, the average two-year impact factors between 2014 and 2019 were: 1.7439 for the PubPeer group; 1.8057 for FJE (excluding PubPeer) journals; 4.2574 for FT50; and 2.2155 for the AJG4 journal group.

$0.7223/1.8057 = 40\%$ increase in average two-year impact factor relative to their pre-ecosystem levels, but this effect is not robust to different model specifications: indeed, the interaction term for Model 2 is not even significant. The Wald test on Model 6 for the difference between the estimated coefficients for PubPeer Journal $\times$ After 2019 and FJE (Excl. PubPeer) $\times$ After 2019 has a p-value of 0.008. Hence, the PubPeer Journal effect (Hypothesis 2) is significantly greater than the ecosystem effect (Hypothesis 1), and this difference is significant at the 1% level. Overall, our results show mixed support for Hypothesis 1, in the sense that the statistical significance depends on the specification, but stronger support for Hypothesis 2.

The other interaction terms in Table 2 show a positive increase in the impact factors of the FT50 journals post-ecosystem, but not the AJG4 journals; in Model 6 the economic significance for FT50 journals is a $1.0216/4.2574 = 24\%$ increase (compared to the average impact factor of these journals in the pre-ecosystem period) which is statistically significant at the 1% level, and a more conservative $0.5891/4.2574 = 14\%$ increase in Model 3, which is only significant at the 5% level. A Wald test on Model 6 for the difference between the estimated coefficients for PubPeer Journal $\times$ After 2019 and FT50 $\times$ After 2019 has a p-value of 0.077. Thus, the PubPeer effect (Hypothesis 2) is also significantly greater than the impact from FT50 journal status.

To check robustness of these findings, Appendix C presents results from estimating the same models but with the dependent variables being three- or four-year average citations per document. Because these impact factors measure over longer periods the changes due to the ecosystem introduction will be muted compared with the two-year results just discussed, and this is reflected in Tables 9 and 10. However, the statistical significance is the same as in Table 2, with the only exception being that the COVID-19 variables show lower (or no) statistical significance for four-year impact factors: but of course this is because the COVID-19 pandemic started in early 2020. From the estimations of the full models in Tables 9 and 10 (Models 12 and 18) the economic significance of being in the PubPeer group is an 81% increase in three-year impact factor and a 73% increase in four-year impact factor. By contrast, the economic significance of the non-PubPeer ecosystem journals is only 37% (three-year IF) or 26% (four-year IF).

4 Journal Citation Analysis

The analysis in this section is based on data obtained from all publications of the twenty-six selected journals, which were downloaded directly from Scopus on 17 January 2025. The key details for each paper include the author names, paper title, year of publication, journal name, number of citations, abstract, keywords, references and publisher. For our analysis we retained publications from 1 January 2014 until 31 December 2024, resulting in a dataset of 65,876 publications having complete details during the eleven-year sample. From this dataset we extract two sub-samples, one consisting of papers published between 1 January 2014 and 31 December 2018 and the other of papers published between 1 January 2019 and 31 December 2024. In each sub-sample we count the number of times journal X cites journal Y and then we divide by the number of citable publications in journal X. Appendix A.2 provides further details of the methodology.

We report both absolute and percentage changes in citation counts to cover different aspects of citation dynamics. The percentage change in average citations per paper measures the growth rate of citations, normalizing for publication volumes, which allows meaningful comparisons across journals of different sizes and citation baselines (Moed 2005, Waltman 2016). This normalization identifies whether, on average, papers published in a given journal are becoming more or less cited over time, irrespective of fluctuations in output. The absolute change in total citations reflects the scale of a journal's influence, incorporating both changes in citation intensity and changes in the number of articles published (Moed 2005). It therefore captures the overall expansion or contraction of a journal's citation footprint within the finance discipline. Reporting both indicators mitigates the limitations inherent in either metric alone: relative measures capture the rate of impact growth and may overstate increases for journals with very low initial citation levels, whereas absolute changes may obscure rapid proportional growth in smaller or emerging journals.

In the following: Section 4.1 analyzes citations made within and between the twenty-six journals during each sub-sample, and focuses on the changes in citation patterns between the pre- and post-ecosystem datasets; Section 4.2 displays the graphical citation networks derived from the citation matrices presented in Section 4.1. In Appendix C.2 we present results from repeating this exercise, but this time focusing only on papers whose title, abstract and/or keywords relate to particularly trendy research topics. This is to investigate whether citations between certain journals have risen because they have been publishing more papers on similar topics.

4.1 Citation Counts

In this section we divide the same twenty-six journals into three *disjoint* groups. As before, the AJG4 group contains the eight most highly-regarded finance journals, namely JCF, JF, JFE, JFI, JFQA, JMCB, RF, RFS, according to (CABS 2021). Next we have the ten journals constituting the Elsevier ecosystem (Elsevier 2024) at the time of this analysis, namely FRL, IRFA, RIBAF, IREF, JBEF, JIFMIM, JIMF, EMR, JEB and NAJEF;[7] we label these the "FJE group". Finally we have the "ATS group" which consists of the eight other Elsevier finance journals which are not in the ecosystem but still participate in the article transfer service. Table A.1 in Appendix A lists the journal acronyms, their two-year impact factors at the time of writing and the group (and later, cluster) to which the journal is assigned. As evident from Table 1, some Elsevier journals now have impact factors as high as those of the top three journals, although they still have much lower ranks according to CABS (2021).

Table 3 summarises cross-journal citation behaviour using both raw and normalised allocations in Panel (a) and measures of structural change and concentration in Panel (b). It is derived from the data displayed in Table 1 of the Online Appendix, which shows the journal-to-journal cross-citation data before it is aggregated, in two 26×26 matrices, one for each subsample. Panel (a) reports the mean number of citations per article from a citing journal group to a cited journal group; the flow from group i to group j is the average number of references per article in group i that cite journals in group j. Below these the row-normalised citation shares are defined for each citing group i as the proportion of citations allocated to group j, so that shares sum to unity within each row. The mean citation flows capture the intensity of knowledge transmission, whereas the row-normalised shares capture how citations are allocated, abstracting from differences in overall citation scale. This distinction is economically important because it separates size effects from citation behaviour. For instance, during the period 2019 – 2024, on average: each article published in an FJE journal cited 4.62 articles from

[7]However, we exclude the Journal of Climate Finance because Scopus did not list its publications at the time, and Heliyon, since it is a general scientific journal, not specialised in finance.

Table 3: Cross-journal citation flows, allocation, and structural change. Panel (a) reports mean citation flows and the corresponding row-normalised shares. Row-normalised shares are computed for each citing group i as the proportion of citations allocated to each cited group j, so that shares sum to unity within each row and capture the allocation of citations across journal groups. Panel (b) reports Δ, defined as the change in mean citation flows between the 2019 – 2024 and 2014–2018 periods, together with concentration measures based on the Herfindahl index (HHI). For each citing group, the HHI is computed as the sum of squared row-normalised shares across cited groups, taking values between 1/3 (equal allocation across groups) and 1 (all citations concentrated in a single group). Higher values indicate greater concentration of citations within a particular destination. Highlighted values indicate statistically significant changes.

Panel (a): Mean citation flows and row-normalised shares (%)

	2014–2018			2019 – 2024		
Citing → Cited	AJG4	FJE	ATS	AJG4	FJE	ATS
Mean citation flows						
AJG4	17.14	0.16	0.86	17.84	0.22	0.72
FJE	6.49	2.18	1.90	6.78	4.62	1.77
ATS	7.82	0.56	2.33	8.24	1.24	2.18
Row-normalised shares (%)						
AJG4	94.4	0.9	4.7	94.9	1.2	3.8
FJE	61.4	20.6	18.0	51.5	35.1	13.4
ATS	72.9	5.2	21.7	70.8	10.7	18.7

Panel (b): Structural change and concentration

Pair	Δ		HHI
AJG4 → AJG4	+0.70	AJG4 (2014–2018)	0.90
AJG4 → FJE	+0.06	AJG4 (2019 – 2024)	0.91
AJG4 → ATS	-0.14		
FJE → AJG4	+0.29	FJE (2014–2018)	0.45
FJE → FJE	+2.44	FJE (2019 – 2024)	0.39
FJE → ATS	-0.13		
ATS → AJG4	+0.42	ATS (2014–2018)	0.58
ATS → FJE	+0.68	ATS (2019 – 2024)	0.54
ATS → ATS	-0.15		

FJE journals; and 35.1% of the references listed in FJE papers cite other FJE papers.

The results reveal a strong asymmetric structure. The AJG4 group receives the largest number of citations per article from all journal groups in both periods, confirming its central role as a knowledge source. However, this dominance is not reciprocated. Citations originating from AJG4 remain overwhelmingly internal, with over 94% of citations directed within the group in both periods, and negligible shares allocated to FJE and ATS journals. By contrast, both FJE and ATS allocate a substantial proportion of their citations to AJG4, with little more than 20% of citations within each group during the first period, indicating a clear directional dependence. This asymmetry is not immediately evident and only becomes clear once citation behaviour is expressed in proportional terms.

Changes over time are considered in Panel (b) of Table 3. Citation flows to AJG4 remain broadly similar in both sub-samples, but in the FJE group increasing internalisation of citation activity is evident. Mean within-group citations rise from 2.18 to 4.62, a statistically significant increase of 2.44 cites per document, highlighted in red in the table. Citations to the FJE group increase markedly during the 2019 – 2024 period. Now 35% of citations from FJE journals are to papers in FJE journals, compared to only 20% in the first sample. By contrast, the allocation of citations from AJG4 remains essentially unchanged, suggesting that the expansion of citation activity to FJE journals is not driven by increased engagement from top-tier journals. Panel (b) confirms these patterns. The largest change in citation flows is the increase in FJE self-citations, which dominates all other pairwise changes, although there is a moderate increase in the proportion of citations from ATS to FJE, from 5.2% in the first period to 10.7% of citations flowing from ATS to FJE during the second period. Concentration measures based on the Herfindahl index (HHI) reinforce this interpretation. The AJG4 group exhibits extremely high concentration in both periods (HHI $\approx$ 0.90), consistent with its near-complete internal citation structure. By contrast, the FJE group becomes less concentrated (HHI declining from 0.45 to 0.39), reflecting a reallocation of citations outside the group alongside increased within-group activity, while ATS displays moderate and slightly declining concentration.

To complement the results displayed in Table 3, we examine changes in citation activity in both relative and absolute terms. Percentage changes capture growth rates but can be misleading when initial citation levels differ substantially, whereas absolute changes capture the scale of expansion. Table 2 in the Online Appendix shows granular data, for journal-to-journal percentage and absolute changes in citations, displayed in two 26×26 matrices. From the raw data it is clear that the FJE group exhibits the strongest growth under both measures. Within-group citations increase by 111.8%, and citations from ATS to FJE increase by 120.3%. In absolute terms, citations from FJE to AJG4 reach 65,736, and within-group FJE citations reach 55,163, far exceeding the corresponding increases for other journal groups. However, any changes involving AJG4 remain modest (e.g. only 548 additional citations from AJG4 to FJE). Extremely large percentage increases for individual journals, such as over 2,500% for IREF to FRL and over 2,100% for JCM to FRL, reflect growth from low initial bases rather than large absolute citation volumes.

Taken together, these findings provide strong support for Hypothesis 1: the post-2019 increase in citation activity is driven primarily by within-group and intra-ecosystem citation flows, rather than increased citations from AJG4 journals. Moreover, the combination of rising within-group citation shares and substantial increases in internal citation intensity is consistent with the structural conditions underlying Hypothesis 2, whereby coordinated or network-driven citation behaviour may amplify citation metrics within subsets of journals.

Appendix C.2 contains a supplementary analysis of "trendy" research topics (ESG and CSR, financial crises, COVID-19, crypto and DeFi, FinTech, and AI). The results show that several FJE journals, and especially FRL and IRFA, publish a markedly greater proportion of articles on these fast-evolving themes than the leading AJG4 journals. Between 2019 and 2024, more than 40% of all papers in FRL and IRFA addressed one or more of these topics, compared with roughly 10-15% in JFE or JF. In relative terms, FRL published nearly four times as many papers on these themes, as a share of total output, as JFE or JF. This topical concentration may help to explain part of the post-2019 rise in citation counts among some FJE journals, since papers on such issues tend to attract attention quickly within the citation window. However, it is also possible that citation increases may reflect shifts in thematic focus rather than improvements in structural connectivity or editorial coordination alone. Hence, while the topic analysis complements our main findings, it also qualifies them by indicating that the post-2019 citation surge may partly arise from the nature of research being published rather than solely from the ecosystem mechanism itself.

4.2 Citation Networks

Next we obtain a deeper understanding of how citation patterns are driving the results just discussed by using the 26×26 citation matrices for each period as the basis for adjacency matrices for a graphical citation network, where each journal represents a node. Figure 2 complements Table 3 by illustrating the network structure and centrality of journals, which cannot be inferred from aggregated citation flows alone. While Table 3 characterises citation intensity and allocation, Figure 2 illustrates how these flows translate into network centrality and clustering. For each journal, Panels (a), (b) and (c) report the values of the three journal centrality metrics (eigenvector, PageRank and closeness) described in Appendix B.1. These values are calculated within the entire network of twenty-six journals. The numbers in the brackets next to the journal names are the averages of the journal ranks based on the three different metrics, and the journals are listed in rank order, so they are ordered differently within each panel. Below these centrality metrics, Panels (d), (e) and (f) of Figure 2 depict the networks generated using the journal-to-journal average citation data displayed in the Online Appendix. We use the centrality results above to determine the size of each node in the network below. Each node represents a journal, with node size proportional to its eigenvector centrality, emphasizing the quality rather than quantity of links within the citation network.[8] Edges between nodes reflect citation strength, highlighting the direction of citation flow from citing to cited journals. Let $c(x, y)$ denote the average number of citations to journal y per paper in journal x. Then an edge between two nodes is drawn only when $c(x, y) + c(y, x) > \varepsilon$. The parameter ε controls the number of edges drawn.[9] The edges are coloured the same as the nodes when citing and cited journals are from the same journal category; otherwise the edge is in gray. The thickness of the edge corresponds to the magnitude of $c(x, y) + c(y, x)$ and each edge drawn is shaded to indicate the direction of net citations. That is, the shade of the edge is the shade of the node y when $c(x, y) > c(y, x)$. The loops above each node portray the number of self-citations.

Panels (a) and (b) of Figure 2 show that the ten most influential journals are identical in both sub-samples. These are (in rank order) JF, JFE, RFS, JFQA, JBF, RF, JMCB, JFM, JFI and JCF. Note that JCF rose to rank eight in the second sub-sample due to a significant increase in closeness and FRL jumped from rank sixteen to rank eleven in the second sub-sample because it gained a higher PageRank than RF and other top-ranked journals. Recall that Table 3 reported some significant changes in citation rates during the second sub-sample, compared with the first sub-sample. Per paper citation rates increased for some journal pairs, and decreased for others, but in Panel (c) of Figure 2 we report centrality measures for *increases* in citation rates alone. The five journals that gained most centrality during the second sub-sample were FRL, JBEF, IRFA, JCF and NAJEF. Comparing Panels (d) and (e) of Figure 2, the AJG4 journal network looks very similar in both sub-samples, and there are many more citations between these journals than there are between FJE journals. Panel (f) shows there is little change in citations patterns between these journals, except for an increase in citations from JCF to JF, JMCB and RF and from JFI to JCF.

The most notable difference between the two sub-sample periods is that FRL changes from being an isolated node to a strongly connected one, receiving a large number of citations from all the FJE journals as well as JCM, QREF and PBFJ, and making a very large number of self citations. A similar but less pronounced pattern is apparent for IRFA. The AJG4 journals (in red) exhibit very little increase in connectivity over time. By contrast, the connectivity between the other Elsevier

[8] There is very little visual difference if we use the other centrality metrics (or their average) because the three are so highly correlated as noted in Appendix B.1.

[9] If we set this too low, the main structure of the network will be obscured by too many edges, but setting it too high would exclude significant connections. Figure 2 depicts the networks corresponding to $\varepsilon = 0.5$ and for the difference network plot in Panel (c) we only draw edges for which $|c(x, y) + c(y, x)| > 0.25$.

Figure 2: Journal centrality ranks and citation networks. In Panels (a) to (c) we rank the journals by the average of the three ranks (according to eigenvector, PageRank and closeness centrality) within the entire collection of twenty-six journals. Panel (d), (e) and (f) depict the networks generated using the average citation displayed in the Online Appendix. The †† and † next to journal names indicate FJE journals and other ATS journals, respectively.

(a) Journal centrality (2014 - 2018)

Journals (average ranks)	Eigenvector	PageRank	Closeness
JF (1)	0.735	0.301	2.035
JFE† (2)	0.551	0.241	1.899
RFS (3)	0.384	0.163	1.492
JFQA (4)	0.074	0.04	0.631
JBF† (5)	0.037	0.034	0.513
RF (6)	0.027	0.018	0.263
JMCB (7)	0.016	0.019	0.265
JFM† (8)	0.025	0.017	0.257
JFI† (9)	0.018	0.014	0.241
JCF† (10)	0.017	0.014	0.255
JIMF†† (11)	0.007	0.014	0.226
JEF† (12)	0.007	0.011	0.175
JEBO† (13)	0.006	0.016	0.084
JFS† (14)	0.003	0.009	0.11
PBFJ† (15)	0.001	0.008	0.093
FRL†† (16)	0.002	0.009	0.062
IRFA†† (17)	0.001	0.008	0.086
JIFMIM†† (18)	0.001	0.008	0.1
EMR†† (19)	0.001	0.008	0.072
QREF† (20)	0.001	0.007	0.059
IREF†† (20)	0	0.008	0.065
JEB†† (22)	0.001	0.007	0.06
NAJEF†† (23)	0	0.007	0.057
RIBAF†† (24)	0	0.007	0.055
JBEF†† (25)	0	0.006	0.015
JCM† (26)	0	0.006	0.005

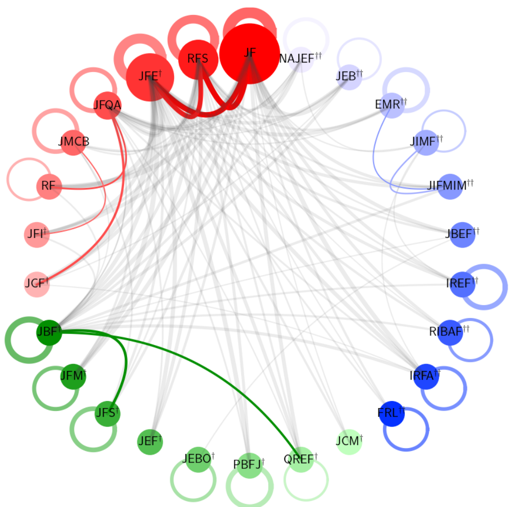
(b) Journal centrality (2019 - 2024)

Journals (average ranks)	Eigenvector	PageRank	Closeness
JF (1)	0.653	0.256	2.099
JFE† (2)	0.583	0.25	2.382
RFS (3)	0.474	0.193	1.798
JFQA (4)	0.077	0.041	0.686
JBF† (5)	0.029	0.025	0.494
RF (6)	0.031	0.019	0.344
JMCB (7)	0.02	0.019	0.281
JCF† (8)	0.013	0.014	0.4
JFI† (9)	0.016	0.013	0.232
JFM† (9)	0.019	0.014	0.216
FRL†† (11)	0.004	0.021	0.208
JIMF†† (12)	0.007	0.013	0.225
JEBO† (13)	0.007	0.015	0.122
JFS† (14)	0.005	0.012	0.192
JEF† (15)	0.006	0.009	0.159
IRFA†† (15)	0.001	0.012	0.171
PBFJ† (17)	0.001	0.008	0.129
IREF†† (18)	0.001	0.008	0.128
EMR†† (19)	0.001	0.008	0.095
JIFMIM†† (20)	0.001	0.008	0.11
NAJEF†† (21)	0	0.008	0.105
RIBAF†† (22)	0	0.008	0.122
QREF† (23)	0.001	0.007	0.086
JEB†† (24)	0.001	0.007	0.056
JBEF†† (25)	0	0.007	0.066
JCM† (26)	0	0.006	0.035

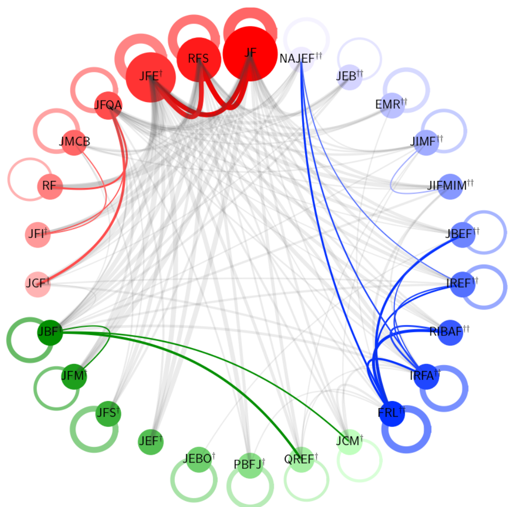
(c) Centrality of % changes in journal citations

Journals (average ranks)	Eigenvector	PageRank	Closeness
FRL†† (1)	0.746	0.192	2.597
JBEF†† (2)	0.322	0.072	1.994
IRFA†† (3)	0.283	0.076	1.787
JCF† (4)	0.219	0.061	2.006
NAJEF†† (5)	0.237	0.046	1.828
JFS† (6)	0.156	0.06	1.621
JCM† (7)	0.162	0.031	1.602
JIFMIM†† (8)	0.128	0.039	1.517
IREF†† (9)	0.131	0.039	1.426
RIBAF†† (10)	0.127	0.043	1.423
JEBO† (11)	0.094	0.037	1.468
RF (11)	0.077	0.03	1.612
QREF† (13)	0.12	0.027	1.564
JIMF†† (14)	0.057	0.029	1.437
PBFJ† (15)	0.087	0.029	1.347
JMCB (16)	0.05	0.02	1.373
JFI† (17)	0.058	0.027	1.108
JFQA (18)	0.044	0.022	1.278
EMR†† (19)	0.05	0.022	1.052
JFM† (20)	0.039	0.018	1.133
JFE† (21)	0.028	0.018	1.141
JBF† (22)	0.03	0.009	1.3
RFS (23)	0.029	0.023	0.828
JF (24)	0.022	0.011	1.112
JEF† (25)	0.018	0.01	0.967
JEB†† (26)	0.015	0.01	0.92

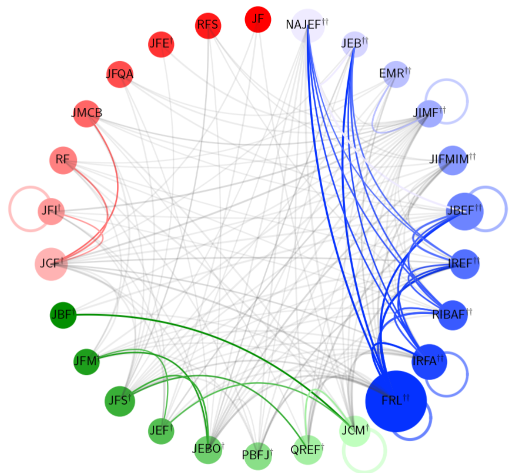
(d) Journal citation network (2014 - 2018)



(e) Journal citation network (2019 - 2024)



(f) Network of positive % changes in journal citations



journals in the ATS network (in green) has grown, even though they are much less inter-connected than the FJE journals (in blue).

