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The enduring influence of retracted research: determinants and citation patterns across three disciplines

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Abstract
Scientific retractions play a crucial role in maintaining the integrity of academic research. However, retracted articles continue to be cited, raising concerns about the persistence of flawed research in scholarly discourse. This study investigates the determinants of post-retraction citations in three disciplines—Business, Social Sciences, and Technology—using a dataset of 531 articles from the Retraction Watch database. We enhance the data with citation metrics from Scopus and Semantic Scholar and institutional prestige from the Academic Ranking of World Universities. Employing a self-controlled case series approach—using each article's pre-retraction citations as a baseline—we apply negative binomial regression for rate modeling to compare citation patterns before and after formal retraction. Our analysis reveals that retracted papers published in prestigious journals and authored by scholars from top-ranked institutions receive more post-retraction citations. Moreover, leveraging Semantic Scholar's citation types (Highly Influential, Background, Methodology, and Results), we assess how retracted articles continue to shape subsequent research. We found that the prestige of journals and authors' institutions also influence highly influential and background citations. Additionally, the severity of misconduct is not significant in any of the models, implying that the scientific community in these three fields appears unaware of questionable research practices. These findings underscore the need for better mechanisms to prevent the spread of erroneous research and raise important questions about the role of academic prestige in the continuation of flawed science.

Keywords Scientific retractions · Post-retraction citations · Self-controlled case series · Negative binomial regression · Academic prestige

Introduction

Scientific misconduct has become an increasingly pressing concern within the academic community, prompting discussions about the reliability of scholarly work and the mechanisms available to address flawed research (Armond et al., 2021; Hall and Martin, 2019; Marcus and Oransky, 2014). Retractions serve as a critical mechanism for journals to formally withdraw erroneous or unethical publications, ensuring the integrity of scientific

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discourse and holding researchers accountable for questionable practices. However, even after an article is retracted, it is often still cited, and sometimes researchers are unaware of its retraction status (Bar-Ilan and Halevi, 2017). This issue undermines the credibility of scholarly discussions and perpetuates the influence of flawed findings.

This study investigates the determinants of citations to retracted papers in Business, Social Sciences, and Technology. These fields share institutional and epistemic characteristics that may shape the continued circulation of retracted research after formal correction. Compared with the biomedical sciences, where most prior studies on post-retraction citations have been conducted, they tend to exhibit less standardized correction mechanisms, weaker replication norms, and more heterogeneous citation practices, potentially increasing the role of reputational signals in sustaining the visibility of retracted work.

Using a dataset of 531 retracted documents from the Retraction Watch (RW) database, supplemented with information from Scopus, the Academic Ranking of World Universities, and Semantic Scholar, we examine how journal prestige, institutional reputation, and the severity of misconduct influence citation persistence. To better understand why these studies continue to be cited, we move beyond total citation counts and analyze four citation types identified by Semantic Scholar's AI-based classification system: Highly Influential, Background, Methodology, and Results. Methodologically, we employ a self-controlled case series approach, in which each article serves as its own baseline, and we use negative binomial regression to compare citation rates before and after formal retraction.

Our findings indicate that retracted papers from highly ranked institutions and published in prestigious journals sustain citation trajectories comparable to those of non-retracted works, evoking a "Matthew effect" (Merton, 1968). Two primary factors may explain this phenomenon. First, a formal retraction notice does not necessarily deter scholars from citing the flawed research. Second, many authors may be unaware that the paper has been retracted, especially if they copy references from prior bibliographies without verifying the source's current status. Both explanations raise essential questions about the robustness of science's self-correcting mechanisms, highlighting how reputation—both of journals and institutions—can inadvertently perpetuate erroneous findings. These results underscore the need for more effective retraction protocols and greater vigilance in scholarly communication to ensure the integrity of future research.

The rest of this paper is structured as follows: Sect. "Background and Hypotheses" provides a literature review and presents our hypotheses. Sect. "Data and variables" describes the research setting, including the dataset and variables. Section "Methodology" outlines the methodology, followed by the results and a robustness analysis in Sect. "Results". Finally, Sect. "Conclusion and limitations" discusses the conclusions, limitations, and avenues for future research.

Background and hypotheses

In this section, we provide a theoretical framework and previous empirical support for the phenomenon of citations to retracted papers, which allows us to set our hypotheses.