This shows that Elsevier's transfer system as a whole is not the main driving factor behind the strong network effects that emerge in the second sub-sample. The emergence of previously peripheral journals as central nodes driven by mutual and self-citation within the group demonstrates the potential for coordinated structures to foster concentrated citation growth. This dynamic is consistent with the concern of Hypothesis 2 that such settings are more likely to produce exaggerated citation metrics, irrespective of individual intent. The network visualization also indicates that the strongest mutual citation activity is concentrated among a subset of FJE journals rather than being a systemic feature of the entire group. These journals are among those identified in the next section as belonging to a "quickly-evolving" (QE) cluster characterized by rapid and concurrent growth across multiple citation-based metrics, including impact factor, CiteScore, and total citation volume.

5 Clustering Analysis

The aim of this section is to establish citation patterns using purely statistical techniques, and then to examine how the patterns observed between 2019 and 2024 were influenced by the most "highly-prolific" authors, in terms of average number of papers published per year, and within this set the "most-cited" authors, and disaggregate the analysis to different 'clusters' of journals. Many journals have a few very highly-cited articles which can distort the journal's impact factor and other metrics based on citations, as discussed in Appendix B.2. Likewise, some journals publish many papers from a few authors who can, potentially, generate higher citation counts than other authors. So our focus here is on the low citation counts for papers by the most productive authors publishing in top three journals compared with the very high citation counts for papers by a few extremely productive authors in the ecosystem journals. When a small number of highly productive authors are responsible for the largest share of citations within the coordinated group, this pattern supports the concern raised in Hypothesis 2: it creates the potential for editorial networks or concentrated authorship to produce amplified impact factor effects, especially in structurally interconnected environments.

The remainder of this section is as follows. Section 5.1 uses a machine-learning algorithm to group journals into clusters according to the evolution of various journal metrics during the period 2014 to 2023. Section 5.2 explains how we identify these most prolific authors, within each of the three journal groups, and then again (for robustness checks) within the three journal clusters that were identified in the previous section. Section 5.3 counts citations to the three different author sets, ranks them in terms of total number of citations received, and describes their citation patterns. Section 5.4 discusses the centrality of these highly-prolific authors within the journal cluster's citation network (not within the entire network of twenty-six journals) and analyzes the change in journal citation patterns after removing the papers written by these authors.

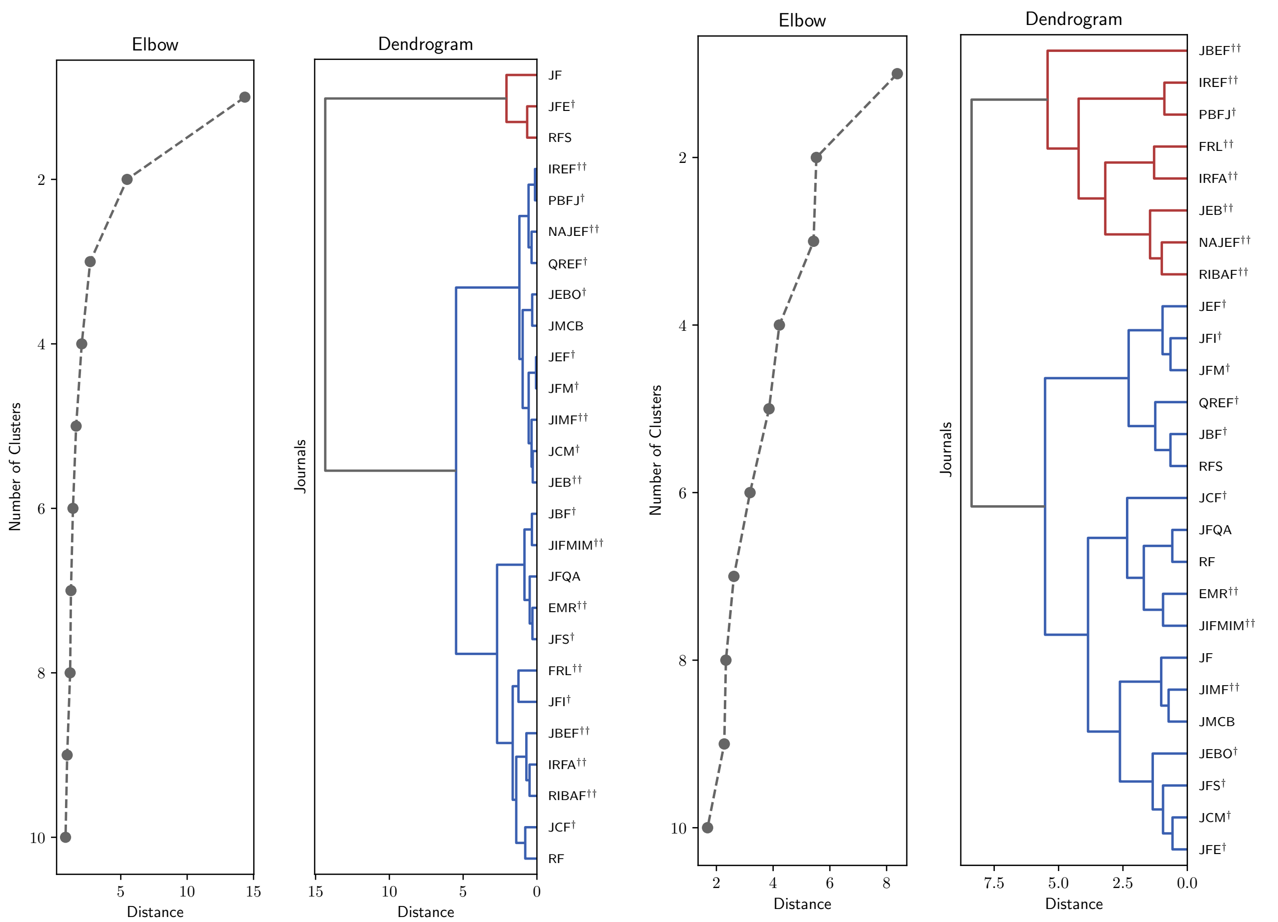
5.1 Identifying Journal Clusters

Hierarchical cluster analysis is a method used to group similar observations into clusters based on measured distances or similarities between them (Sokal & Michener 1958). It begins by treating each journal as an individual cluster, and then sequentially merging and splitting clusters based on the proximity of the data provided, creating a hierarchy that is visually represented by a *dendrogram*, which is a tree-like diagram which in our case illustrates how journals are incrementally grouped into clusters. The horizontal distance at which two clusters merge indicates their degree of similarity, so that the longer the line the more appropriate is the cluster boundary. We also compute an *elbow plot* for each dendogram, which shows the number of clusters against the total within-cluster variation. The optimal number of clusters corresponds to the point of maximum inflection (namely, the ‘elbow’) where adding more clusters yields minimal improvement in distance.[10]

Figure 3: Hierarchical Clustering Analysis of Journals. For Panel (a), the algorithm was calibrated using the time series of SJR, CiteScore, SNIP and impact factor (two-year); for Panel (b), the algorithm was calibrated using the annual percentage changes of: SJR, CiteScore, SNIP and impact score, total number of articles, total number of publications for the past three years, total number of papers for the past three years, total number of citations received, and average number of citations received per article.

(a) Clustering using impact metrics

(b) Clustering using impact metrics, no. of papers and citations



The algorithm requires a two-dimensional input with one dimension being journal and the other year,[11] and we construct journal-level time series by calculating the annual average of the four impact

[10] In these plots the axis labeled “Distance” measures the cost of merging the two clusters based on Ward’s linkage. At each step, Ward’s method chooses to merge the two clusters whose union minimizes the increase in overall sum-of-squared deviations from the cluster’s average Euclidean distance (Ward Jr 1963). The distance at which two branches merge indicates the similarity between the clusters being combined; the longer the line the more dissimilar the clusters and the less optimal would be their merging. In the elbow plots the inflection point at which the distance reduction slows considerably is normally considered the optimal number of clusters. Hierarchical clustering with Ward’s method is particularly suitable for datasets like ours because the results for relatively small samples are more robust than those produced by other clustering algorithms (Rodriguez et al. 2019, Abdalla 2021).

[11] Between 2019 and 2023 because each journal metric for the previous year is normally published in the summer, so 2023 is the latest year available at the time of writing.

metrics displayed in Figure 8 of Appendix B.2. These are SJR, Citescore, SNIP and the impact factor (IF, two-year).[12] Then Panel (a) of Figure 3 presents the dendogram and elbow plot results of this analysis, showing a very distinct cluster of the top three finance journals.[13]

To identify journals within a "quickly-evolving" (QE) cluster we use data that captures the *growth* in size and/or citations counts. To this end, we first extend our dataset from just the four impact metrics to include all the journal characteristics that we could obtain from SJCR and Scopus.[14] In particular, we obtain annual time series on three additional metrics related to the number of published articles and two concerning article citations. These are displayed in Figure 9 of Appendix B.2, where the almost exponential growth in both size and citations of some journals motivates our use of the log scale. The annual average change across all nine metrics is then used to capture evolving journal characteristics, yielding a suitable annual measure for each journal in every year. We apply the clustering algorithm to these data and the elbow and dendrogram results are presented in Panel (b) of Figure 3. A set of eight journals consistently emerges as one distinct cluster.[15] Examining Figures 8 and 9 in the Appendix confirms that these eight journals exhibit rapid growth across multiple impact metrics relative to their peers. Consequently, we classify these eight journals as the QE cluster.[16]

To summarize, two different applications of hierarchical clustering suggests the grouping of the twenty-six journals shown in Table 4 below. The QE cluster identifies journals whose publication volumes and citation trajectories have grown rapidly since around 2019, setting them apart from the remaining journal groups. Although many of these journals also belong to the FJE group the overlap is incomplete, indicating that the mechanisms behind the sharp rise in citations are not confined to formal ecosystem membership. Within the QE cluster itself, the four PubPeer ecosystem journals saw citations per document increase by 340% on average between 2019 and 2024, compared with 249% for the other four journals in the cluster – confirming that the PubPeer identifier captures the most extreme cases even within an already rapidly changing group. This pattern is consistent with

[12]The IS is the metric that is most similar to Clarivate's two-year Impact Factor (IF), being the average citations per document over a two-year period. We do not have historical data on IF, so we use IS instead. As discussed in detail in Appendix B.2, these four metrics capture slightly different aspects of journal quality. For instance, IS is less influenced by a recent expansion in the journal's size than is CiteScore.

[13]In fact, we repeated the same exercise across six sub-sample periods {2014 — 2023, 2015– 2023, ..., 2019 — 2023} deliberately repeating the algorithm to examine potential variability in clustering outcomes, which might indicate either insufficient data or a lack of clearly distinguishable clusters. The top three journal cluster is consistent, irrespective of the sample used. The repeated clustering analysis also demonstrates stable results in terms of which journals are allocated to two other clusters: namely {JFM, JIMF, JEBO, JMCB, NAJEF, IREF, PBFJ, JCM, JEF, JEB, QREF} and {FRL, JBEF, IRFA, RIBAF, JFQA, JFI, RF, JCF, JIFMIM, JBF, EMR, JFS. But the elbow plots clearly indicate that there should only be one other cluster. In other words, there is some doubt about the reliability of distinguishing between a second and a third cluster. Visual examination of the original impact metric data displayed in Figure 8 also supports the distinctiveness of the top three journal cluster; and ranking metrics for other journals exhibit much more variability over time.

[14]The correlation in Appendix C.3 indicates that some of metrics on the number of papers are very highly correlated, which could cause the analysis to over-weight the highly-correlated metrics – but given that we have only three out of nine metrics depicting one of three features (impact, number of papers and citations), such bias is limited.

[15]We repeated the same analysis using six subsamples starting from 2014 through to more recent years. The results from these alternative subsample periods appear less stable: while the same eight journals consistently form the smaller cluster, additional journals occasionally appear or drop out. Moreover, the dendrograms generated for these periods show somewhat lower stability compared to those in Figure 3 Panel (b). However, this does not undermine our main finding. If certain journals began to evolve more rapidly from around 2019 onward, we would expect structural breaks in the patterns of journal-level metrics around that time. Such breaks could naturally lead to greater instability in clustering results for those periods.

[16]From an exercise of repeated sub-sampling and dendogram generation we found that three additional journals sporadically joined this group but due to the inconsistency of their clustering we decide not to include them in the QE cluster.

broader structural features of publishing behaviour, including dense co-authorship networks, high output from productive authors, topical proximity across journals, and relatively short publication cycles that favour fast-moving research areas. The concentration of unusually strong citation activity within only part of the coordinated journal set, rather than across the entire ecosystem, suggests that these structural dynamics rather than deliberate citation practices account for the elevated impact metrics observed. In this sense, the QE cluster provides empirical support for Hypothesis 2, which proposes that structural characteristics within a coordinated group can produce disproportionate gains in measured impact for certain journals.

Table 4: Journal Clusters.

Cluster	Initial	Journal members
Highly-influential journals	HI	JF, JFE† and RFS
Quickly-evolving journals	QE	FRL††, IRFA††, RIBAF††, IREF††, JBEF††, JEB††, NAJEF††, PBFJ†
Remaining journals	RE	JFQA, JMCB, RF, JFI†, JCF†, JIFMIM††, JIMF††, EMR††, JEB††, JEBO†, JEF†, JFM†, JFS†, QREF†, JBF†

5.2 Identifying Highly-Prolific Authors

The starting point of our author-level analysis is to count the number of publications of a particular author in any of the twenty-six journals between 1 January 2019 and 31 December 2024. Figure 1 of the Online Appendix displays the number of authors that published n articles in any of the twenty-six journals between 1 January 2019 and 31 December 2024, for $n = 1, ..., 60$. We truncated the number of papers at 60 – which represents an average of ten publications per year – although some authors published considerably more than this. Using the non-truncated data, Table 5 reports summary measures of author productivity concentration across the three journal clusters during 2019 – 2024. Distinct Authors denotes the total number of unique authors assigned to each cluster; Max Papers reports the maximum number of papers published by any single author within the cluster during the sample period; No. Highly-Prolific Authors gives the number of authors whose publication counts exceed the threshold; Share of Papers by Highly-Prolific Authors reports the percentage of all papers published in the cluster that are attributable to these highly-prolific authors. The last column is the standard Gini inequality index which takes values between zero (all authors produce same number of publications) and one (only one author wrote all the papers).

Table 5: Author Productivity Concentration by Journal Cluster, 2019 – 2024
This table reports summary statistics on author publication concentration across journal clusters. Distinct Authors denotes the total number of unique authors in each cluster. The No. Highly-Prolific Authors, Proportion of Prolific Authors, and Share of Papers by Highly-Prolific Authors summarise the contribution of the most prolific authors. Higher Gini coefficients indicate greater inequality in publication output across authors within each cluster.

Cluster	Distinct Authors	Max Papers	No. Highly-Prolific Authors	Proportion of Prolific Authors	Share of Papers by Highly-Prolific Authors	Gini Coefficient
HI	3,507	15	49	1.40%	6.6%	0.322
QE	22,485	116	387	1.72%	14.5%	0.356
RE	18,083	50	137	0.75%	5.6%	0.294

Because publication concentration differs so markedly by cluster, we decided to let the publication threshold above which an author is classified as "highly-prolific" to vary according to the clusters. In QE, several authors published exceptionally large numbers of articles during the six-year sample period. By comparison, the most prolific author in the RE cluster published 50 papers, whereas the maximum within HI, comprising only the traditional top three finance journals, was just fifteen papers, published by a single author during the six years of our sample. Hence, authors in the HI cluster are classified as highly prolific if they published at least seven papers, but in the other two clusters we use eight as the threshold number of publications for an author to be considered "highly-prolific". This yields 49 highly-prolific HI authors, 387 QE authors and 137 RE authors.[17] Notably, 51 of the 60 most prolific authors overall are assigned to the QE cluster.

Given that some of these journals are extremely large, publishing well over one thousand articles annually, it is unsurprising that this cluster attracts substantially more contributing authors. For comparison, while 3,507 distinct authors published at least one paper in the HI (top-three) journals between 2019 and 2024, there were 22,485 distinct authors who published at least once in the eight QE journals over the same period. Overlap between the QE and HI author bases is minimal: only 287 authors, representing 1.3% of all QE authors, also published in at least one top-three journal during the sample period. The upper tail of the QE productivity distribution is particularly extreme: 39 authors published more than 25 papers during 2019 − 2024, including seven authors who published more than 50 papers. By contrast, no author in HI and only three authors in RE published more than 25 papers, yet a few most-prolific QE authors published more than 50 papers, showing that the concentrated authorship patterns which characterize the QE journals are unusual.

The evidence in Table 5 indicates that author productivity is substantially more concentrated in the QE cluster than in either the HI or RE clusters. The QE journals exhibit the highest maximum individual publication count, the largest number of highly prolific authors, the greatest proportion of papers attributable to such authors, and the highest Gini coefficient of publication concentration. Publication activity in the QE cluster therefore appears disproportionately driven by a relatively small subset of repeat contributors, whereas authorship is materially more diffuse in the HI and RE clusters. This concentration pattern is consistent with Hypothesis 2 and suggests that rapidly expanding journals with shorter publication pipelines may facilitate repeated publication by a concentrated core of highly active authors.

5.3 Most-Cited Author Analysis

For each of the highly-prolific authors identified above we downloaded from Scopus all the articles published between 1 January 2019 and 31 December 2024, in any of the twenty-six journals, which cited any of the author's work that had ever been published. Then for each cluster, we select two nested sub-sets of the set of highly-prolific authors according to the number of citations they received. This way, we form the top-fifty ('All 50') set, and within this the top-thirty ('All 30') author set, of the fifty (thirty) most-cited authors in each cluster. The 'All 30' set is then ranked from one to thirty,

[17] An eight-paper threshold could also have been applied to the HI cluster, but this would have produced too few authors for the subsequent analysis. There is some overlap between the QE and RE highly-prolific sets: 41 authors selected in the RE cluster were also selected in the QE cluster. To ensure mutually exclusive author groups, authors are allocated to the cluster in which they published the greatest number of papers. Because the majority of papers for each of these 41 authors were published in QE journals, they were reassigned to the QE cluster, leaving 95 distinct highly-prolific authors in the RE cluster.

with rank one being the most-cited author.[18] To preserve anonymity we label these authors *1, *2, ..., *30 where * is HI, QE or RE depending on the author's cluster.

Figures 4 through 6 together constitute this section's central empirical contribution, documenting the concentration of citation activity within a small author network in the QE cluster. For each of the thirty most-cited authors in the QE cluster, Figure 4 reports the percentage of publications between 1 January 2019 and 31 December 2024 that appeared in one of the QE journals (first line) and the percentage that appeared in one of the RE journals (second line). The two percentages almost always sum to 100% because only one paper written by this cluster appeared in one of the top three (HI) journals. For the author set {QE1, QE2, QE3, QE4} the proportion of papers published in the twenty-six journals during 2019 – 2024 that appeared in the QE journal cluster was {73.8%, 77.2%, 86.6%, 77.5%}. Some top-cited, highly-prolific QE authors published almost exclusively in the same cluster of journals. For example, 94.7% of the papers published by QE11 were in the QE cluster and only 5.3% were in the RE cluster.

Figure 4: Publications by the thirty-most cited authors in the QE cluster. We count the total papers in our twenty-six journals, published between 1 January 2019 and 31 December 2024, by the thirty-most cited authors in the QE cluster. Then we divide this total into those published in QE journals and those published in RE journals. Finally, we express the result as a percentage of the total number of publications in all twenty-six journals.

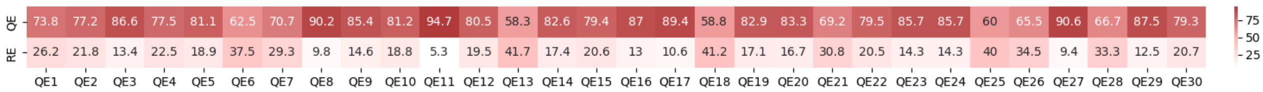


Figure 5 presents the results of self-citation and mutual citation counting between the three sets of thirty most-cited authors. The row labeled 'All 30' reports the column sum, namely the total number of cites to that author – only from themselves and the twenty-nine other authors – and the row labeled 'All 50' is the total number of cites the author receives from the set of fifty most-cited highly-prolific authors in this journal cluster.[19] The last row reports the column sum as a percentage of these citations. All citation counts are taken from the twenty-six journals between 1 January 2019 and 31 December 2024.

The thirty most-cited authors from those that published at least seven papers in the HI journal cluster exhibit the citation pattern displayed in Panel (a) of Figure 5. This shows a prominent diagonal driven by a large number of self-citations but relatively few citations to each other's work, as evident from the row labeled 'All 30'. For example, HI1 received 69 cites from the 'All 30' group of thirty authors, including 23 self-citations. These represents 59% of the total citations that this author's papers have received from all fifty most-cited authors.[20] Notably, HI16 received 54 cites from the 'All 30' set of authors, including 29 self-citations. These represent 95% of the total citations that this author's papers have received from all fifty most-cited authors. More generally, from the relatively low numbers in these bottom rows compared with the equivalent rows in Panel (b), we conclude that the very high numbers of citations per paper in the top three (HI) finance journals are certainly not being driven by circular citations between the authors that publish the most papers in the top three finance journals.

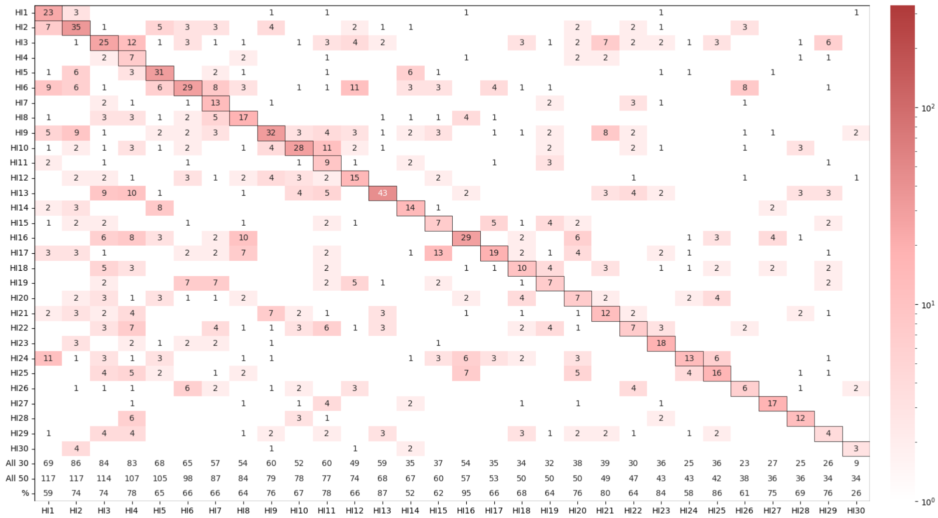
[18]It is possible to generate results for more or less than thirty authors, although selecting substantially more than thirty makes a concise representation of results rather cumbersome. Besides, using the top thirty most-cited authors already reveals some significant patterns in citations.

[19]Except for the HI journal cluster where there are only 49 most-cited authors in total.

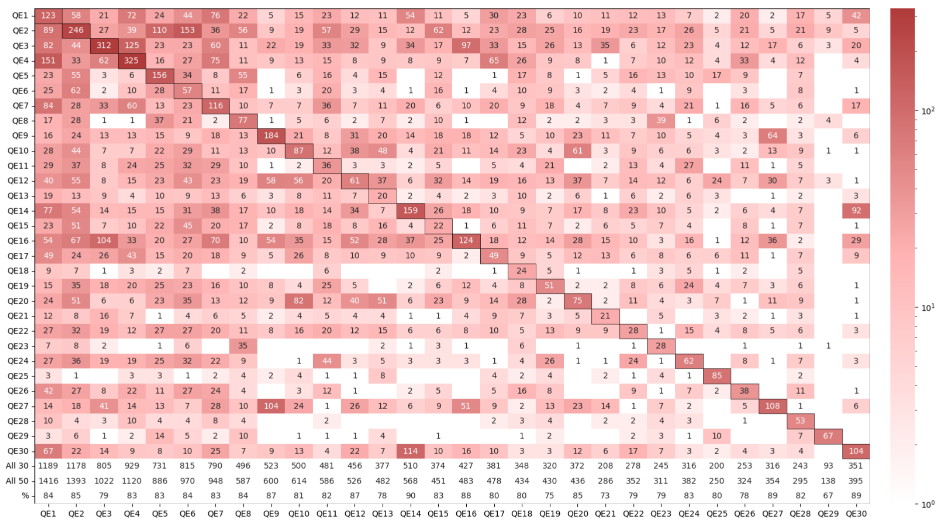
[20]Recall, these calculations are based on all the papers published in the twenty-six journals between 2019 and 2024.

Figure 5: Citation counts between the thirty most-cited authors in each journal cluster. Panels (a), (b) and (c) reports citation counts between the thirty most highly-cited authors in the HI, QE and RE cluster, respectively. The colour coding is on a log scale as shown on the right so values lower than 0.005 are omitted.

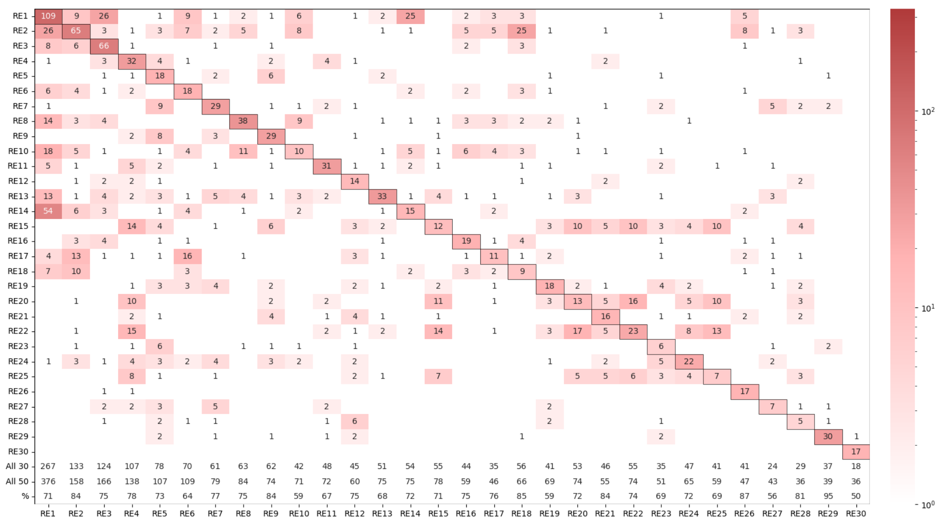
(a) HI cluster



(b) QE cluster



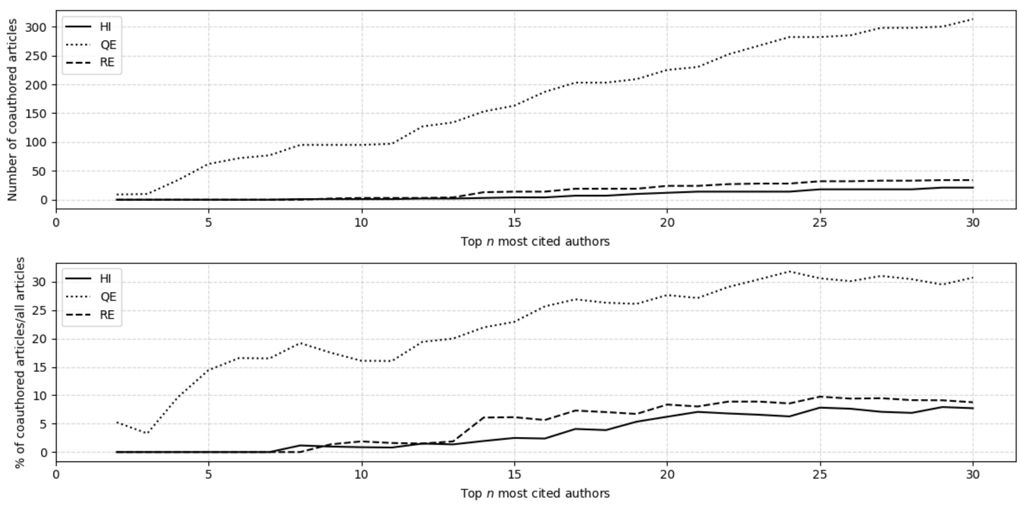
(c) RE cluster



A remarkably different picture is presented in Panel (b) of Figure 5. First, the total numbers of citations reported in rows labeled 'All 30' and 'All 50' are very much larger for the other two author clusters. For comparison, in the HI cluster the top five authors had between 105 and 117 cites from the 49 authors, and between 59% and 78% of these came from the top thirty most-cited authors. In the RE author set in Panel (c), RE1 received 376 citations from the fifty most-cited authors in this set, with 71% being made by the thirty most-cited authors and 29% being self-citations. But the citations counts for the other authors in this set are commensurate with those made within the HI author set. By contrast, within the QE cluster the five most-cited authors had between 886 and 1,416 citations from the fifty most-cited authors, and between 79% and 84% of these citations came from the thirty most-cited authors. Also, the other authors in this set received a large number of citations compared with the other two author sets. Even the least-cited QE author (QE30) received 395 citations from the top fifty authors, 89% of which came from the top thirty and 26% of which were self-citations.

For our final comparison, we focus on the author sets {*1, ..., *4}, although similar conclusions can be drawn if we examine the top n most-cited authors, for $n > 4$. Just as in Table 3, where it was clear that the top AJG4 journals very frequently cited themselves and each other, in the QE set we observe a handful of authors who very frequently cite their own and each other's work. There is no evidence of such a pattern among the highly-cited authors in other clusters. The most highly-cited QE cluster author (QE1) made 123 self-citations and received 89 citations from QE2, 82 from QE 3, 151 from QE4, and 84 from QE7. Other authors made even more self-citations. For instance, QE3 and QE4 each cited their own work more than 300 times. A total of 1,006 self-citations were made by the four most highly-cited QE authors, and they made a total of 803 citations to the others in this set. By contrast, the top four most-cited RE authors made only 272 self-citations and together made a total of 84 citations to other authors, and the top four most-cited HI authors made only 90 self-citations and a total of 53 citations to other authors.

Figure 6: Co-authored papers by the thirty most-cited authors in each journal cluster. A co-authored paper is defined as one whose author list contains two or more authors from the top n authors in that cluster. The upper chart reports the number of co-authored papers by the top n authors as n increases from two to thirty. The lower chart reports the number of co-authored papers by the top n authors as a percentage of the total number of papers published by these n authors between 1 January 2019 and 31 December 2021.



One explanation for the high citation counts between the QE authors is the extent of their research collaboration. Figure 6 displays the number of co-authored papers by the top n cited authors, where

n runs from two to thirty along the horizontal axis. The top-thirty authors in the QE cluster together co-authored 313 papers, with the top-eight cited authors generating over a hundred co-authored papers between them. In the other groups there were relatively few co-authored works: 21 papers were co-authored between the top-thirty authors in the HI cluster and 34 papers were co-authored in the RE author cluster. As a percentage of the total number of papers published in any of the twenty-six journals by the authors in each cluster, the lower chart in Figure 6 shows that 20% of papers written by the top-eight highly-cited authors in the QE cluster were co-authored by at least two people both in the top-thirty authors of the QE cluster. The corresponding figures for the other two author clusters were less than 2%.

5.4 Author Network Analysis

The importance of an author within a network is not necessarily related to the number of citations received, especially if the author makes a habit of self-citations. Next we show that, according to different measures of centrality, many of the highly-cited authors examined in Section 5.3 actually have very little importance to a citation network. In fact, the most prolific authors in the QE journals are not necessarily central according to alternative impact measures.

To show this, we follow the same methodology as Section 4.2 but this time we rank the importance of an author using betweenness, in addition to ranking authors according to three centrality metrics used for the journal clustering study. Because the journals operate in distinct clusters, several journals had zero betweenness when the network of twenty-six journals is considered as a whole, as in Section 4.2. However, in Figure 6 we examine the three 'All 30' author sets as individual networks, so it make sense to include betweenness within each individual network (see Appendix B.1). That is, we take three different networks of the thirty most cited authors, in each journal cluster, rank them using first eigenvector centrality, then PageRank, then closeness and then betweenness, and we measure each authors relative importance to the network using the arithmetic average of these four ranks. Figure 6 reports the raw measures for each metric and lists the authors in order of their relative importance, as given by the average of the centrality ranks. In each case we find a few authors having fewer citations than the top cited authors but who are nevertheless very important to the network.

Table 6 shows that the QE network has very much greater closeness and smaller betweenness than the other two author networks, but the eigenvector and PageRank centrality measures are similar. The closeness measures depend on the edge weights, which in turn depend on the number of citations from one author to another. The very high closeness in the QE author set is because these authors cite each other so frequently. The lower betweenness in the QE author network indicates that it is more decentralized, in that no single author dominates the flow of citations, whereas the other two networks have a small set of authors who play pivotal roles in linking different parts of the network.

A further insight emerges when comparing changes in total citation counts with changes in network-weighted prestige measures such as eigenvector centrality. Several QE journals exhibit large increases in citation volume without a corresponding rise in eigenvector centrality, indicating that their additional citations originate mainly from lower-impact journals, or closely-related journals, rather than from more influential journals within the QE author network. This divergence supports the interpretation that recent citation growth reflects expansion in publication volume and intra-group connectivity rather than a broadening of network-weighted academic influence.

Table 6: Network centrality of thirty most-cited authors Within each journal cluster we list the authors {*1, ..., *30} in order of the average of their ranks according to each of the four centrality metrics.

(a) HI cluster

group_order	Eigenvector	PageRank	Closeness	Betweenness
HI2	0.493	0.046	2.203	0.043
HI4	0.253	0.053	2.358	0.033
HI3	0.284	0.056	1.735	0.083
HI11	0.179	0.052	1.971	0.034
HI1	0.295	0.04	2.189	0.024
HI6	0.238	0.043	1.96	0.032
HI5	0.309	0.038	2.014	0.025
HI9	0.246	0.037	1.931	0.066
HI7	0.188	0.042	2.153	0.02
HI8	0.127	0.041	1.602	0.029
HI12	0.178	0.033	1.951	0.025
HI10	0.156	0.031	1.466	0.032
HI29	0.078	0.034	1.415	0.026
HI14	0.108	0.033	1.612	0.008
HI20	0.083	0.032	1.603	0.019
HI21	0.139	0.023	1.928	0.012
HI15	0.074	0.032	1.468	0.021
HI23	0.089	0.04	1.269	0.017
HI13	0.253	0.025	1.299	0.013
HI18	0.065	0.031	1.353	0.027
HI22	0.104	0.027	1.55	0.013
HI16	0.102	0.029	1.32	0.021
HI19	0.072	0.032	1.589	0.008
HI26	0.092	0.022	1.674	0.008
HI17	0.059	0.022	1.456	0.01
HI28	0.055	0.026	1.126	0.003
HI24	0.032	0.022	1.015	0.017
HI27	0.036	0.02	1.194	0.009
HI25	0.053	0.018	1.329	0.003
HI30	0.023	0.018	1.06	0.001

(b) QE cluster

group_order	Eigenvector	PageRank	Closeness	Betweenness
QE1	0.426	0.038	22.54	0.01
QE2	0.396	0.038	21.989	0.01
QE6	0.272	0.038	19.784	0.005
QE8	0.144	0.038	16.942	0.008
QE4	0.416	0.036	18.696	0.005
QE3	0.271	0.037	15.816	0.009
QE5	0.237	0.038	19.357	0.003
QE7	0.269	0.034	18.527	0.004
QE11	0.15	0.036	16.737	0.003
QE15	0.112	0.035	16.462	0.004
QE12	0.107	0.032	14.584	0.007
QE17	0.135	0.034	14.703	0.004
QE18	0.105	0.038	14.027	0.002
QE10	0.109	0.032	12.535	0.007
QE23	0.066	0.038	11.95	0.006
QE14	0.141	0.031	16.511	0.003
QE19	0.083	0.036	12.581	0.005
QE22	0.072	0.037	11.685	0.006
QE24	0.087	0.035	12.686	0.004
QE26	0.086	0.035	12.574	0.003
QE13	0.083	0.032	12.685	0.004
QE16	0.105	0.029	13.943	0.002
QE28	0.066	0.038	11.43	0.001
QE30	0.096	0.027	15.138	0.001
QE9	0.092	0.028	12.862	0.001
QE20	0.078	0.032	11.335	0.003
QE21	0.059	0.032	11.792	0.003
QE25	0.031	0.029	10.631	0.001
QE27	0.052	0.026	11.116	0
QE29	0.013	0.014	6.515	0.001

(c) RE cluster

group_order	Eigenvector	PageRank	Closeness	Betweenness
RE3	0.364	0.059	2.301	0.032
RE2	0.195	0.041	1.923	0.052
RE1	0.874	0.038	2.133	0.034
RE5	0.02	0.061	2.272	0.035
RE4	0.01	0.067	1.764	0.046
RE9	0.015	0.05	1.829	0.023
RE7	0.018	0.045	1.558	0.037
RE18	0.075	0.035	1.825	0.015
RE13	0.023	0.031	1.334	0.055
RE6	0.096	0.033	1.794	0.013
RE26	0.06	0.04	1.748	0.001
RE12	0.009	0.045	1.491	0.018
RE14	0.192	0.021	1.963	0.006
RE10	0.062	0.021	1.634	0.022
RE23	0.009	0.038	1.252	0.028
RE19	0.005	0.032	1.181	0.045
RE28	0.006	0.034	1.597	0.021
RE17	0.037	0.024	1.392	0.022
RE11	0.001	0.029	1.286	0.044
RE16	0.039	0.027	1.421	0.007
RE8	0.039	0.018	1.482	0.018
RE21	0.003	0.03	1.195	0.025
RE15	0.002	0.024	1.146	0.036
RE27	0.004	0.028	1.194	0.019
RE29	0.001	0.025	0.946	0.039
RE20	0.002	0.02	1.06	0.029
RE30	0	0.049	0.504	0
RE24	0.001	0.015	0.992	0.012
RE25	0	0.01	1.039	0.005
RE22	0	0.009	1.04	0.002

The patterns identified in Figures 5 and 6 and discussed in Section 5.3 raise the question of whether the very large number of self-citations, co-authored papers, and citations between a small set of authors has influenced the journal citation patterns that we documented in Section 4. If such a relationship exists, it justifies a deeper exploration into the causal connections between the behaviour of prominent authors and notable shifts in journal citations. To this end, we shall now examine how self-citations and co-citations among the thirty most-cited authors have influenced citation patterns between the twenty-six journals.

We now examine whether citation growth is concentrated within a relatively small number of prolific author networks. First we recompute the citation matrices after removing all papers either authored by, or citing, the thirty most-cited authors in each of the HI, QE and RE clusters respectively. For each removal exercise, we compare the resulting citation matrix with the original full-sample citation matrix and record both proportional and absolute declines in citation activity. The results, in percentage and absolute terms, are displayed in Tables 3 and 4 of the Online Appendix. In each Table there are three 26×26 matrices, one for each cluster. Using these data, we calculate the mean percentage citation reduction as the average proportional decline across all journal-pair citation observations following removal of the relevant author set, while total citation loss reports the aggregate absolute reduction in citation counts across the full citation matrix. To distinguish between internal and external citation effects, we separately compute the mean within-cluster percentage reduction, defined as the average proportional decline in citations where both the citing and cited journals belong to the same cluster as the removed author group, and the mean cross-cluster percentage reduction, defined as the corresponding average decline for citation pairs involving journals outside that cluster. The within/cross ratio is then calculated as the ratio of within-cluster to cross-cluster citation reductions and measures the degree to which citation dependence is concentrated internally within the corresponding journal ecosystem. A higher within/cross ratio indicates that citation losses are disproportionately concentrated within the same cluster, implying that citation growth depends primarily on internally-reinforcing author networks rather than external recognition, which directly tests whether the amplification mechanism in Hypothesis 2 operates through endogenous citation concentration.

Table 7: Citation Dependence on Top-Cited Authors by Cluster, 2019 – 2024
This table summarises the effect on citation activity of removing all papers authored by or citing the thirty most-cited authors in each journal cluster. Mean Percentage Citation Reduction reports the average proportional decline in citation counts across all journal-pair observations following removal. Total Citation Loss reports the aggregate absolute reduction in citation counts. Mean Within-Cluster Percentage Reduction is the average percentage reduction in citations where both the citing and cited journals belong to the same cluster as the removed author group. Mean Cross-Cluster Percentage Reduction is the corresponding average reduction where only one journal belongs to that cluster. The Within/Cross Ratio measures the relative concentration of citation dependence within the cluster.