The phenomenon of post-retraction citations

Retracted papers continue to be cited frequently, as confirmed by numerous studies. For example, Chen et al. (2013) found that retracted papers receive an average of 22 citations.

More concerningly, retractions do not appear to significantly reduce overall citation counts (Bolboacă et al., 2019). This persistence poses a critical challenge to scientific integrity for two main reasons. First, it reflects a failure in the self-correction mechanisms of science, allowing discredited research to remain part of the scholarly discourse. Second, these citations may influence subsequent research, propagating flawed findings and potentially distorting scientific progress (Schneider et al., 2020; van der Vet & Nijveen, 2016).

Retractions are intended to correct the scientific record, yet research shows that retracted articles continue to be cited long after the retraction notice is issued (Bar-Ilan and Halevi, 2018). Alarmingly, such citations often appear in high-impact journals, amplifying the spread of discredited findings (Neale et al., 2010). This phenomenon highlights significant shortcomings in academic publishing, including delays in updating citation databases and the ineffective dissemination of retraction notices (Brainard & You, 2018). Some studies have found that many authors citing retracted papers do not acknowledge the retraction, suggesting a widespread lack of awareness (Madlock-Brown & Eichmann, 2015). The motivations behind these citations vary, ranging from simple oversight to the deliberate use of discredited findings to support particular arguments (Fang et al., 2012).

Despite the significance of, this issue, relatively few studies have systematically analyzed post-retraction citations. In biomedicine, Hsiao and Schneider (2022) found that retracted publications continued to be cited even after retraction. Similarly, Halevi and Bar-Ilan (2020) analyzed medical and biomedical retractions using the Retraction Watch database and found that the average time between publication and retraction decreased from 2.67 years in 2010 to 1.07 years in 2014. They attributed this decline to technological advancements and increased post-publication scrutiny (Bar-Ilan & Halevi, 2018).

In the field of Economics, Bolland et al. (2022) expressed concern over the significant number of citations to retracted papers that fail to acknowledge their retracted status. They emphasize the need to assess the impact of citing retracted papers on research outcomes and conclusions.

Candal-Pedreira et al. (2020) analyzed 304 biomedical papers retracted between 2014 and 2016 and examined citation patterns before and after retraction. They found that retracted papers continued to be cited, particularly in lower-impact journals. Notably, only articles published in first-quartile journals exhibited a decline in citations following retraction.

An important factor influencing citation persistence is the expertise of the citing researchers. Woo and Walsh (2024) found that scholars unfamiliar with the field of a retracted paper were more likely to cite it compared to experts in the field. This suggests that retraction awareness and domain expertise help mitigate the spread of discredited research.

A key challenge in analyzing post-retraction citations is determining whether they criticize or reinforce the validity of flawed research (Athar, 2011). If citations propagate incorrect findings rather than critically addressing them, the consequences can be severe, particularly in fields that directly impact public health. Research shows that citations explicitly acknowledging retractions remain a minority. Schneider et al. (2022) found that negative citations and those explicitly stating the retraction status represent only a small fraction of citations to retracted papers. Similarly, Bar-Ilan and Halevi (2017) examined the sentiment of citations to retracted articles and found that most were positive, meaning the retracted paper was cited in support of the citing study's findings rather than as an example of flawed research.

Consequently, it is crucial to further investigate the persistence of post-retraction citations and why they remain predominantly positive.

The determinants of post-retraction citations (hypotheses)

A review of the literature has identified several key determinants influencing the citation counts of retracted papers. First, articles published in high-impact journals tend to receive more citations overall, even after retraction. Second, the reputation of the authors' affiliated institutions has a positive effect on the number of citations a retracted paper continues to receive (Lu et al., 2013). Third, the severity of the retraction—whether due to ethical misconduct, data falsification, or honest errors—can shape how the research community responds, influencing the persistence of citations. However, this relationship is not uniform across disciplines. Some academic fields exhibit greater vigilance toward retracted papers, resulting in fewer citations regardless of journal recognition (Cokol et al., 2007). Additionally, the visibility and clarity of retraction notices can mitigate continued citations, even in high-prestige journals (Fang et al., 2012). The following subsections provide theoretical and empirical support for our study hypotheses.