Removed	Mean % Citation Reduction	Total Citation Loss	Mean Within-Cluster % Reduction	Mean Cross-Cluster % Reduction	Within/ Cross Ratio
HI Top 30	18.0%	251,787	53.9%	29.4%	1.83
QE Top 30	16.5%	101,387	44.8%	20.1%	2.23
RE Top 30	16.9%	161,038	24.1%	15.8%	1.53

The results reported in Table 7 reveal important differences across author groups. Removal of the top-cited HI authors generates the largest aggregate citation loss overall, reducing citation counts by 251,787 and lowering average citation activity by 18.0%, indicating that the most-cited HI authors exert the greatest influence in absolute citation volume. However, the most striking pattern concerns the QE cluster. Although removal of the top-cited QE authors produces a slightly smaller overall citation reduction than for HI authors, the QE group exhibits by far the highest within/cross ratio, at 2.23, compared with 1.83 for HI and 1.53 for RE. This indicates that the citation influence of highly cited QE authors is disproportionately concentrated within the QE journal ecosystem itself, with within-cluster citations falling more than twice as much as cross-cluster citations when those authors are removed. The largest proportional declines following removal of QE authors are also observed among QE journals themselves, confirming that their citation activity is sustained primarily by dense internal citation networks rather than broad influence across the wider finance journal landscape. Taken together, these findings support Hypothesis 2 by showing that the rapid citation growth observed in the QE cluster is closely associated with a relatively concentrated group of prolific and highly cited authors whose citation behaviour is strongly intra-group and mutually reinforcing.

6 Conclusions

This paper investigates what happened to citation patterns in finance journals following the formal establishment of Elsevier's Finance Journal Ecosystem (FJE) in 2019. The answer is not simple, and we have taken great care not to overstate it. The ecosystem, as a structural intervention, had a modest and not always statistically robust effect on citations across its member journals – approximately 40% for non-PubPeer ecosystem journals, controlling for other factors – which is greater than the increases in top-tier (FT50 and other AJG4) journal groups, but not robust across different model specifications. However, more robust evidence points consistently to a small, tightly-networked group of authors and editors being associated with the most extreme citation inflation, rather than ecosystem membership per se. We make no claim about the intent of any individual editor or author; our analysis is of structural patterns in citation data, not of motivation. The strong association between concentrated author networks and citation growth does not establish causality at the level of individual behaviour.

What is not modest, and is not mixed, is what happened in a specific subset of those journals. Four ecosystem journals that have had an editor-in-chief with three or more co-authored papers commented upon by PubPeer, show a 104% increase in citations per document: an effective doubling relative to pre-ecosystem levels. This finding is statistically robust across all specifications and is not explained by topic concentration, publication volume, or general time trends. The increase in average citations to these four journals is significantly greater than the corresponding increase to the other journal groups. This pattern – modest ecosystem effect, large network concentration effect – is precisely what the nested structure of our two hypotheses predicts. Ecosystem membership alone is not sufficient to produce large citation inflation; what matters additionally is the density of the author and editorial network within the ecosystem.

The machine-learning analysis tells us why. The four PubPeer ecosystem journals belong to a "quickly-evolving" (QE) cluster of eight journals distinguished not just by citation growth but by a constellation of correlated features: near-exponential growth in publication volume, submission-to-acceptance times averaging 205 days compared with 311 days in the remaining clusters, and – most importantly – extraordinary concentration of citation activity within a small network of highly-prolific authors. The top four most-cited authors by journals in the QE cluster made 1,006 self-citations among themselves and 803 citations to each other between 2019 and 2024, compared with 90 self-citations and 53 mutual citations among the four most-cited authors by the traditional top three journals over the same period. And, when papers by the thirty most-cited QE authors are removed from the citation counts, citations to QE journals fall dramatically; the same exercise has a much more modest effect on other journal groups.

We draw three conclusions from this evidence. First, the ecosystem is a structural amplifier. The formal coordination of the FJE created structural conditions – overlapping editorial roles, a shared transfer pipeline, publisher-supported conferences – that reduced the expected cost and increased the expected reward of concentrated citation networks. We do not claim the ecosystem caused individual actors to behave as they did. The evidence is consistent with the interpretation that certain editorial and author networks pre-existed the ecosystem and exploited its infrastructure, rather than being created by it. But the ecosystem amplified the effects of those networks, and the amplification was not uniform: journals without dense author networks did not see the same citation effects, even within the ecosystem. The policy implication is that formal journal coordination systems need explicit governance mechanisms to monitor and limit citation concentration, particularly where submission fee structures create transfer incentives that can accumulate citations across rejection rounds.

Second, our data show there are limits to citation-based metrics. Our results illustrate how impact factors can be systematically inflated by a small, tightly-networked group of authors operating within a formally coordinated publishing structure, without any change to the underlying quality of the work being published. The QE cluster journals that saw the largest citation increases also saw the largest reductions in submission-to-acceptance times and the largest expansions in publication volume, neither of which is consistent with a quality-driven explanation for their rising impact factors. Quality-adjusted metrics, notably the SJR, which weights citations by the prestige of the citing journal, showed no comparable increase in metrics for the QE journals. This divergence between raw citation counts and quality-adjusted metrics is precisely the kind of signal that should be monitored by evaluation bodies including university promotion committees, national research assessment exercises, and journal ranking bodies such as the Chartered Association of Business Schools. Our findings offer concrete empirical support, in the context of finance publishing, for the DORA recommendation that journal-level citation metrics should not be used as proxies for individual research quality.

Third, the lessons here highlight issues with the broader sociology of finance publishing. The ecosystem emerged, at least in part, as a legitimate response to the well-documented concentration of reward in a narrow set of top-tier journals. The top three journals have their own circular citation patterns, their own editorial networks, and their own structural advantages. These are advantages that this paper documents, but that have not materially changed during our sample period. The difference is that the top three journals' citation patterns have been stable, while the quickly-evolving cluster's patterns changed dramatically and rapidly after 2019. Stability is not the same as fairness, and we do not wish to imply that the existing hierarchy is beyond critique. But the evidence presented here suggests that the ecosystem, as currently governed, has not succeeded in creating a more meritocratic tier of journals: the citation gains have been concentrated in a small network of authors and editors rather than distributed broadly across the ecosystem's membership.

Future research could usefully examine several questions this paper leaves open. First, are similar patterns observable in other disciplines where publishers operate large journal coordination systems? The structural mechanisms we identify are not specific to finance, and the governance implications may be broader. Second, what role do submission and handling fees play in creating transfer-based citation incentives? A careful analysis of the relationship between fee structures and citation accumulation across the transfer pipeline would add precision to the mechanism described in Hypothesis 1.

This paper combines difference-in-differences regressions with machine-learning clustering and citation network analysis. Each method has limitations: the regression analysis cannot fully rule out confounding from unobserved journal-level trends; the clustering results are sensitive to the choice of metrics and sample period; and the author network analysis, while striking, is descriptive rather than causal. We have tried to be transparent about these limitations throughout. What gives us confidence in the overall picture is the convergence of evidence across methods: the regression results, the clustering, the author citation counts, the co-authorship patterns, and the divergence between raw and quality-adjusted metrics all point in the same direction. That convergence, across methods that make different identifying assumptions, is the strongest argument for taking the paper's central finding seriously.

Declaration of Competing Interests

Carol Alexander declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Douglas Cumming has served in editorial roles for several academic journals, including as Editor-in-Chief of Finance Research Letters (2015–2017), Journal of Corporate Finance (2018–2020), British Journal of Management (2020–2022), and Journal of Alternative Investments (2025–present), for which he receives a stipend. Douglas Cumming is also the founding Editor-in-Chief of Review of

Corporate Finance (2021–present), with NOW Publishers. In connection with that role, he previously received a 20% ownership interest and royalty rights, but no stipend. NOW Publishers was acquired by Emerald Publishers in May 2025 and Douglas' 20% ownership interest was valued at $0. He has received minimal royalties from Review of Corporate Finance.

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Data Availability

The data that support the findings of this study are derived from Scopus and are subject to licensing restrictions, so are not publicly available. Further details on data construction are available from the corresponding author upon reasonable request.

Author Contributions

Both Carol Alexander and Douglas Cumming: Conceptualisation, Methodology, Formal analysis, Writing – original draft, reviewing and editing.

References

Abdalla, H. I. (2021), A brief comparison of k-means and agglomerative hierarchical clustering algorithms on small datasets, *in* 'International Conference on Wireless Communications, Networking and Applications', Springer, pp. 623–632.

Adams, R. & Xu, J. (2023), 'The inequality of finance', *Review of Corporate Finance* **3**(1), 35–68.

Bajo, E., Barbi, M. & Hillier, D. (2020), 'Where should I publish to get promoted? A finance journal ranking based on business school promotions', *Journal of Banking and Finance* **114**, 105780.

Berninger, M., Kiesel, F. & Schnitzler, J. (2024), 'Commercial data in financial research', *Review of Corporate Finance* **4**(3), 293–335.

Brogaard, J., Engelberg, J. & Parsons, C. A. (2014), 'Networks and productivity: Causal evidence from editor rotations', *Journal of Financial Economics* **111**(1), 251–270.

CABS (2021), 'Academic Journal Guide 2021 by Chartered Association of Business Schools', via https://charteredabs.org/academic-journal-guide. [Online; accessed 16 March, 2026].

Colussi, T. (2018), 'Social ties in academia: A friend is a treasure', *Review of Economics and Statistics* **100**(1), 45–50.

Commodity Futures Trading Commission (2025), 'CFTC enhances market oversight with advanced surveillance technology platform', https://www.cftc.gov/PressRoom/PressReleases/9110-25.

Currie, R. R. & Pandher, G. S. (2011), 'Finance journal rankings and tiers: An active scholar assessment methodology', *Journal of Banking and Finance* **35**(1), 7–20.

Currie, R. R. & Pandher, G. S. (2020), 'Finance journal rankings: Active scholar assessment revisited', *Journal of Banking and Finance* **111**, 105717.

Docampo, D. & Safón, V. (2022), 'Finance journal rankings: A paper affiliation methodology', *Managerial Finance* **48**(5), 760 – 783.

Eleftheriou, K. & Polemis, M. (2020), 'One list to fit them all: What do we learn from journal ranking?', *Finance Research Letters* **35**.

Elsevier (2024), 'Finance journals ecosystem', via https://www.elsevier.com/en-gb/subject/finance/journals-ecosystem. [Online; accessed 16 March, 2026].

Financial Markets Standards Board (2022), 'Behaviour-pattern conduct analysis: Market misconduct through the ages', https://fmsb.com/wp-content/uploads/2022/05/22020525_BCA_Report_2022_FINAL.pdf.

Guo, H., Wang, B., Qiao, X. & Liu, R. (2016), 'A review of studies on citations and journal ranking in finance', *Managerial Finance* **42**(4), 303 – 311.

Harzing, A. & Wal, R. v. d. (2009), 'A google scholar *h*-index for journals: An alternative metric to measure journal impact in economics and business?', *Journal of the American Society for Information Science and Technology* **60**(1), 41–46.

Heckman, J. J. & Moktan, S. (2020), 'Publishing and promotion in economics: The tyranny of the top five', *Journal of Economic Literature* **58**(2), 419–470.

Holden, C. W. (2017), 'Do acceptance and publication times differ across finance journals?', *Review of Corporate Finance Studies* **6**(1), 102–126.

Laband, D. N. & Piette, M. J. (1994), 'Favoritism versus search for good papers: Empirical evidence regarding the behavior of journal editors', *Journal of Political Economy* **102**(1), 194–203.

Mingers, J., Macri, F. & Petrovici, D. (2012), 'Using the *h*-index to measure the quality of journals in the field of business and management', *Information Processing and Management* **48**(2), 234–241.

Moed, H. F. (2005), *Citation Analysis in Research Evaluation*, Springer, Dordrecht.

Rodriguez, M. Z., Comin, C. H., Casanova, D., Bruno, O. M., Amancio, D. R., Costa, L. d. F. & Rodrigues, F. A. (2019), 'Clustering algorithms: A comparative approach', *Public Library of Science San Francisco* **14**(1), e0210236.

Sokal, R. & Michener, C. (1958), 'A statistical method for evaluating systematic relationships', *University of Kansas Science Bulletin* **38**, 1049–1438.

Waltman, L. (2016), 'A review of the literature on citation impact indicators', *Journal of Informetrics* **10**(2), 365–391.

Ward Jr, J. H. (1963), 'Hierarchical grouping to optimize an objective function', *Journal of the American Statistical Association* **58**(301), 236–244.

Appendix

A Data

A.1 Journal Details

Journal	Acronyms	Two-Year IF	Group	Cluster	Submission to Acceptance
Journal of Financial Economics	JFE	10.226	AJG	HI	497
Finance Research Letters	FRL	8.454	FJE	QE	101
International Review of Financial Analysis	IRFA	7.764	FJE	QE	188
Review of Financial Studies	RFS	7.548	AJG	HI	N/A
Research in International Business and Finance	RIBAF	7.136	FJE	QE	261
Journal of Corporate Finance	JCF	6.909	AJG	RE	350
Journal of Finance	JF	6.727	AJG	HI	N/A
Review of Finance	RF	6.183	AJG	RE	N/A
Journal of Financial Stability	JFS	6.037	ATS	RE	282
Emerging Markets Review	EMR	5.896	FJE	RE	269
International Review of Economics and Finance	IREF	5.268	FJE	QE	205
Journal of International Financial Markets, Institutions and Money	JIFMIM	5.259	FJE	RE	244
Pacific-Basin Finance Journal	PBFJ	4.921	ATS	QE	186
Journal of Behavioural and Experimental Finance	JBEF	4.507	FJE	QE	226
Journal of Financial and Quantitative Analysis	JFQA	4.495	AJG	RE	N/A
North American Journal of Economics and Finance	NAJEF	4.331	FJE	QE	217
Journal of Commodity Markets	JCM	3.761	ATS	RE	247
Journal of Banking and Finance	JBF	3.741	ATS	RE	508
Journal of Economics and Business	JEB	3.716	FJE	QE	257
Journal of Financial Intermediation	JFI	3.205	AJG	RE	269
Journal of International Money and Finance	JIMF	2.943	FJE	RE	258
Quarterly Review of Economics and Finance	QREF	2.925	ATS	RE	288
Journal of Economic behaviour and Organization	JEBO	2.394	ATS	RE	285
Journal of Financial Markets	JFM	2.117	ATS	RE	326
Journal of Empirical Finance	JEF	2.067	ATS	RE	411
Journal of Money, Credit and Banking	JMCB	1.532	AJG	RE	N/A

The table above presents the twenty-six journals' names, acronyms, two-year impact factors (sorted from the highest to the lowest), and the groups (clusters) they belong (are assigned) to. We have also retrieved from their homepages (as hyperlinks labelled with the journal name in the table) data on the time from submission to acceptance of those journals, measured in days.[21]

A.2 Calculation of Citation Counts

Figure 7 provides a snapshot of our search results. For example, we found that the paper with the EID 2-s2.0-85145231409 cited 9 publications from JF, 7 papers from JFE, 1 paper from JFQA, etc.

Figure 7: Counts of citations from each of all twenty-six journals for each paper in our dataset.

EID	JF	JFE	RFS	JFQA	RF	JCF	JFI	JMCB	JIMF	FRL	JBEF	RIBF	IRFA	EMR	IREF	JEB	JIFMIM
2-s2.0-85145231409	9	7	1	0	0	1	0	0	0	0	0	1	1	1	3	0	0
2-s2.0-85143212424	1	0	1	0	0	0	0	0	4	0	0	0	0	0	1	1	0
2-s2.0-85144256612	12	14	1	5	1	13	2	0	0	0	0	0	0	0	0	0	0
2-s2.0-85184683986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2-s2.0-85146131214	1	1	0	1	0	0	1	2	0	0	0	0	0	0	0	0	0

Now we explain how we transform these data into journal citation counts, using a toy example. Consider three journals, A, B and C. Journal A published papers a and d, journal B published papers

[21] We also examined data from Holden (2017), though these appear to be from 2015 or earlier and show some inconsistencies when compared with more recent figures reported on the official websites of several journals.

b and c and journal C published paper e. The citing relationships between these papers are listed in Table 8a. From the references in Table 8a we construct citation counts at the journal level as listed in Table 8b. This way, we obtain the average journal citation count presented in Table 8c.

Table 8: A pseudo example of journal reference counts.

(a) A pseudo example on citation relationships between five papers from three journals. Journal A published papers a and d, journal B published papers b and c, and journal C published paper e. The third column lists which of these papers were cited by the paper in column two.

Journal	Paper	Cites to
A	a	b,c,d,e
B	b	c,d,e
B	c	d,e
A	d	e
C	e	

(b) Citation counts at the journal level of the five publications.

Paper	Journal	Cited by		
		A	B	C
a	A	1	2	1
b	B	1	1	1
c	B	1	0	1
d	A	0	0	1
e	C	0	0	0

(c) Journal citation counts.

Journal	Paper count	Total Citation			Average Citation		
		A	B	C	A	B	C
A	2	1	2	0	0.5	1	0
B	2	2	1	0	1	0.5	0
C	1	2	2	0	2	2	0

B Metrics

B.1 Network Centrality Metrics

Here we describe the centrality metrics we use for determining the size of each node and for ranking the twenty-six journals in order of importance. Eigenvector centrality computes the centrality for a node by adding the centrality of its predecessors. More specifically, the eigenvector centrality for a node u is the u-th element of a left eigenvector associated with the largest eigenvalue of the adjacency matrix $\mathbf{A}$ of the network. Such an eigenvector $\mathbf{w}$ is defined (up to a multiplicative constant) by the equation $\lambda\mathbf{w}' = \mathbf{w}'\mathbf{A}$. By definition, this eigenvector relationship is equivalent to $\lambda C(u) = \sum_{s\to u} C(u_s)$. That is, one obtains the eigenvector centrality of u by adding the eigenvector centralities of the predecessors of u. PageRank was the foundational algorithm for ranking web pages in Google's search engine. It measures a node's importance by iteratively distributing a fixed value of importance across a network, weighting contributions by the rank of linking nodes and accounting for random jumps through a damping factor. And the closeness centrality of a node is the reciprocal of the average shortest-path distance to that node, over all reachable nodes. We use the inverse of the weights in the adjacency matrix as distances between nodes.

These three centrality measures are often highly correlated. For example, in our network of twenty-six journals the (Pearson) correlation of eigenvector with either PageRank or closeness centrality exceeds 0.98.[22] Nevertheless, they do represent slightly different aspects of importance in a network. Eigenvector centrality determines a node's importance based on the importance of its neighbouring nodes. It focuses on the quality of connections, rather than the quantity. PageRank is a more complex variation of eigenvector centrality which ensures importance spreads proportionally even

[22] Results are available from the authors on request.

from less-central nodes. Closeness centrality determines a node's importance based on how many connections it has to other nodes. Betweenness measures how often a particular node lies on the shortest paths between other nodes. Thus, betweenness measures are high for nodes that serve as important connectors between different nodes in a network. So, for instance, betweenness indicates which authors lie at the heart of a citation network. And in a journal network having two highly-connected but distinct subgroups that rarely cite each other, nodes in each subgroup that have a high eigenvector, PageRank and closeness can have low betweenness when measured over the whole network.

B.2 Journal Metrics

This appendix describes and compares various impact factor methodologies used to rank journal quality, specifically focusing on their calculation, main characteristics, and their effectiveness in controlling for the number of published articles.[23] Clarivate's Impact Factor (IF) is often regarded as preferable to Scopus-based metrics like CiteScore, SNIP, and SJR due to its longstanding academic credibility and recognition as the gold standard in scholarly evaluation.[24] It is deeply embedded in institutional decision-making, influencing tenure, promotions, and funding opportunities. Its calculation is also more straightforward and transparent compared with metrics which involve complex weighting or normalization.[25] On the other hand, like several other metrics, the IF is one of the journal citation metrics that is heavily influenced by a small number of highly-cited papers. Harzing & Wal (2009), Mingers et al. (2012) and others show that the h-index is much less sensitive to the very highly cited papers that skew the IF and other metrics,[26] but historical data on a journal's h-index are not available. Neither do we have historical data on IFs, although we do have historical data for a metric that is similar to the two-year IF, based on Scopus rather than Web-of-Science data, called the Impact Score (IS). This is defined as the ratio of the number of citations a journal receives in the latest two years (including the year of calculation) to the number of publications in those two years.[27]

We also have historical data on three other Scopus-based citation metrics.[28] CiteScore is the average number of citations per article over a four-year window, including the current year.[29] With a four-year window the normalization for an increase in journal size in the current year is diluted, so this one is particularly susceptible to distortion created by sudden increases in the number of citable papers. The SCImago Journal Rank (SJR) uses weighted citations that assign greater importance to citations from the more influential journals, as measured by a variant of the eigenvector centrality. SJR divides

[23] See Wikipedia and the description of Elsevier's impact methodology for further details.

[24] Clarivate uses Web-of-Science data to calculate the IF of a journal in year y as the total number of citations received in year y to the citable articles published in years $y-1, y-2, ..., y-n$, divided by the total number of citable articles published in those n years. In finance n is typically set to one or five.

[25] Alternative finance journal rankings have been developed by a number of authors, and from Currie & Pandher (2011, 2020) in particular. However, we do not have historical data on these. See also Docampo & Safón (2022) and, for an older review of finance journal rankings and citations, Guo et al. (2016). These authors introduce an 'active scholar assessment' (ASA) methodology which tends to assign a higher rank to the more prestigious finance journals compared with journal metrics like SJR, which are based on citation counts. Another novel approach, introduced by Bajo et al. (2020), even advocates ranking finance journals by their impact on career advancement. Eleftheriou & Polemis (2020) analyze the common trends of eighteen finance journals appearing in thirteen different rankings, finding that extent of the agreement between rankings depends on the 'clubs' to which a journal belongs.

[26] The h-index, defined as the maximum value of h such that the journal has published at least h papers that have each been cited at least h times.

[27] See Researchify.

[28] See Scopus journal metrics.