The effect of journals' prestige

Research suggests that articles published in high-impact journals continue to receive citations post-retraction at higher rates than those in less prestigious outlets (Fang et al., 2012). Furman et al. (2012) found that articles in well-known journals maintain strong citation trajectories due to their initial impact and visibility within the academic community. Similarly, studies by Mott et al. (2019) and Neale et al. (2010) confirm that journal prestige influences citation persistence, even for retracted papers.

Several factors contribute to this phenomenon. Recognized journals benefit from extensive distribution networks and broader accessibility, increasing the likelihood of their articles being cited (Larivière & Sugimoto, 2018). Moreover, publications in prestigious journals are often perceived as more credible, leading researchers to cite them regardless of their retraction status (Budd et al., 1998). Additionally, network effects within elite academic circles amplify the dissemination of articles from high-profile journals (Borgman & Furner, 2002). Based on this evidence, we propose our first hypothesis:

H1 *Publishing in a high-prestige journal causally increases the number of post-retraction citations a paper receives.*

The effect of the institutions' reputation

Numerous studies have demonstrated that research produced by scholars affiliated with prestigious institutions tends to receive more citations, even after retraction. One possible explanation is that institutional prestige enhances visibility and perceived credibility. Furman et al. (2012) found that retracted biomedical papers from top-ranked universities continued to be cited at higher rates than those from lesser-known institutions, suggesting that institutional reputation mitigates the negative effects of retraction.

Similarly, Azoulay et al. (2017) investigated the impact of retractions on authors' careers and found that while retractions reduce citation rates overall, this effect is weaker for authors affiliated with prestigious institutions. Their findings suggest that institutional reputation plays a role in sustaining the visibility of retracted research.

The continued citation of retracted papers from elite institutions underscores the persistence of prestige-based biases in academic publishing. Even after formal retraction, the credibility and influence associated with high-ranking universities contribute to the continued dissemination of their research. Based on these insights, we propose our second hypothesis:

H2 *The prestige of the authors' affiliated institutions causally increases the number of post-retraction citations their retracted papers receive.*

The effect of misconduct severity

Empirical evidence consistently indicates that the severity of misconduct influences how sharply citations decline following a retraction. Severe cases, such as data fabrication or falsification, lead to more significant decreases in citation counts than retractions due to honest errors or authorship disputes.

For example, Budd et al. (1998) categorized retraction reasons and examined subsequent citation patterns, finding that papers retracted due to fraud or plagiarism experienced a more substantial drop in citations compared to those retracted for less severe issues. Redman and Merz (2008) also highlighted that the academic community responds more harshly to severe misconduct, with greater reputational penalties and steeper declines in citation rates.

Similarly, Wager and Williams (2011) analyzed retractions in medical journals and found that the reasons for retraction significantly influenced post-retraction citation rates. Papers retracted due to data falsification saw a more pronounced decline in citations compared to those retracted for methodological errors. Van Noorden (2011) further explored, this issue and noted that while severe misconduct generally leads to fewer citations, some cases exhibit variation based on discipline, author prominence, and the visibility of the retraction notice.

Furman et al. (2012) found that retractions due to scientific fraud resulted in the sharpest declines in citation counts, reinforcing the role of retractions in maintaining scientific integrity. Resnik and Dinse (2013) confirmed this trend, demonstrating that papers retracted for ethical violations experienced a more significant reduction in citations than those retracted for unintentional errors.

However, the degree to which misconduct affects citations varies across fields. Lu et al. (2013) found that fraudulent papers in certain disciplines faced substantial declines in citations, while those retracted for honest mistakes saw only moderate reductions. The academic community's trust in scientific research appears to influence citation behaviors, with researchers avoiding citations to papers linked to serious ethical breaches to preserve their own credibility.

Azoulay et al. (2017) further demonstrated that authors involved in severe misconduct face substantial career setbacks, indirectly affecting the citation rates of their retracted publications. This erosion of trust highlights the broader implications of misconduct on academic reputations and knowledge dissemination.

In summary, the severity of misconduct plays a crucial role in determining post-retraction citation patterns. Papers retracted due to severe violations of academic integrity experience sharper declines in citations due to the loss of credibility and trust within the scientific community. Based on these findings, we propose our third hypothesis:

H3 *The severity of the misconduct leading to a retraction causally decreases the number of post-retraction citations a paper receives*.

Figure 1 illustrates the hypothesized relationships between journal prestige, institutional reputation, and misconduct severity in shaping post-retraction citation patterns. It visually represents our theoretical framework, highlighting the expected positive effects of journal and institutional prestige on citation persistence and the anticipated negative impact of misconduct severity.