[29] See Wikipedia

the weighted citations by the total number of published articles, thus directly normalizing for journal size. By controlling for publication volume explicitly, SJR discourages journals having an excessive number of publications, promoting quality rather than quantity. The only metric that controls for subject-specific citation patterns is Elsevier's Source Normalized Impact per Paper (SNIP) which is similar to the three-year IF calculation except that it normalizes a journal's citation impact by the average citation rate of its subject area, thereby allowing for cross-disciplinary comparisons.[30]

Figure 8 depicts the annual evolution of the four journal ranking metrics (IS, SJR, SNIP and CiteScore) between 2014 and 2023. [31] Until 2020 the AJG4 journals had much higher IS than other journals, and among the AJG4 journals the "top three" journals had the highest IS. After 2020 the IS for some Elsevier journals started to increase quite remarkably, namely for JFE and JCF in the AJG4 group and for FRL, IRFA and RIBAF in the FJE group – and each of these three journals now has an IS on a par with the top three. The other ATS journals have lower IS, but among these PBFJ and JEF have the fastest-growing IS. The SJR for each of the top three journals is very much greater than the SJRs of other journals, with JF retaining the top rank according to this metric. Between 2014 and 2017 the SJR of the JFM fell to the level of the other Elsevier journals. The SNIP has also remained higher and more stable for the top three than it is for other journals, but the SNIP of JF has been falling and by now it has fallen below RFS and JFE. The CiteScore has recently increased for RFS, JFE and JCF in the AJG4 group, and JBEF, FRL, IRFA and RIBAF. In 2023 the CiteScores of RFS, JFE and JBEF each exceeded that for JF, whose CiteScore is now on a par with FRL, IRFA and RIBF. What is clear from our description of these metrics, and from their evolution shown in Figure 8 is that they often disagree about journal ranking and that JF – the traditional top finance journal – is no longer top according to several metrics.

A tangible discerning factor between journals is that some have increased in size considerably while others have not. The CiteScore and IS have increased, while the SJR has not, for journals that have significantly increased the number of papers published during the last few years. Figure 9 exhibits the total number of papers published per year and the total number of citations received during that year and the two previous years, both on a log scale. This shows that the number of papers published in many journals has remained relatively stable over time. In particular all these journals exhibit no significant expansion in size: JF, RF and JFI in the AJG4 group; JEB, EMR and JIFMIM in the FJE group; and JBF, JFS, JEF JCM and JFM in the ATS group.[32] However, FRL shows almost exponential growth in the number of papers and it now dominates the time series plot, having grown from less than 300 papers in 2020 to almost 1500 publications three years later. Correspondingly, we also see an exponential increase in citations to FRL. Several other Elsevier journals have also expanded since 2020. In 2023 IRFA, IREF and RIBAF, JEBO and PBFJ all published over 200 articles – as did JBF, but this has been one of Elsevier's largest journals for decades. Since 2020 the numbers of citations to JFE and JCF have more than doubled, as have citations to IRFA, RIBAF, IREF, PBFJ and JEBO, and citations to RFS and JBF have also noticeably increased.

[30] See CWTS journal indicators

[31] These were downloaded from the SCImago website.

[32] Also note that JCF published an unusually large number of papers in 2020 and 2021, as did JFQA in 2023.

Figure 8: Evolution of Journal Impact Metrics.

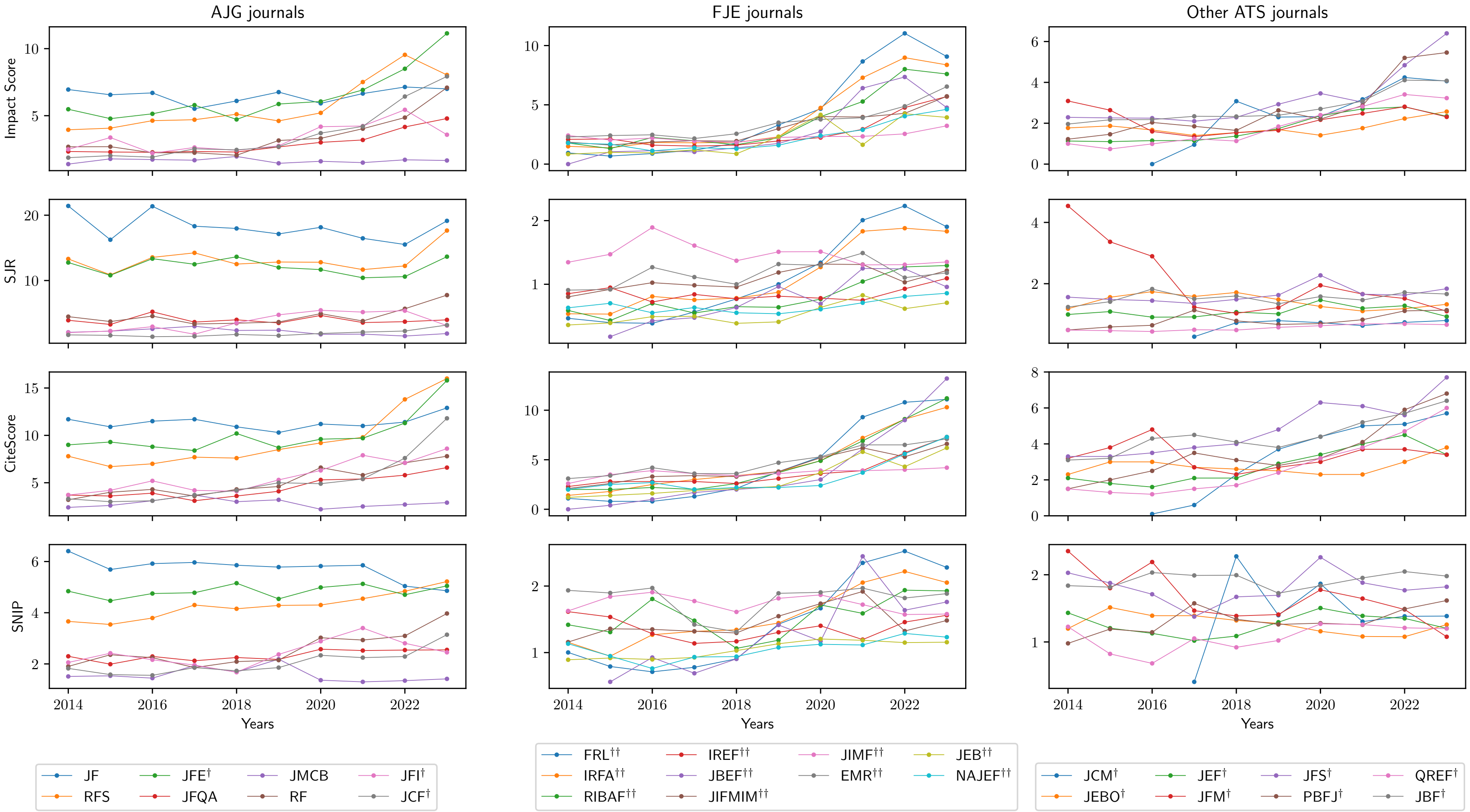
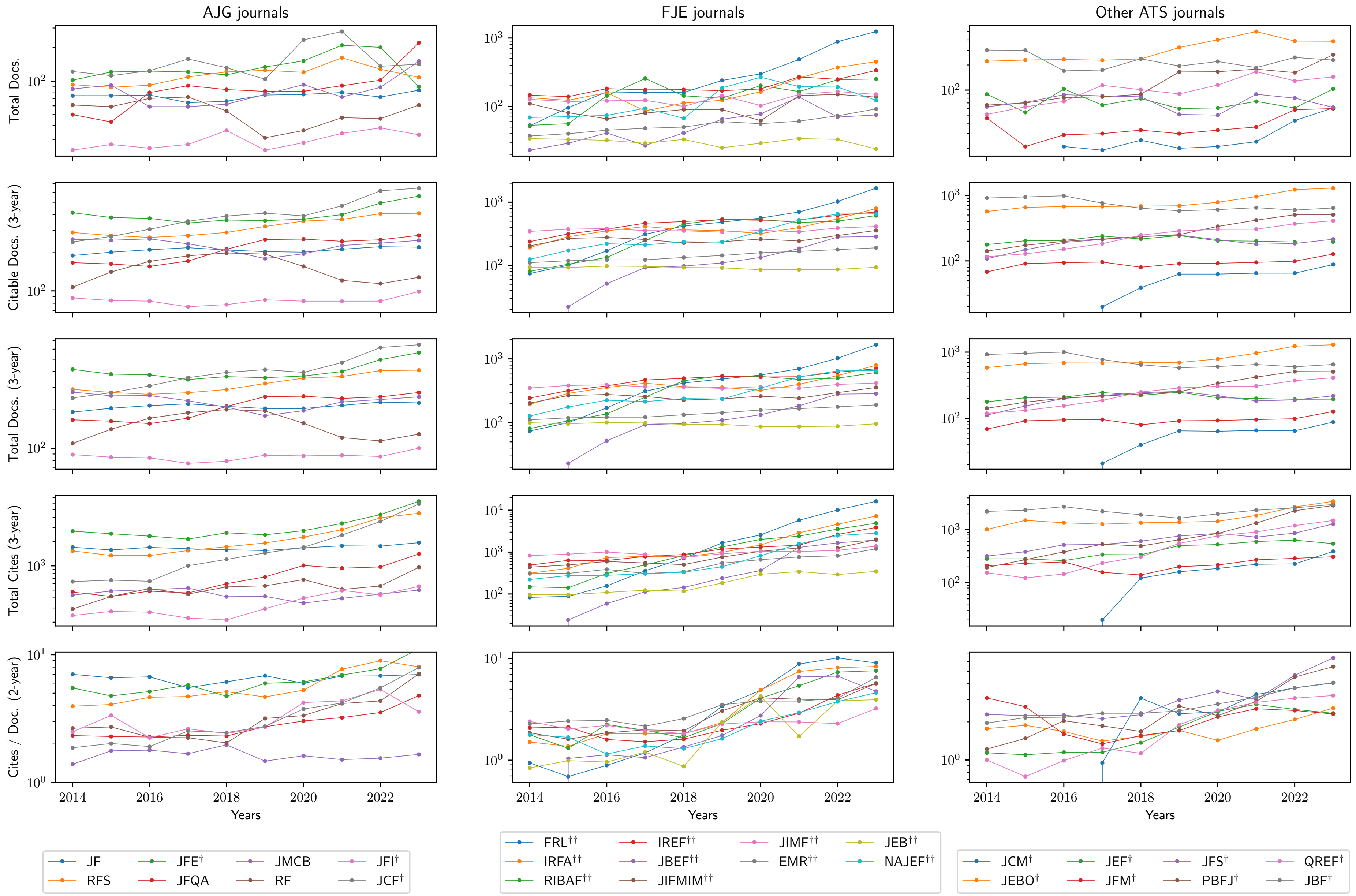


Figure 9: Evolution of Other Journal Metrics. Including the number of published documents per year, the number of citable documents during the last three years, the total number of documents during the last three years, the number of citations received during the last three years, and the two-year average number of citations per document. These were downloaded from SJCR.



C Further Empirical Results

C.1 DiD Regression Results

Table 9: DiD Regression Results: Three-Year Impact Factors

	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Post 2019	3.0128***	2.9614***	2.8805***	2.8314***	2.9949***	2.4746***
	(10.70)	(10.14)	(10.00)	(9.70)	(10.29)	(7.70)
PubPeer Journal × After 2019	0.9992**					1.4922***
	(2.51)					(3.53)
FJE (Excl. PubPeer) × After 2019		0.1057				0.7210**
		(0.41)				(2.46)
FJE (All) × After 2019			0.4763*			
			(1.93)			
FT50 × After 2019				0.5842**		1.0269***
				(2.10)		(3.32)
AJG4 × After 2019					-0.0406	0.5507
					(-0.12)	(1.51)
Number of Papers	-0.0059***	-0.0067***	-0.0062***	-0.0065***	-0.0067***	-0.0049**
	(-2.80)	(-3.15)	(-2.91)	(-3.09)	(-3.17)	(-2.34)
ESG & CSR	0.0085	0.0115*	0.0101	0.0119**	0.0115*	0.0076
	(1.39)	(1.90)	(1.67)	(1.98)	(1.90)	(1.28)
Crisis	0.0115	0.0126	0.0122	0.0094	0.0127	0.0042
	(0.81)	(0.88)	(0.86)	(0.66)	(0.88)	(0.30)
COVID-19	0.0175**	0.0199**	0.0186**	0.0215**	0.0198**	0.0203**
	(2.01)	(2.27)	(2.13)	(2.46)	(2.25)	(2.35)
Crypto & DeFi	0.0438***	0.0512***	0.0462***	0.0519***	0.0516***	0.0378**
	(2.76)	(3.25)	(2.91)	(3.33)	(3.27)	(2.41)
FinTech	0.0306	0.0297	0.0305	0.0247	0.0298	0.0202
	(0.87)	(0.83)	(0.86)	(0.70)	(0.84)	(0.58)
AI	0.0434	0.0426	0.0419	0.0392	0.0426	0.0394
	(1.64)	(1.59)	(1.58)	(1.48)	(1.58)	(1.51)
Safe Haven	-0.0120	0.0102	0.0061	0.0164	0.0085	0.0037
	(-0.21)	(0.18)	(0.11)	(0.29)	(0.15)	(0.07)
Constant	2.9904***	3.0229***	2.9887***	3.0443***	3.0264***	2.9858***
	(12.73)	(12.72)	(12.64)	(12.93)	(12.73)	(12.93)
Observations	282	282	282	282	282	282
R-squared (within)	0.7789	0.7732	0.7765	0.7772	0.7730	0.7900
R-squared (between)	0.0015	0.0001	0.0001	0.0251	0.0004	0.0459
R-squared (overall)	0.3688	0.3597	0.3527	0.4064	0.3627	0.4270
F-statistic	43.94***	42.52***	43.35***	43.50***	42.48***	40.02***

Table 10: DiD Regression Results: Four-Year Impact Factors

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Post 2019	3.2153***	3.1602***	3.0932***	3.0541***	3.1765***	2.6635***
	(11.79)	(11.20)	(11.11)	(10.81)	(11.30)	(8.56)
PubPeer Journal × After 2019	0.8506**					1.3552***
	(2.20)					(3.32)
FJE (Excl. PubPeer) × After 2019		0.1351				0.7359**
		(0.54)				(2.59)
FJE (All) × After 2019			0.4473*			
			(1.88)			
FT50 × After 2019				0.5227*		0.9841***
				(1.94)		(3.28)
AJG4 × After 2019					0.1014	0.6755*
					(0.31)	(1.91)
Number of Papers	-0.0060***	-0.0067***	-0.0062***	-0.0065***	-0.0067***	-0.0050**
	(-2.93)	(-3.24)	(-3.01)	(-3.19)	(-3.26)	(-2.45)
ESG & CSR	0.0093	0.0118**	0.0105*	0.0122**	0.0117**	0.0083
	(1.57)	(2.02)	(1.80)	(2.10)	(2.01)	(1.43)
Crisis	0.0113	0.0123	0.0119	0.0094	0.0120	0.0039
	(0.82)	(0.88)	(0.86)	(0.68)	(0.86)	(0.29)
COVID-19	0.0119	0.0139	0.0127	0.0153*	0.0142*	0.0148*
	(1.40)	(1.64)	(1.50)	(1.81)	(1.67)	(1.78)
Crypto & DeFi	0.0495***	0.0556***	0.0511***	0.0564***	0.0560***	0.0433***
	(3.22)	(3.65)	(3.33)	(3.73)	(3.68)	(2.85)
FinTech	0.0401	0.0393	0.0400	0.0348	0.0387	0.0294
	(1.18)	(1.14)	(1.17)	(1.02)	(1.12)	(0.88)
AI	0.0415	0.0407	0.0401	0.0378	0.0418	0.0387
	(1.62)	(1.57)	(1.56)	(1.47)	(1.61)	(1.53)
Safe Haven	-0.0287	-0.0092	-0.0136	-0.0042	-0.0110	-0.0134
	(-0.52)	(-0.17)	(-0.25)	(-0.08)	(-0.20)	(-0.25)
Constant	3.1644***	3.1901***	3.1595***	3.2110***	3.1991***	3.1612***
	(13.91)	(13.90)	(13.82)	(14.10)	(13.93)	(14.14)
Observations	282	282	282	282	282	282
R-squared (within)	0.7889	0.7848	0.7877	0.7879	0.7846	0.7998
R-squared (between)	0.0015	0.0040	0.0067	0.0060	0.0027	0.0180
R-squared (overall)	0.3033	0.2959	0.2894	0.3383	0.2996	0.3571
F-statistic	46.61***	45.49***	46.28***	46.34***	45.44***	42.50***

C.2 Analysis of Research Topics

We have identified the following six topics as those attracting considerable new attention from finance researchers since 2019: (1) Environmental, Social, and Governance and Corporate Social Responsibility (ESG & CSR); (2) Financial market crisis (Crisis); (3) Covid pandemic (COVID-19); (4) Crypto assets and decentralized finance (Crypto & DeFi); (5) Financial technology (FinTech) and (6) Artificial Intelligence (AI).[33] Together, the twenty-six journals published a total of 25,914 articles over the entire six-year period, of which 8,818 (34%) were on these six topics.

Panel (a) of Figure 10 counts all the papers on a given topic over the six-year period in each journal,

[33] To find articles on each topic we search for the following terms in the titles and abstracts of articles published between 2019 and 2024: (1) ESG & SCR: "ESG", "sustainable", "sustainability", "environment", "climate", "CSR", "corporate social responsibility"; (2) Crisis: "crisis", "crises"; (3) COVID-19: "COVID" and "pandemic"; (4) Crypto & Defi: "crypto", "bitcoin", "ether", "NFT", "non-fungible token", "digital asset", "blockchain", "digital wallet", "DeFi", "decentralized", "web3", "DAO" and "DApp"; (5) FinTech: "crowdfunding", "FinTech", "financial technology", "P2P", "peer-to-peer", "Robo-advisor", "marketplace lending", "mobile transfer", "mobile payment", "business-to-business", "B2B", "direct-to-consumer", "D2C", "Apps", "embedded finance", "PropTech", "FemTech", "EdTech", "WealthTech", "RegTech", "CleanTech", "GreenTech", "RetailTech", "PSD2", "payment services directive", "open banking"; (6) AI: "AI", "artificial intelligence", "machine learning", "LLM", "large language model", "NLP", "natural language process", "ChatGPT", "Gemini", "generative AI", "intelligence".

then sums these counts over all topics and presents the result as a percentage of the total number of papers published in the journal between 1 January 2019 and 31 December 2024. As expected given its aims and scope, JCF published 161 papers on ESG & CSR, from a total of 1018 publications between 2019 and 2024. Over 40% of the papers published in JFS were on these trendy topics, mainly because it published a 98 papers on financial market crises, as one would expect given the journal's aims and scope. Between 2019 and 2024 FRL published 1,979 papers on the trendy topics, representing about 42% of the 4,682 papers published in this journal. IRFA also published more than 43% of its 2,114 papers on these topics, and RIBAF published over 46% of its 1,383 papers on these topics.

Figure 10: Number of articles on trendy topics. Panel (a) reports the number of articles on each topic by journal, and the final column expresses the total number of papers on these topics as a percentage of the total number of papers the journal published between 1 January 2019 and 31 December 2024. Panel (b) ranks each journal, within the collection of all papers published on each topic in the twenty-six journals, according to the average of the three ranks determined by eigenvector, PageRank and closeness centrality. The rank in parentheses after the journal acronym is the journal rank based on the average of the topic ranks, and the journals are listed in this rank order.

(a) Number of articles on trendy topics published by each journal

Journals	ESG & CSR	Crisis	COVID-19	Crypto & DeFi	FinTech	AI	All topics	All	Percentage
JF	14	15	8	8	7	9	58	466	12.45
RFS	42	23	19	13	18	16	118	737	16.01
JFE†	35	28	23	11	9	11	110	898	12.25
JFQA	30	10	22	4	10	9	73	631	11.57
JMCB	30	33	10	6	1	2	77	577	13.34
RF	28	16	1	5	7	3	56	280	20
JFI†	7	19	5	3	7	1	36	182	19.78
JCF†	161	23	18	7	22	6	225	1018	22.1
JBF†	95	89	55	10	17	8	246	1234	19.94
JFM†	13	12	3	5	0	4	35	256	13.67
JFS†	60	81	30	11	5	10	169	438	38.58
JEF†	20	12	7	13	6	11	64	437	14.65
JEBO†	227	52	94	16	13	31	392	2389	16.41
PBFJ†	225	59	72	16	30	23	373	1260	29.6
QREF†	57	63	56	44	4	2	192	765	25.1
JCM†	20	16	23	4	0	5	55	217	25.35
FRL††	916	194	450	435	134	120	1938	4682	41.39
IRFA††	451	143	197	150	47	71	890	2114	42.1
RIBAF††	255	117	166	159	45	47	626	1383	45.26
IREF††	424	127	147	88	26	32	719	2043	35.19
JBEF††	58	19	51	32	13	24	172	528	32.58
JIFMIM††	117	90	66	66	23	16	305	725	42.07
JIMF††	59	103	46	15	7	6	204	867	23.53
EMR††	79	29	27	11	9	7	146	439	33.26
JEB††	21	11	18	8	12	3	61	180	33.89
NAJEF††	73	114	123	73	12	20	341	1168	29.2

(b) Average rank of journal centrality by trendy topic

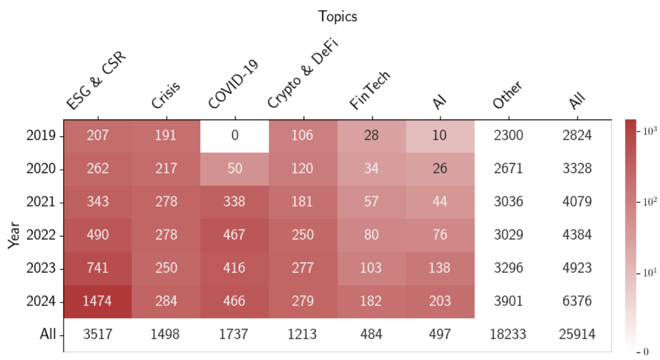
Journals	ESG & CSR	Crisis	COVID-19	Crypto & DeFi	FinTech	AI
JFE† (1)	1	1	1	3	2	2
JF (2)	3	2	2	1	3	1
RFS (3)	2	3	3	2	1	2
JFQA (4)	4	6	4	6	4	4
JBF† (5)	5	4	6	7	6	6
FRL†† (6)	8	9	5	4	7	7
RF (7)	6	10	10	7	9	5
JMCB (8)	10	5	7	13	8	11
JFI† (9)	11	7	11	12	4	12
IRFA†† (10)	13	13	9	5	12	14
JCF† (11)	6	12	12	21	10	9
JFM† (11)	11	15	8	10	18	8
JFS† (13)	14	8	13	19	13	17
JIMF†† (14)	16	10	13	16	16	16
JEBO† (15)	9	20	17	25	14	9
JEF† (16)	16	16	21	14	15	13
RIBAF†† (17)	21	21	15	9	19	21
JIFMIM†† (18)	25	14	20	11	21	22
IREF†† (19)	18	18	18	21	21	18
NAJEF†† (20)	23	18	16	15	24	20
JBEF†† (21)	20	25	19	18	25	15
JEB†† (21)	24	22	25	21	11	19
QREF† (23)	22	24	23	17	17	25
PBFJ† (24)	15	23	22	23	23	23
EMR†† (25)	19	17	24	26	20	24
JCM† (26)	26	26	26	24	26	26

To obtain the journal ranks displayed in Panel (b) we fix a topic, then rank the journals three times, once by eigenvector, then by PageRank and then by closeness centrality, based on the citation network of the set of all papers published on a given topic between 2019 and 2024. Then we take the average of these three ranks, and report the result in the cell corresponding to the journal and the topic. For example, in the citation network of "Crisis" papers, RF has an average rank of ten. Then journals are ordered by their average rank over all six topics. This shows that JFE was the most important journal publishing papers on these trendy topics, followed by JF, RFS, JFQA and JBF. FRL is ranked sixth overall, and IFRA is ranked tenth overall, mainly due to the high ranking of publications on COVID-19 and Crypto & DeFi in these two journals.[34]

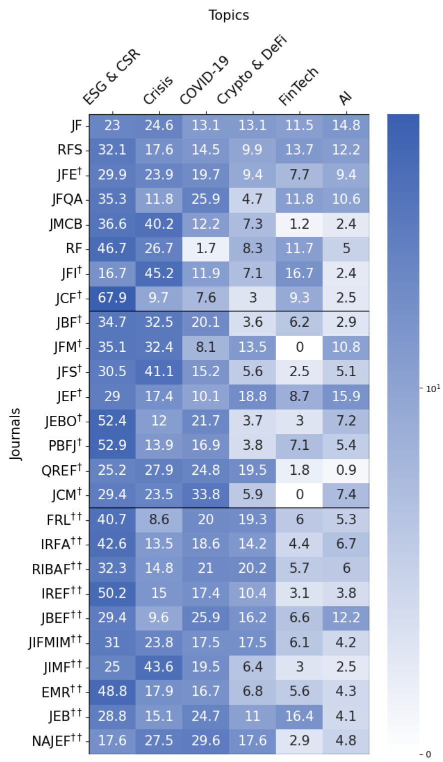
For reasons of space we do not display the citation networks between journals based solely on the articles on these six trendy topics. Instead we just summarize our findings, namely: (i) The AJG4 group has similar citation patterns for each topic; (ii) The ATS group exhibits more variation, with strong citations to JBF on all topics except Crypto & DeFi and FinTech, especially from QREF and JCM; (iii) The FJE group shows the greatest variation by topic. Although FRL is the main journal being cited on every topic, followed by IRFA, the main topics being cited are Crypto & Defi and COVID-19.

Figure 11: Number of articles on trendy topics. Panel (a) reports the number of articles on each topic, and the number of other articles published, year by year. Panel (b) reports the number of articles on each topic in a given journal, as a proportion of the total number of articles published on each topic.

(a) No. of articles on trendy topics by year



(b) Percentage by row



Panel (a) of Figure 11 reports the number of articles published on each topic in each year. The ESG & CSR topic attracted the most articles, with 3,517 articles published in these twenty-six journals of which 1,474 were published during 2024 alone. The heat map colouring represents the number of papers on that topic in a given year as a proportion of the total number of papers on that topic over the six-year window. Panel (b) of Figure 11 reports the number of papers published on a particular topic as a percentage of the journal's publications on all six topics. This shows that most journals published more on the traditional topics (Crisis and ESG & SCR) than emerging topics (Crypto & DeFi, Covid, AI and FinTech). Also, FJE journals published the highest proportion of papers on the emerging topics. Between 2019 and 2024 over 30% of the "trendy topic" papers published by several FJE journals were on "Crypto & DeFi" and "COVID-19".

[34]Figure 11 in Appendix C.2 presents a descriptive analysis of how the distribution of the six topics evolved across different journals and time from 2019 to 2024. The results echos our finding that many of the topics surged post-2019 especially in FJE journals whereas other journals tend to publish fewer articles on trending topics across the board.

C.3 Correlations Between Journal-Level Metrics

	SJR (Scopus)	CiteScore (Scopus)	SNIP (Scopus)	IF (four-year, Clarivate)	IF (three-year, Clarivate)	IF (two-year, Clarivate)	Total Docs. (SJCR)	Citable Docs. (3 years, SJCR)	Total Docs. (3 years, SJCR)	Total Cites (3 years, SJCR)	Cites / Doc. (2 years, SJCR)
IS (Researchify)	0.5721	0.9173	0.6838	0.9358	0.9631	0.9947	0.3565	0.3063	0.302	0.7187	0.9968
SJR (Scopus)		0.7352	0.953	0.7681	0.7078	0.6085	-0.0813	-0.0308	-0.0316	0.2419	0.5892
CiteScore (Scopus)			0.8169	0.9612	0.9692	0.922	0.2075	0.2434	0.2403	0.6291	0.9225
SNIP (Scopus)				0.8589	0.811	0.7185	-0.0185	0.0213	0.0202	0.3396	0.6999
IF (four-year, Clarivate)					0.9843	0.9482	0.2521	0.238	0.2346	0.637	0.9417
IF (three-year, Clarivate)						0.9724	0.299	0.2664	0.2625	0.6795	0.9688
IF (two-year, Clarivate)							0.3447	0.2924	0.2882	0.7031	0.9976
Total Docs. (SJCR)								0.8444	0.8419	0.8161	0.3517
Citable Docs. (3 years, SJCR)									0.9999	0.7495	0.3023
Total Docs. (3 years, SJCR)										0.7458	0.2981
Total Cites (3 years, SJCR)											0.7164

Online Appendix

Coordinated Journals, Concentrated Networks and Citation Growth: Evidence from Finance

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Table 1: Average citation counts between journals. We report the average number of citations that an article published in the journal on the horizontal axis (cited journal) received from articles published in the journal on the vertical axis (citing journal) for the periods (a) 2014–2018 and (b) 2019–2024. Cell color indicates citation intensity, with the midpoint set at the 84.13th percentile (corresponding to one standard deviation above the mean in a normal distribution). The symbols †† and † indicate FJE journals and other ATS journals, respectively.

(a) 2014 - 2018

Cited journals (articles published any time)

Citing journals (articles published between 2014 and 2018)

	JF	RFS	JFE†	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	PBFJ†	QREF†	JCM†	FRL††	IRFA††	RIBAF††	IREF††	JBEF††	JIFMIM††	JIMF††	EMR††	JEB††	NAJEF††
JF	8.36	4.23	5.59	0.74	0.15	0.3	0.18	0.15	0.29	0.23	0.03	0.06	0.08	0.01	0.01	0	0.03	0.01	0	0	0.01	0	0.06	0	0.01	0
RFS	8.71	4.8	6.1	0.71	0.17	0.31	0.2	0.2	0.4	0.3	0.02	0.1	0.07	0.01	0.02	0	0.02	0	0	0	0	0	0.08	0.01	0.01	0
JFE†	7.94	3.99	6.56	0.83	0.12	0.27	0.18	0.2	0.34	0.26	0.03	0.07	0.04	0.01	0.01	0	0.02	0	0	0	0	0	0.05	0.01	0.01	0
JFQA	8.76	4.39	7.28	1.62	0.15	0.35	0.29	0.38	0.52	0.35	0.06	0.18	0.04	0.03	0.01	0	0.02	0.01	0	0.01	0	0.01	0.12	0	0.01	0
JMCB	1.36	0.81	0.91	0.11	1.48	0.13	0.3	0.02	0.6	0.01	0.08	0.07	0.05	0	0.01	0	0.01	0.01	0	0.01	0	0.01	0.19	0.01	0.03	0.03
RF	7.61	3.58	5.02	0.95	0.33	0.66	0.39	0.19	0.86	0.3	0.1	0.15	0.09	0.03	0.03	0	0.03	0.02	0	0.01	0	0.03	0.24	0	0.02	0
JFI†	3.3	1.84	3.51	0.37	0.64	0.26	0.18	0.16	0.96	0.04	0.11	0.01	0.02	0	0.01	0	0.01	0.01	0	0	0.01	0	0.01	0	0.03	0
JCF†	0.26	3.18	8.46	1.48	0.08	0.04	0.01	0.44	0.09	0.12	0.03	0.01	0.07	0.11	0.03	0	0.01	0.03	0	0	0	0.02	0	0.03	0.02	0
JBF†	4.63	2.17	3.92	0.83	0.46	0.22	0.37	0.29	2.48	0.2	0.13	0.2	0.07	0.05	0.05	0	0.04	0.06	0.01	0.02	0	0.09	0.3	0.03	0.06	0.01
JFM†	4.02	3.92	6.07	1.4	0.03	0.16	0.11	0.06	0.4	1.27	0.01	0.08	0.04	0.04	0	0	0.06	0.01	0	0.01	0	0.06	0.08	0.01	0.02	0
JFS†	1.79	0.9	1.72	0.23	0.92	0.19	0.19	0.15	1.94	0.05	1.57	0.06	0.13	0.01	0.04	0	0.05	0.08	0.03	0.04	0.01	0.1	0.45	0.05	0.07	0.06
JEF†	1.67	2.86	4.18	0.93	0.19	0.08	0.03	0.07	0.3	0.33	0.03	0.32	0.08	0.02	0.02	0	0.07	0.05	0	0.01	0	0.08	0.09	0.03	0.02	0.04
JEBO†	0.37	0.14	0.21	0.04	0.06	0.04	0	0.01	0.09	0	0.01	0.02	1.06	0	0.01	0	0.01	0	0	0.01	0	0	0.03	0.01	0	0
PBFJ†	0.2	2.18	4.97	0.96	0.1	0.04	0.01	0.14	0.08	0.49	0.05	0.07	0.14	1.82	0.03	0	0.04	0.17	0.02	0.01	0	0.22	0.01	0.18	0.06	0.03
QREF†	3.52	1.27	2.93	0.66	0.22	0.17	0.16	0.32	1.53	0.16	0.1	0.35	0.08	0.14	0.62	0	0.08	0.22	0.1	0.18	0	0.2	0.43	0.18	0.1	0.08
JCM†	0.59	0.89	1.37	0.48	0.03	0.03	0.02	0	0.13	0.13	0.03	0.08	0.05	0.06	0.03	0.11	0.06	0.19	0	0.05	0	0.13	0.14	0.03	0.05	0.03
FRL††	1.43	0.65	0.99	0.21	0.05	0.05	0.01	0.04	0.46	0.03	0.03	0.06	0.01	0.02	0.02	0	1	0.13	0.05	0.07	0.01	0.02	0.13	0.02	0.03	0.07
IRFA††	4.98	1.92	3.77	1.05	0.26	0.2	0.26	0.53	2.44	0.28	0.15	0.49	0.12	0.23	0.15	0	0.13	1.08	0.14	0.21	0.01	0.21	0.58	0.17	0.09	0.09
RIBAF††	2.29	0.54	1.59	0.4	0.25	0.09	0.04	0.19	1.31	0.08	0.09	0.19	0.07	0.08	0.1	0	0.13	0.22	0.84	0.14	0.02	0.19	0.38	0.18	0.1	0.1
IREF††	2.54	1	2.23	0.47	0.21	0.08	0.13	0.26	1.12	0.16	0.08	0.27	0.06	0.17	0.1	0	0.04	0.16	0.06	1.83	0	0.14	0.6	0.12	0.06	0.17
JBEF††	3.13	0.91	1.55	0.16	0.05	0.23	0.02	0.05	0.58	0.16	0.02	0.19	0.59	0	0.01	0	0.15	0.14	0.09	0.03	0.3	0.05	0.07	0.06	0.04	0.01
JIFMIM††	2.33	1.12	2.45	0.48	0.4	0.11	0.08	0.13	1.73	0.19	0.11	0.19	0.05	0.11	0.05	0	0.12	0.27	0.05	0.08	0	0.42	0.8	0.15	0.07	0.11
JIMF††	0.71	0.32	0.31	0.06	0.27	0.06	0.01	0.01	0.2	0.01	0.02	0.02	0.01	0.02	0.01	0	0.02	0.02	0.01	0.03	0	0.03	0.5	0.02	0.01	0.06
EMR††	0.05	1.61	3.73	0.71	0.25	0.04	0	0.09	0.1	0.21	0.19	0.06	0.05	0.43	0.11	0	0.13	0.33	0.02	0	0	0.61	0.01	1.65	0.07	0.09
JEB††	2.92	0.95	2.92	0.54	0.44	0.14	0.33	0.59	2.12	0.07	0.21	0.24	0.06	0.07	0.16	0	0.03	0.08	0.05	0.04	0	0.13	0.28	0.11	0.56	0.02
NAJEF††	3.14	1.16	2.26	0.52	0.31	0.1	0.14	0.24	1.66	0.18	0.13	0.41	0.05	0.16	0.16	0	0.08	0.23	0.1	0.28	0	0.27	0.64	0.13	0.08	1.13

Color scale: 0.00, 1.00, 2.00, 3.00, 4.00, 5.00, 6.00, 7.00, 8.00

(b) 2019 - 2024

Cited journals (articles published any time)

Citing journals (articles published between 2019 and 2024)

	JF	RFS	JFE†	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	PBFJ†	QREF†	JCM†	FRL††	IRFA††	RIBAF††	IREF††	JBEF††	JIFMIM††	JIMF††	EMR††	JEB††	NAJEF††
JF	8.61	5.25	5.94	0.7	0.21	0.4	0.24	0.08	0.31	0.23	0.03	0.07	0.08	0.01	0.01	0	0.02	0	0	0	0	0	0.06	0.01	0.01	0
RFS	7.59	5.46	6.19	0.76	0.18	0.38	0.22	0.17	0.3	0.17	0.06	0.07	0.09	0	0.01	0	0.01	0	0	0	0.01	0	0.07	0	0.01	0
JFE†	5.14	4.9	6.54	0.83	0.17	0.19	0.01	0.09	0.19	0.18	0.03	0.05	0.05	0	0	0	0.03	0.01	0	0	0	0	0.05	0.01	0.01	0.01
JFQA	8.2	5.36	8.28	1.81	0.17	0.51	0.26	0.57	0.53	0.27	0.03	0.11	0.06	0.02	0	0.01	0.02	0.01	0	0.01	0.02	0.01	0.06	0.01	0.01	0
JMCB	1.53	1.06	1.27	0.16	1.49	0.21	0.35	0.05	0.55	0.02	0.22	0.03	0.07	0.01	0.01	0	0.01	0.01	0.01	0.02	0.01	0.03	0.39	0.01	0.01	0.01
RF	7.47	5	6.6	1.14	0.26	0.68	0.46	0.29	0.48	0.25	0.09	0.12	0.07	0.04	0.01	0	0.05	0.01	0.01	0	0.02	0.01	0.09	0	0.02	0.01
JFI†	3.77	3.24	4.34	0.53	0.61	0.36	0.49	0.25	0.37	0.05	0.26	0.02	0.02	0	0.02	0	0	0.01	0.01	0.01	0	0	0.07	0.01	0.03	0.01
JCF†	0.69	4.02	8.52	1.78	0.2	0.21	0.03	0.19	0.04	0.13	0.12	0	0.11	0.1	0.01	0	0.08	0.1	0	0	0	0.05	0.01	0.06	0.03	0.01
JBF†	4.5	3.05	4.9	1.09	0.47	0.28	0.14	0.52	1.65	0.18	0.22	0.16	0.13	0.03	0.02	0	0.14	0.07	0.02	0.03	0.02	0.05	0.16	0.03	0.03	0.02
JFM†	7.22	5.27	7.41	1.71	0.15	0.46	0.17	0.27	0.64	0.97	0.02	0.17	0.08	0.1	0.02	0	0.18	0.06	0.01	0.05	0.03	0.07	0.12	0	0	0.04
JFS†	1.36	1.9	3.49	0.7	0.85	0.17	0.29	0.08	0.34	0.08	2.31	0.05	0.16	0.02	0.02	0	0.34	0.23	0.03	0.04	0	0.13	0.3	0.05	0.07	0.07
JEF†	6.25	4.29	6.12	1.31	0.2	0.29	0.05	0.39	0.17	0.05	0.04	0.14	0.07	0.01	0.03	0.01	0.34	0.14	0.05	0.07	0.01	0.07	0.31	0.01	0.02	0.08
JEBO†	0.37	0.29	0.42	0.08	0.1	0.03	0.01	0.04	0.11	0.02	0.04	0.02	1.46	0.01	0.01	0	0.08	0.05	0.01	0.02	0.05	0.02	0.03	0.01	0.01	0.02
PBFJ†	0.3	2.34	4.92	0.97	0.15	0.1	0	0.04	0.04	0.31	0.23	0.01	0.16	1.62	0.02	0.01	0.62	0.49	0.02	0.04	0	0.27	0.02	0.27	0.05	0.16
QREF†	2.61	1.08	2.36	0.48	0.22	0.19	0.24	0.43	1.71	0.16	0.34	0.25	0.12	0.25	0.77	0.03	0.78	0.56	0.4	0.31	0.07	0.27	0.56	0.2	0.08	0.27
JCM†	1.78	1.19	1.35	0.38	0.19	0.23	0	0.04	0.87	0.13	0.01	0.26	0.02	0.12	0.2	0.84	1.42	1.17	0.24	0.38	0.06	0.39	0.59	0.11	0.05	0.4
FRL††	0.89	0.62	1.14	0.2	0.05	0.04	0.02	0.3	0.22	0.05	0.07	0.07	0.06	0.08	0.06	0.01	3.25	0.68	0.17	0.15	0.05	0.06	0.09	0.04	0.02	0.13
IRFA††	3.7	2.05	4.02	0.83	0.15	0.3	0.19	1.4	1.86	0.25	0.29	0.39	0.15	0.41	0.16	0.04	1.4	2.29	0.39	0.48	0.11	0.21	0.43	0.18	0.06	0.24
RIBAF††	1.24	1.23	2.73	0.56	0.19	0.03	0.09	0.11	0.24	0.16	0.32	0.11	0.12	0.05	0.05	0.05	2.27	1.08	0.4	0.07	0.07	0.3	0.21	0.22	0.08	0.35
IREF††	2.46	1.33	2.6	0.55	0.04	0.16	0.16	0.85	1.37	0.13	0.17	0.27	0.1	0.37	0.14	0.03	0.94	0.76	0.28	1.32	0.05	0.3	0.43	0.16	0.03	0.25
JBEF††	2.35	1.27	2.44	0.57	0.11	0.19	0.04	0.37	0.06	0.05	0.09	0.04	0.57	0.04	0.09	0.01	1.59	0.5	0.23	0.1	0.93	0.12	0.09	0.04	0.05	0.17
JIFMIM††	2.04	1.89	4.05	0.7	0.32	0.19	0.09	0.25	1.42	0.14	0.36	0.06	0.17	0.16	0.13	0.02	1.79	0.82	0.22	0.18	0.05	0.4	0.61	0.13	0.06	0.31
JIMF††	1.14	0.86	1.58	0.26	0.77	0.13	0.04	0.06	0.66	0.04	0.17	0.05	0.06	0.04	0.03	0.01	0.18	0.09	0.01	0.06	0.01	0.05	1.05	0.06	0.03	0.06
EMR††	0.05	1.53	3.76	0.71	0.23	0.08	0	0.03	0.02	0.16	0.44	0.01	0.18	0.46	0.03	0.01	0.62	0.49	0.01	0.02	0	0.37	0.02	1.44	0.07	0.16
JEB††	2.86	1.26	2.73	0.51	0.3	0.12	0.32	0.56	1.46	0.08	0.33	0.12	0.13	0.15	0.11	0	0.47	0.27	0.23	0.16	0.05	0.15	0.29	0.18	0.59	0.12
NAJEF††	2.78	1.31	2.35	0.51	0.22	0.17	0.13	0.4	1.61	0.22	0.26	0.42	0.07	0.32	0.21	0.04	1.18	0.86	0.38	0.58	0.09	0.43	0.62	0.2	0.05	1.16

Color scale: 0.00, 1.00, 2.00, 3.00, 4.00, 5.00, 6.00, 7.00, 8.00

Table 2: Growth and overall impact changes between 2014–2018 and 2019–2024. Panel (a) displays the percentage change in average citation counts for each journal (reported in Table 1). Panel (b) presents the absolute change in total citation counts for each journal over the same periods. In both panels, the color scale is centred at the 84.13th percentile (corresponding to one standard deviation above the mean in a normal distribution). The symbols †† and † next to a journal name indicate FJE journals and other ATS journals, respectively.

(a) Percentage changes between average citation counts

Cited journals (articles published any time); rows: Citing journals (changes between two periods)

	JF	RFS	JFE†	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	PBFJ†	QREF†	JCM†	FRL††	IRFA††	RIBAF††	IREF††	JBEF††	JIFMIM††	JIMF††	EMR††	JEB††	NAJEF††
JF	3	23.9	6.3	-4.7	43.7	35.7	30.4	-46.9	8.1	1.2	18.5	12.8	-0.3	-26	-26		-32.7	-50.6			-63	-26	-1.3		-1.3	
RFS	-12.9	13.9	1.5	7.4	2.2	23	10.1	-15.5	-25	-43	253.3	-25.7	26	-77	-61.7		-5.2		-31.1			106.8	-12.6	-48.3	-31.1	
JFE†	-35.3	22.9	-0.3	-0.8	45.3	-27.7	-92.5	-54.6	-44.1	-30.6	2.8	-25.6	15.9	-78.4	-56.9		58.8	94.1	29.4	-3		-35.3	4	-22.4	-44.5	
JFQA	-6.3	22.3	13.7	11.9	16.5	45.1	-9.8	50.8	1.5	-23.2	-42.4	-41.5	28.3	-26.7	-45		19.1	10		92.5		-17.5	-48.8	120	10	
JMCB	12.9	29.8	38.7	51.3	1.1	60.1	16.6	216.1	-8.4	10.1	154.9	-49	47.5		114.1		22.4	22.4		37.7		205.9	101.5	63.1	-59.2	-72.8
RF	-1.9	39.8	31.6	19.3	-21.3	2.4	15.8	53.3	-44.5	-17.4	-8.9	-19.5	-22.7	24.6	-77.6	-100	96.3	-43.9	124.3	-72		-50.2	-62.1	-100	12.1	
JFI†	14.5	76.1	23.8	44.2	-4.4	39	169.9	55.1	-60.9	51.6	142.6	13.7	1.1		13.7		-100	-24.2			-100		354.9		-5.2	
JCF†	164.8	26.4	0.7	19.8	131.5	413.9	154.6	-57.3	-53.1	10.6	324.4	-60.2	59.1	-7.2	-57.6		663.9	195.1		154.6		231	409.2	79.4	110.1	
JBF†	-2.9	40.9	24.8	30.9	2.4	27.6	-63.3	80.4	-33.3	-7.8	63	-22.1	90.3	-46.6	-54.1		236.9	31.7	24.9	41.1	724.5	-49.4	-46	-13	-48.5	60.5
JFM†	79.6	34.6	22.2	22.6	501.8	177.7	59.7	332	59.7	-23.5	85.2	126.3	85.2	167.4			215.5	393.8		702.3		23.4	54.3	-69.1	-100	
JFS†	-24.2	110.9	102.4	207.4	-7.5	-8.8	55.7	-42.3	-82.4	82.6	47.1	-26	18.4	77.6	-44.5		630.2	196	-11.2	-5.3	-11.2	28.8	-33.9	-2.7	-1.3	7.3
JEF†	273.2	49.6	46.5	40.4	3.3	265.6	114.2	423.2	-42.3	-84.5	30.4	-54.7	-13.6	-25.6	91.2		411.4	202.4		591.6		-7.8	225.6	-55.4	-10.8	123.1
JEBO†	1.3	112.5	96.3	107.6	84.1	-22.3	236.4	239.6	19	265.2	348.5	29	37.1	124.3	9.8		1357.6	2494.9	53.8	152.3	1317.6	909.1	8.9	-13.5	236.4	344.5
PBFJ†	51.5	7.5	-1.1	1.3	54.8	188.1	-7.6	-73.1	-50	-37.5	361.9	-80.6	19.7	-11	-36		1604.6	184.5	-23	474.8		26.8	254.1	47.9	-14	512.8
QREF†	-26	-14.8	-19.5	-27.9	4	12.3	53.5	36.5	12.2	-1.2	255	-29.2	43.8	87.8	25.3		935.3	150.4	321.1	73.8	1259.5	29.4	29.1	14.1	-16.3	264.3
JCM†	203.7	34.3	-1.4	-19.7	495.2	625.8	-100		582.3	5.2	-71	225.2	-51.6	88.7	524.2	654.8	2142.7	514.5		703.2		208.5	316.1	248.4	-3.2	1148.4
FRL††	-37.8	-4.9	15.5	-3.1	-3.4	-17.2	71.1	569.4	-51	84.2	118.1	17.8	288.7	277.7	155.7		225.1	428.3	228.8	125.8	478.6	288.9	-34.6	116.4	-8.3	102.5
IRFA††	-25.8	6.9	6.7	-20.7	-40	52.2	-25.9	163.5	-23.6	-7.6	96.3	-20.9	27.4	74.9	6.9	793	942	111.8	169.1	129.3	826	-0.7	-24.7	8.8	-33.6	179.8
RIBAF††	-46.1	125.6	71.6	39.8	-26.3	-67.8	124.8	-40	-81.8	100.4	260.1	-42.4	77.6	-31.2	-47.8		1599.9	392.9	-52.8	-51.8	255.4	60	-45.6	17.5	-18.4	247.4
IREF††	-3.1	33.3	16.7	19.2	-80.3	107.7	19.7	232.6	22.7	-19	119.4	-2.2	59.6	117.8	46.4	2293.5	2552.2	386.2	388.9	-27.8	2034.2	114.2	-29.1	37.1	-42.4	50.3
JBEF††	-25	40.5	57.6	257.6	118.6	-17.6	125	651.7	-89.6	-71.7	401.1	-79.5	-2.5		667		970	252.2	160.8	231.4	208.1	149.3	33.9	-41.7	14	1311.4
JIFMIM††	-12.2	68.5	65.4	44	-20.5	78.8	2.8	93.1	-18.2	-28.9	230	-65.5	228.5	51.5	151.1		1456.5	207.8	311.3	114.9		-5.5	-24.1	-14.5	-17.7	183.6
JIMF††	61.6	168.9	414.7	313.3	183.3	131.7	434.3	751.5	225.3	451	816.7	173.2	701.4	88.2	119.4		871.4	385.7	144.9	100.3		57.1	108.1	183.8	129	1.1
EMR††	-3.9	-5.4	0.7	0.2	-8.1	100.5	-49.9	-71	-84.1	-22.7	130.3	-89.3	221.6	6	-69.9		368.3	49	-37.4			-38.7	150.6	-13.3	3.6	87.3
JEB††	-2.4	32.7	-6.5	-4.9	-32.4	-18.8	-4.4	-4.5	-31.5	13.1	58.9	-48.5	113.3	118.2	-31.6		1393.3	228.2	355.6	268.3		14.3	4.7	58	4.7	522.2
NAJEF††	-11.4	13.1	3.9	-1.5	-29.2	71	-9.3	63.4	-2.9	24.5	109.4	1.8	27.4	99.2	25.3		1420	275.8	266.7	102.2		57.1	-3.5	57.9	-33.1	2.2

Color scale: 0 – 500 – 1,000 – 1,500 – 2,000 – 2,500

(b) Absolute changes between total citation counts

Cited journals (articles published any time); rows: Citing journals (changes between two periods)

	JF	RFS	JFE†	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	PBFJ†	QREF†	JCM†	FRL††	IRFA††	RIBAF††	IREF††	JBEF††	JIFMIM††	JIMF††	EMR††	JEB††	NAJEF††
JF	1127	984	840	73	48	85	48	-15	46	29	6	11	9	0	0	1	-1	-1	1	1	-1	0	7	3	1	0
RFS	1170	1589	1466	201	42	124	61	23	18	-26	33	4	29	-4	-4	3	3	2	0	1	5	2	11	-1	0	1
JFE†	3	2084	2062	258	86	18	-91	-34	-27	11	10	6	19	-4	-2	0	16	4	1	1	0	0	17	1	-1	5
JFQA	2139	1862	2698	582	57	200	64	230	154	48	1	4	20	3	0	4	7	4	1	5	10	2	-3	3	3	0
JMCB	405	322	408	56	340	76	97	25	106	4	95	-4	24	3	5	0	3	2	3	5	3	12	156	5	-4	-5
RF	-299	277	273	19	-31	-18	4	22	-137	-25	-6	-13	-9	1	-8	-1	6	-3	1	-3	7	-5	-49	-1	0	2
JFI†	232	336	306	46	23	30	64	23	-64	5	33	1	1	0	1	0	-1	0	1	1	-1	0	10	2	1	2
JCF†	534	2033	3189	848	145	191	21	-93	-15	56	102	-3	66	32	-6	0	77	80	0	3	2	42	7	40	23	14
JBF†	114	1223	1438	366	41	89	-266	303	-870	-7	112	-43	80	-25	-30	5	122	25	5	14	23	-52	-151	-3	-33	11
JFM†	1213	731	939	218	35	91	27	60	100	48	4	32	14	20	4	1	37	14	3	12	7	9	18	-1	-3	10
JFS†	-102	481	857	219	15	2	55	-20	-605	19	400	-4	17	5	-6	1	130	70	0	1	0	18	-45	2	3	5
JEF†	2078	756	1046	208	12	96	14	141	-41	-105	6	-61	-1	-1	8	6	123	43	24	27	6	1	98	-6	0	21
JEBO†	470	544	756	156	184	29	12	91	155	33	75	32	2260	11	9	3	176	106	11	34	114	40	38	8	18	33
PBFJ†	298	2106	4267	850	149	117	4	-7	20	198	266	-10	153	1332	14	9	761	552	12	53	5	262	21	270	43	189
QREF†	584	320	632	101	85	78	120	203	700	56	220	50	56	140	345	24	564	341	268	165	50	121	254	84	24	179
JCM†	350	203	206	53	39	48	-1	9	180	21	0	51	2	22	41	175	305	242	51	80	12	77	120	22	7	84
FRL††	3265	2483	4717	812	204	170	82	1365	758	203	289	287	251	379	252	32	14590	3099	750	647	210	279	324	181	93	576
IRFA††	4783	3168	6204	1118	170	514	250	2639	2449	371	529	525	243	720	252	90	2884	4186	734	884	218	318	567	286	73	453
RIBAF††	215	1344	2741	513	93	-19	98	33	-527	169	385	27	119	23	7	63	3050	1352	1	2	85	292	38	179	49	414
IREF††	2959	1898	3494	753	-86	265	214	1526	1892	132	279	321	156	611	211	59	1899	1421	529	1207	105	498	382	234	20	382
JBEF††	733	526	1038	277	49	64	19	188	-62	-2	46	-10	207	20	48	5	813	241	105	49	443	57	37	9	19	90
JIFMIM††	489	891	1891	299	60	94	27	128	289	17	217	-33	101	71	72	12	1249	479	138	93	39	109	99	30	12	176
JIMF††	581	563	1194	192	509	79	28	47	453	29	140	34	44	20	16	5	149	69	8	36	7	23	618	39	17	18
EMR††	11	315	828	156	45	27	0	-8	-15	25	151	-11	65	106	-10	3	242	144	1	10	0	30	8	266	16	52
JEB††	46	75	24	6	-17	-2	4	7	-78	3	26	-16	14	16	-6	0	79	35	33	22	9	6	8	14	16	18
NAJEF††	2079	1099	1901	406	143	166	98	376	1264	195	262	336	60	310	179	45	1355	918	410	567	101	401	485	190	33	932

Color scale: 0 – 2,000 – 4,000 – 6,000 – 8,000 – 10,000 – 12,000 – 14,000

Figure 1: Histogram of Number of Articles Published by a Single Author. The upper chart displays the number of authors that published n articles in any of the twenty-six journals between 1 January 2019 and 31 December 2024, for $n = 1, ..., 60$. The lower chart disaggregates the results by journal cluster.

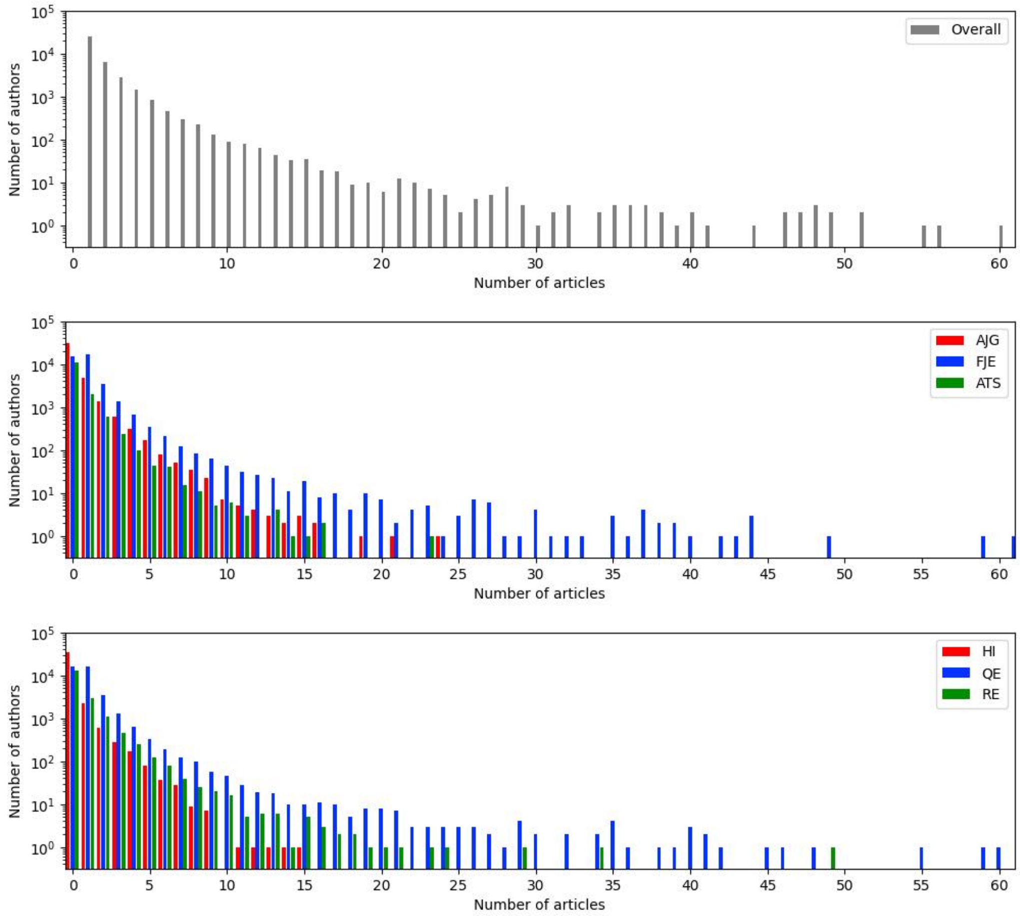


Table 3: Percentage change in average citation counts after removing the top-cited authors. We first compute the average number of citations received between 1 January 2019 and 31 December 2024 by articles published in the cited journals (horizontal axis) from articles published in the citing (vertical axis), as shown in Panel (b) of Table 1. Then we recompute these averages after removing all papers authored by or citing the top thirty most cited authors in the HI, QE or RE journal clusters respectively. Panel (a), (b) and (c) below presents the percentage changes in citation averages due to such exclusions. Journals are ordered by cluster here, and the colour coding is on a log scale, as shown on the right. Values less than 0.005 are omitted. The †† and † next to a journal name denote FJE journals and other ATS journals, respectively.

(a) Removing the thirty top-cited authors from HI journal cluster

Cited journals (articles published any time)

Citing journals (changes between two periods)	JF	JFE†	RFS	FRL††	IRFA††	RIBAF††	JBEF††	JEB††	IREF††	PBFJ†	NAJEF††	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	QREF†	JCM†	JIFMIM††	JIMF††	EMR††
JF	-57.5	-50.6	-53	-24.8	-100	-100	651.6	87.9	-100	-100		-51.7	6.3	-63.8	-39.1	-40.7	-27.9	-65.2	-53	-76.5	71.8	150.5	-100	-100	-46.3	-100
JFE†	-55.6	-39.5	-50	-30.7	-100	-100		-100	-100	-100	274.2	-54.6	69	-51.1	-22	-88.3	14.2	-31.6	-30.7	-79.7	52.3	133.9		-100	24.7	-100
RFS	-58.7	-61.7	-58.5	-100	-100	-100	293.1	145.7	882.7	-100	-100	-49.2	-1	-37.3	-39.7	-21.4	-15.5	-100	-28.1	-64.3	115	-100	227.6	-100	32.3	-100
FRL††	-45.3	-41.2	-45.6	7	12	8	13	-7	3.7	-9.2	8	-40.4	-9.8	-34.3	-36	-17.1	-19.6	-38.5	-13.4	-22.9	-8.7	12.7	4.1	-5.8	0.7	-5.8
IRFA††	-61.3	-59	-63.6	32.7	15.3	31.1	-1.6	3.3	14.2	-23.5	26.6	-56.1	-18.5	-48.3	-42	-36.1	-26.4	-42.2	-11.5	-21.5	-16.6	24.4	70	-2.2	1.1	6.3
RIBAF††	-50	-52.9	-58.1	20.3	5.5	5.7	8.7	-24.5	-3.9	-22.3	-1	-47.6	-17.4	-62.3	-62.6	-38.6	-21.9	-59.6	-27.5	-36.6	-14.1	-2.2	25.4	5	-22.2	-13.2
JBEF††	-56	-52.7	-62.2	-3	-35.3	-11	-13.5	-34.3	-36.7	28.2	-38.7	-41.9	16.9	-41.4	-22.3	-42.5	-35.9	-78.6	11.6	-65.8	1.8	-18	2.5	-39.5	-14.6	-55
JEB††	-53.2	-46.6	-41.9	6.1	-29.5	-30.5	38.6	-15.9	-20.1	-14.2	18.8	-38	-10.9	-49.1	-37.5	-8.2	-33.3	-74.5	-18.4	-59.5	4	-37.6		-1	-22.7	-5.3
IREF††	-61.5	-61.1	-62.4	14.1	4	2.2	-5	-29.4	-1.6	-23.5	5.9	-60.5	9.3	-55.5	-55.1	-45.4	-33.9	-60.3	-35.6	-26.5	-3.8	5.7	14.8	-4.1	4.1	-5.6
PBFJ†	-55.9	-43.8	-54.7	25.6	8.9	-36.6	102.8	-5.4	-9.5	5.4	27.4	-45.8	-15.5	-38.1	-15.5	-53.4	-56.1	-54.5	-11	4.4	15.7	-6.1	40.8	16.5	21.2	0.4
NAJEF††	-51.9	-57	-50.1	13.9	3	4.7	13.4	-6.3	6.5	-13.5	2.9	-40.4	5.5	-44.7	-39.1	-43.9	-19.6	-37.1	-20.2	-9.1	-19.7	22.2	31.1	1.4	8.8	3.5
JFQA	-47.8	-35.1	-40.9	-37	-100	-100	-18.1	36.6	17.1	-31.7		-9	21.4	-38.9	-35	24.5	-14.6	-70.9	-25.5	22.3	110.7	-100	-100	-100	-18.1	-100
JMCB	-79.8	-79.9	-80.6	-16.6	-58.3	11.2	-100	-37.5	-25.9	-100	25.1	-75.2	-4.3	-85.1	-77.1	-94.6	-65.5	-100	-40	-83.3	-6.5	-52.4		-11.1	-12.9	4.2
RF	-51.2	-50.2	-51.1	-55.6	107.4	211.1	-11.1	3.7	-100	-100	211.1	-37.4	-14.8	-41.1	-51.4	-46.9	-53.6	-64.4	-52.1	-100	148.9	211.1		-100	49.3	
JFI†	-55.3	-50.3	-65.3		-100	-100		13.8	-100		468.8	-12	-7.8	-65.5	-68	-100	33.8	70.6	18.5	-100	-100	-100			42.2	-100
JCF†	-56.2	-33.6	-38.4	33.2	-1.3		459.3	18.6	-100	91.9	59.8	-34.1	-60.8	-23	-60	-50	-60	-36.4	-39.4	-100	6.8	-53.4		-24.7	-100	44.3
JBF†	-60.3	-59.8	-58	-46.4	-35.6	-21.1	-4.4	16.8	-13.3	-9.4	99.4	-53.6	19.4	-46.8	9.1	-54.8	1.5	-51.7	15.5	-4.4	19.1	3.5	65.6	-36.8	27.6	81.2
JFM†	-47.5	-53.9	-32	131.9	166.7	255.6	-100		-100	392.3	-100	-41.7	-45.3	27.6	239.4	98.1	30.9	11.4	-100	21.2	1.6	-100	-100	18.5	42.2	-100
JFS†	-57.5	-59	-62	-35.3	-13	58.2	45	25.7	-27.5	-100	-30	-65.2	10.1	-38.9	-43.3	-13.8	-32.3	-68.6	2	-27.5	-23.2	-13	-100	-25	12.9	-24.3
JEF†	-54.6	-48.7	-52.7	24.1	37.8	22.6	-30	80.1	-32.2	-16	-52	-36.7	-9.3	-57	-82.5	-11	-60.8	-80.9	10.6	13.4	12.1	12.1	40.1	-45.8	-3.5	180.1
JEBO†	-69.6	-73.8	-70.7	-50.4	-71.1	-63.8	-7.8	-17.4	-31.1	-100	-53.1	-74.9	-34	-57.4	-83.5	-70.5	-66.6	-81.7	-60.1	-75	0.2	-56.6	-22.9	-72.5	-16.6	-48.6
QREF†	-53.9	-56.8	-58.7	12.1	-1.2	-6.2	-24.2	-21.1	1.6	-19.5	2.6	-50.1	4.2	-44.9	-64.5	-53.5	-35.9	-57.6	-28.5	-32.3	-6.8	-0.9	31.4	-11.4	-10.6	-32.8
JCM†	-34	-49.6	-47.1	-4.4	-6.1	-4.8	-4.8	14.2	-17.4	-12.1	-15.3	-29.5	4.5	-54.3		-36.5	-28.6	-16.3	42.8	-13.3	14.2	-10.4	-9.8	-19.4	-10.4	-22.7
JIFMIM††	-60.6	-57.7	-62.6	16	19.8	-1.8	-79.7	19.3	-9.4	-22.7	5.7	-54.6	-23.2	-49.2	-12.1	-21.2	-18.4	-65	-22.1	-27.1	22.2	29	9.8	-22.2	-0.9	-9.4
JIMF††	-63.8	-69.5	-70.7	-41	-26	-12.7	-77.1	-53.3	30.3	-63.9	-0.4	-72.1	-2.7	-56.8	-70	-59.2	-47	-66.1	-30.1	-46.7	-16.7	-2.6	28	-52	-3	9.8
EMR††	-25.6	-42.6	-50.1	4.5	-1.9	-24		10.3	-24	-43.3	-1	-46.4	-11.7	-31.4	-100	20.9	35.7	-59.9	-26.1	-36.7	-38.3	39.4	90	-11.9	71	-4.1

Colour scale: 0, -20, -40, -60, -80, -100

(b) Removing the thirty top-cited authors from the QE journal cluster

Cited journals (articles published any time)

Citing journals (changes between two periods)	JF	JFE†	RFS	FRL††	IRFA††	RIBAF††	JBEF††	JEB††	IREF††	PBFJ†	NAJEF††	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	QREF†	JCM†	JIFMIM††	JIMF††	EMR††
JF	0.1	0.3	-0.1	0.6	-49.7	0.6	0.6	0.6	0.6	0.6		0.3	0.6	-1	0.6	0.6	0.6	0.6	0.6	0.6	-2.2	0.6	0.6	0.6	0.6	0.6
JFE†	-0.3	-0.2	-0.1	-7.1	0.3	-49.8		0.3	0.3	0.3	0.3	0.2	0.3	0.3	0.3	0.3	0.3	-0.9	0.3	-4	0.3	-24.7		0.3	0.3	0.3
RFS	-0.5	0.1	-0.1	-8.1	-49.5	-100	1.1	1.1	1.1	1.1	1.1	-0.3	-1.3	0.4	1.1	-2.1	-2.6	-0.5	-1.4	-2.6	-3.6	1.1	1.1	1.1	-0.8	-32.6
FRL††	11.6	14.4	6.7	-40.1	-25.6	-47.1	-57.1	-15.4	-24.6	-7	-50.6	13.6	13.4	16.2	28.1	15.7	2.4	-5.1	-17.8	-20	10	-54.2	-85.4	-56.2	-30.3	-22.3
IRFA††	17.9	16.3	9.2	-66.5	-40.5	-60.7	-67.9	-7.1	-38.4	-15.7	-61.6	16.5	-0.3	9.3	20.3	20.1	-8.2	-8.7	-22.9	-34.5	-0.1	-59.1	-92.4	-62.6	-38.5	-29.3
RIBAF††	29.4	27.8	11.5	-85.4	-59	-23.6	-82.1	9.6	-43.4	-18.9	-71.2	20.6	14.7	12.3	55.5	59.4	22.9	-7.8	-2.5	-11.7	-6.6	-51.3	-96.5	-45.5	-42.3	-9.8
JBEF††	-6.9	-0.2	-3.7	-72.2	-64.4	-69.7	-29.9	-35.6	-59.5	-16.3	-67.8	-2.2	-2.8	8.6	-0.5	-2.1	-3.4	-19.5	-15.9	-61.4	8.7	-45.9	-48.5	-58.4	-22.2	-66.1
JEB††	-4.6	0.3	-6	-79.4	-51.9	-40.9	15.4	-12.9	-24.4	-14.5	-23.1	-3.4	6.8	-1.1	-0.8	-9.7	-8.4	-34.1	-12	-26.6	5.8	-13.5		-44.4	-17.3	-38.7
IREF††	14.2	13.9	4.3	-62.4	-54.2	-57	-67.1	-16.5	-18.7	-27.8	-57.7	11.7	10	14.5	17.4	15	-2.6	-5.8	-14.8	-27.8	-6.9	-43.4	-85.3	-59.5	-23.5	-37.8
PBFJ†	4.6	6.7	4.7	-59.5	-47.4	-67.3	-100	-18	-32.2	-15.7	-64.5	6.8	-1.5	-0.1	-12.8	1.5	-17	-1.4	-28.4	-15.3	-17.4	-17.6	-100	-47.4	-54.5	-35.5
NAJEF††	21.2	24.9	18.2	-80.5	-69.1	-67.3	-89.9	-35	-43.5	-31.1	-37.4	22.2	6.2	16.2	37.8	37.7	-3.5	-1.7	-10.1	-31.3	0.2	-53.1	-73.5	-63.7	-25.6	-47.7
JFQA	-0	-0.3	0.4	-14.2	-11.2	1.4	1.4	-15.5	1.4	1.4		-0.9	-0.4	0.5	-2.3	-2.8	-3.1	0.2	-7.8	-1.6	-4.4	1.4	1.4	1.4	-3.6	-23.9
JMCB	0.2	0.2	0	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2		0.2	-0.7	0.2
RF	0.2	0.2	-0.1	-42	-32.4	1.4	-42	1.4	1.4	1.4	-49.3	-0.5	1.4	-0.7	1.4	1.4	-2.3	-1.4	1.4	-1.6	-3.6	1.4		-49.3	1.4	
JFI†	-1.5	-0.1	-0.3		0.6	0.6		-19.6	0.6		0.6	-1.5	-7.6	-2.5	0.6	-1.7	-11.3	0.6	0.6	0.6	0.6	0.6			0.6	0.6
JCF†	3.5	0	0.2	-15.8	-21.3		5.6	-16.8	-20.8	-9.9	-1.9	-1.4	2.4	0.3	-1.9	1.2	0.6	-4.8	-1.4	5.6	-5	-20.8		-22.8	5.6	-11.4
JBF†	0.2	-0.9	-0.9	-29.7	-24.8	-34.5	5.7	-2.4	-11.5	-4.2	-29.5	-0.1	4.3	3.3	1.9	3.4	-0.6	-7.5	0.6	-9.4	-0.9	5.7	-36.6	-33.7	-9.2	-20.7
JFM†	1.8	0.6	0.5	-57.6	-59.3	-27.7	-7		-33.2	-8.2	-34.9	0.8	5.7	-3.6	8.5	5.4	-13.5	0.6	-27.7	-21.1	-1.9	8.5	8.5	-15.6	-34.9	-100
JFS†	5.9	-4.8	-5.7	-65.7	-51.5	-59	-43.6	-9.7	-1.2	-54.8	-33.8	-5.1	6.8	5.5	12	-11.5	12.1	-35.9	-7.3	-9.7	4.6	-21	-100	-24.1	5.1	-26.4
JEF†	2.4	2.3	0.8	-75.7	-68.4	-67	-5.7	-3	-27	-9.4	-35.3	-0.5	-7.4	-1.1	13.2	-6.8	-1.9	-7.4	-22.5	-10.1	-35.8	-17	-24.5	-45.2	-20.3	13.2
JEBO†	-10	-14.6	-10.7	-73.6	-65.9	-68	-4.7	-17.2	-44	-63.5	-50.2	-13.3	-1	-1.8	-12.3	-13.2	-18.2	-38.1	-17.2	-43.9	-1.3	-10.5	-65.9	-46.4	-11.3	-31.8
QREF†	11.4	14.2	3.7	-81.1	-68.2	-57.6	-64	1.3	-48.1	-25	-58.6	5.2	14.6	-6.3	13.2	10.3	-0.1	-8	-12.3	-25.3	-0.1	-27.5	-82	-45.4	-34.5	-25.6
JCM†	9.6	17.2	11.7	-93.7	-83.8	-96.2	-100	-41.4	-81.2	-54.9	-95.5	27.2	24	48.6		8.6	-39.7	1.1	-100	-65.1	95.5	-68.2	-38.8	-81.6	-22.7	-91.9
JIFMIM††	10.4	8.7	3	-80.5	-62.3	-66.7	-77.1	-6.5	-40	-46.1	-60.6	7.5	26.6	22.4	24.7	3.8	11.5	-16.2	-21.5	-8.8	-26	-81	-70.2	-35.5	-13.8	-38.6
JIMF††	-5.8	-8	-6.5	-67.3	-43	-29.3	-68.2	-25.9	-5.3	-35.5	-32.9	-11.2	2.5	-8.9	0.7	-17.2	-9.9	-9.1	-7.2	-18.5	-5.1	-42	-100	-27.8	-4.7	-10.6
EMR††	-21.5	-1.4	-3.6	-65.1	-43.7	11.1		-28.3	-30.5	-28.1	-62.8	-6	2.4	-3.5	38.9	13.7	19.1	-37.4	-17.2	38.9	-9.8	-63	-100	-40.7	-16.6	-19.5

Colour scale: 0, -20, -40, -60, -80, -100

(c) Removing the thirty top-cited authors from the RE journal cluster

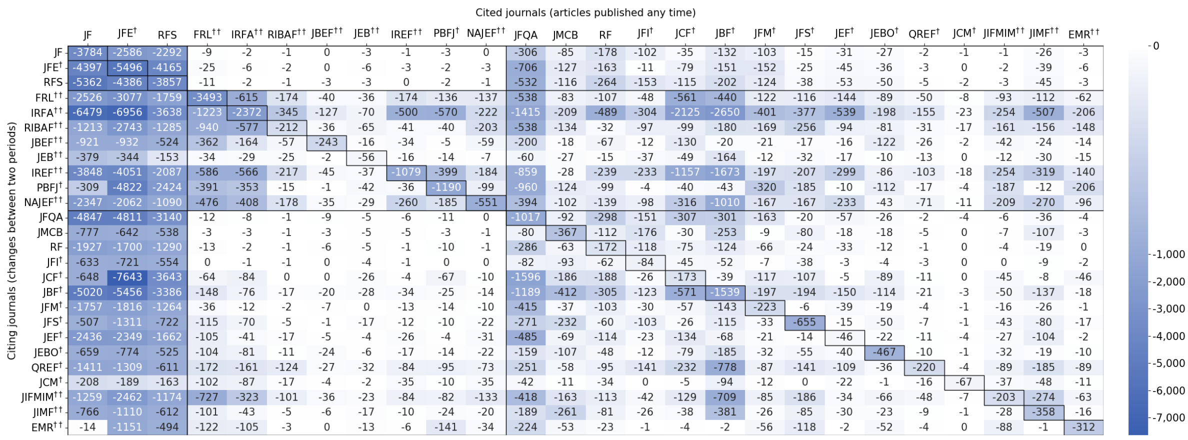
Cited journals (articles published any time)

Citing journals (changes between two periods)	JF	JFE†	RFS	FRL††	IRFA††	RIBAF††	JBEF††	JEB††	IREF††	PBFJ†	NAJEF††	JFQA	JMCB	RF	JFI†	JCF†	JBF†	JFM†	JFS†	JEF†	JEBO†	QREF†	JCM†	JIFMIM††	JIMF††	EMR††
JF	1.3	-4.3	-2.8	10.6	-30.9	38.3	38.3	-30.9	38.3	-7.8		-4.4	-26	-11.3	-62.6	-30.9	-31.8	22.9	-82.7	21	2.7	-7.8	38.3	38.3	8.6	-53.9
JFE†	-6.9	-8.3	-2.4	-1.2	-50.6	-100		-25.9	48.2	-100	48.2	-8.7	-11.1	-13.8	-50.6	-50	-24.2	-12.4	-61.6	-3.4	3.4	11.1		-100	-1.2	-50.6
RFS	-7.3	-13.5	-7.5	-5.1	49.2	49.2	49.2	11.9	49.2	49.2	-100	-12	-7.5	-12.2	-55.2	-30.8	-28.4	5.9	-34.5	19.4	16.6	-10.5	49.2	49.2	-11.1	-0.5
FRL††	-10.6	-20.8	-11.8	4.8	6.8	1.5	5.8	-22.6	4.1	-8.2	9.8	-22.6	-25.2	-16.3	-51.9	-34.8	-24.1	-9	-22.6	2.2	-12.5	5.2	3.1	-1	6.1	-3.7
IRFA††	-18.4	-31.8	-16.1	18.9	-2.7	7.3	4.7	-27.7	2	-20.8	23.1	-30.5	-32.4	-24.9	-76.4	-62.4	-30	6.9	-39.6	6	-6.7	16.7	35.5	-2.1	7.8	-19.2
RIBAF††	-15.3	-34.5	-24.6	16.8	5.3	-14.3	7.1	-45.2	-11.1	-39	16.5	-27.1	-56.3	-41.8	-70.5	-56.6	-50.9	-2.9	-58.4	0.3	-20.5	-11.7	38.8	-12.8	2.6	-21.3
JBEF††	-15.6	-35.3	-23.8	2.5	-14.5	-18.4	12.9	-47.4	-6.3	2.6	-13.8	-34.5	-47.2	-12.8	-68.9	-67.9	-48.7	-3.1	-72.1	-17.9	11	-17.9	36.8	-11.6	-17.4	8
JEB††	-31	-39.7	-37.5	25.7	-20.7	-11.4	34.6	-23.3	-28.4	-55.1	-9.3	-45.4	-13.5	-25.8	-75.7	-65.7	-59.7	23.6	-56	-5.6	1	-13.5		-35.9	-5.3	-40.5
IREF††	-23	-33.9	-18.5	5.8	4.8	-11.5	-12.5	-36.4	-2.3	-22.3	8.1	-30.8	5	-25.7	-70	-58.9	-37	-4.1	-45.5	1.4	-17.2	-1.7	21.7	-6.6	10.3	-17.8
PBFJ†	-1.2	-19.1	-12.2	10.4	2.1	10.9	47.8	-36.6	22.1	-5.7	9.6	-15.6	-56.3	-28.1	-69.2	-51	-28.9	9.9	-54.6	19.5	-40.8	-24.7	2.6	-21	28.5	-29.6
NAJEF††	-11.6	-24.2	-11.3	11.5	6	-4.1	8.7	-22.8	3.5	-7	6.2	-14.3	-26.1	-10.7	-71.1	-57.8	-22.7	0.5	-31.3	5.1	-12.6	5.5	16.5	-4.5	3.2	-8.8
JFQA	-4.1	-12.8	-2.9	-67.6	-21.1	-100	89.3	-64.9	-70	-12.4		-14.9	-35.7	-5.9	-64.1	-54.7	-36.1	17	-80.9	25.6	-27.9	-100	57.8	40.2	47.2	-100
JMCB	-43.8	-55.5	-45.6	6.6	-36	-14.7	-14.7	-52	-14.7	-100	-4	-48.3	-5.9	-53.2	-71.8	-71.1	-57.1	-57.4	-56	-16.8	12.3	-45.2		-40.3	-4.6	11.9
RF	-6.6	-11	-13.8	-74.5	18.9	78.3	1.9	-70.3	-100	-64.3	-10.8	-8	-41.4	-21.2	-62.4	-43.5	-13.5	9.6	-24.5	29.7	-1.9	-10.8		-55.4	14.1	
JFI†	-16.9	-13.7	-23.2		-100	-100		-100	256.9		-100	6.7	-38.9	-40.5	-59.9	-60.3	-21.3	7.1	-33.1	-100	-100	-100			-70.3	-100
JCF†	51.4	-24.3	-20.9	-11.9	-9.3		362.7	-43.9	15.7	-50.1	65.3	-31.4	-37.5	-13	-100	4.7	21.2	-36.9	-73	-100	-15.9	-22.9		-28.8	131.4	-55.2
JBF†	-6.9	-25.3	-8.1	-17.4	-11.8	6.7	9.6	-68.7	27.9	-55.5	5.6	-15.1	-39.2	-11	-56.1	-69.8	-19.2	23.3	-48.5	30.5	9.5	-12.7	22.2	-31	3.9	20.9
JFM†	-9	-11.7	-9.4	15.3	-0.5	-55.8	-62.1		22.4	22.4	32.6	-13.6	5.4	-18.4	-18.6	-37.5	-8	-2.5	-33.7	-3.5	-55.8	32.6	-100	25.3	19.4	32.6
JFS†	-12.6	-46	-33	11.4	-18.9	47.5	35.2	-54.9	35.2	-73	-16.1	-48.2	-40.7	-32.4	-62	-41.5	-65.8	9.6	-33.6	-18.9	-36.4	-18.9	170.4	-34.7	-11.3	-6
JEF†	-4.2	-15.7	-4.5	29.5	-1.8	3.5	21.8	-16.5	-5.7	-12.3	25.3	-9.6	-10.3	-13.7	-51.3	-68.2	-27.9	-26.9	-30.8	-21.1	-22.1	7.2	-26.9	-24.6	0.7	46.2
JEBO†	-30.1	-44.1	-25.1	-27.4	-33.4	-27.3	0.4	-29.5	-32	-62.2	-28.5	-43.2	-21.4	-27.6	-69.8	-71.1	-47.1	-27.6	-39.6	-17.1	-1	-14.1	-29.5	-49.6	-11.4	-53
QREF†	-19.3	-28.8	-20.4	11.1	7.1	-14.5	-8.6	-27.9	2.5	-22.9	-7	-27.2	-24.8	-25.3	-80	-71.5	-46.3	11.6	-59.3	-0.4	0.1	-3.6	22.4	-16.6	-9.6	-18.8
JCM†	-14.3	-20.9	-26.4	0	-2.6	-6	-26.4	-11.7	3.4	-22.4	5.6	-16.4	-7.7	-26.8		-57.9	-10.1	-21.7	26.2	-27.9	26.2	-12	-15.4	-3.5	-9	-5.4
JIFMIM††	-11.8	-27	-15.3	23.8	8.1	23.1	1.7	-28.1	12.1	-54.4	35.2	-16.6	-36	-15	-82	-68.2	-47.8	19.4	-57.1	0.4	-47.8	8.5	-21.3	-12.8	29.9	-15.4
JIMF††	-23.3	-34.6	-25.6	1.3	-27.6	5.2	10.3	-62.5	9.6	-37.8	-2.9	-23.6	-15.6	-37.4	-71.9	-59.6	-40.2	-18.1	-37	-2.8	-3.5	-21.7	2.9	-26	-5.1	-14.2
EMR††	-2.9	-27.5	-17.3	22.9	12.3	-25.6		-4	-25.6	-23.2	10	-39.2	-23	-17.3	-100	-49.3	-20.3	-16.2	-51.8	-38	-22.7	-0.8	-38	-18.3	11.6	-15.8

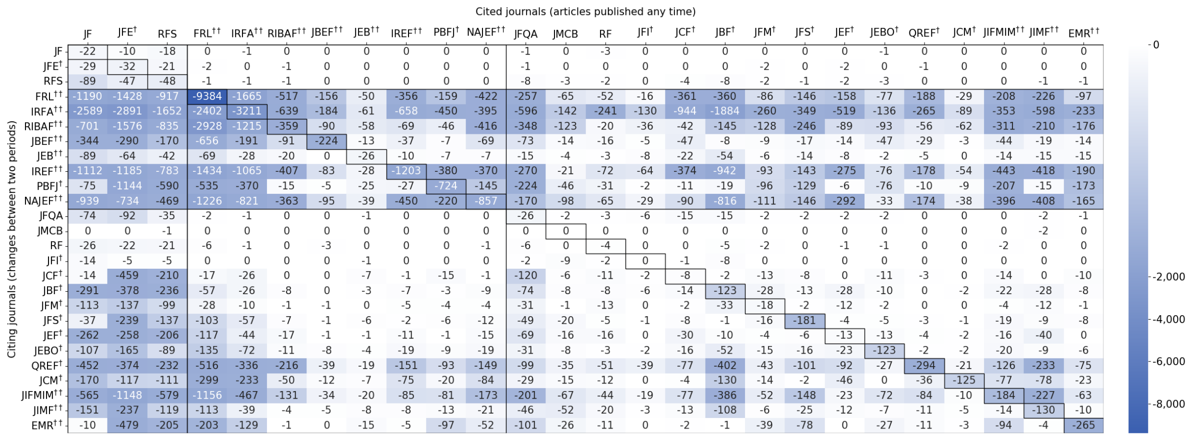
Colour scale: 0, -20, -40, -60, -80, -100

Table 4: Absolute change in total citation counts after removing the top-cited authors. We first compute the total number of citations received between 1 January 2019 and 31 December 2024 by articles published in the cited journals (horizontal axis) from articles published in the citing (vertical axis). Then we recompute these total values after removing all papers authored by or citing the top thirty most cited authors in the HI, QE or RE journal clusters respectively. Panel (a), (b) and (c) below presents the absolute changes in citation averages due to such exclusions. Journals are ordered by cluster here, and the color scale is centred at the 15.87th percentile (corresponding to one standard deviation below the mean in a normal distribution). The †† and † next to a journal name denote FJE journals and other ATS journals, respectively.

(a) Removing the thirty top-cited authors from HI journal cluster



(b) Removing the thirty top-cited authors from the QE journal cluster



(c) Removing the thirty top-cited authors from the RE journal cluster