Measuring misconduct severity

Various criteria have been proposed to classify retractions based on the severity of misconduct. For example, Bar-Ilan and Halevi (2018) distinguish between ethical misconduct, scientific distortion, and administrative errors. Azoulay et al. (2015) offer a different approach, categorizing retractions into three groups: (i) "Strong shoulders" (retractions that do not invalidate the results), (ii) "Shaky shoulders" (retractions that partially invalidate the results), and (iii) "Absent shoulders" (retractions due to fraudulent results). Kuroki (2018) introduced an alternative classification framework based on truth, trust, and risk, identifying three types of misconduct: (i) betrayal of truth (fabrication and falsification), (ii) betrayal of trust (plagiarism, irreproducibility, and inadequate research practices), and (iii) risk to public safety and industrial applications. More recently, Hall and Martin (2019) developed a misconduct taxonomy that categorizes retractions into four levels of severity: (i) appropriate conduct, (ii) questionable conduct, (iii) inappropriate conduct, and (iv) blatant misconduct. For this study, we adopted Hall and Martin's (2019) taxonomy, as it provides a comprehensive and detailed framework for classifying misconduct.

We classified research retractions using the reasons for retraction provided by Retraction Watch (RW), focusing on the types and severity of misconduct. We identified five distinct categories of misconduct: data manipulation; use of others' work, which includes plagiarism and data theft; use of one's own work, encompassing self-plagiarism and redundant publication; authorship disputes; and manipulation of materials and methods. The last category was added to Hall and Martin's original taxonomy to address methodological distortions.

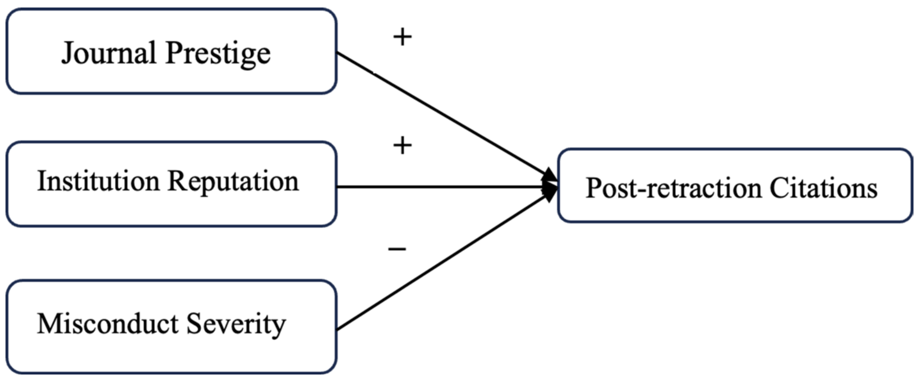

Fig. 1 Causal diagram of factors influencing citations to retracted papers

To evaluate the severity of the misconduct, we categorized retractions into four levels, as defined by Hall and Martin (2019). These levels include appropriate conduct, questionable conduct, inappropriate conduct, and blatant misconduct. This classification helps to better understand the seriousness of the issues leading to retractions in the research community. Since no standardized methodology exists for classifying misconduct severity, we relied on the examples provided in the original taxonomy as a guideline for classification. We acknowledge the inherent subjectivity in this process and emphasize the need for a universally accepted misconduct classification system within the scientific community.

Given that many retracted articles have multiple reasons for retraction, we developed a methodology to simplify this information into a single severity measure. We refer to this as the Maximum Blame Criterion (MBC). This ensures that each retracted article is assigned a single severity level by following these steps.

- If a retracted article has only one stated reason that classification is used.
- If a retracted article has multiple reasons that fall within the same category, we preserve that classification.
- If a retracted article has multiple reasons across different categories, we assign it the highest level of misconduct severity among them.
- In cases where multiple reasons exist with the same highest severity level, we retain all unique nature-severity combinations for reference.

The MBC approach provides a systematic way to aggregate and standardize misconduct classifications while minimizing information loss. However, we acknowledge that this method does not quantify the degree of misconduct beyond its categorical assignment. Future research should explore ways to develop a quantifiable measure of misconduct severity to improve standardization across studies.

Data and variables

Database

Our dataset integrates variables from four distinct sources, allowing for a comprehensive analysis of post-retraction citation patterns. The first source is the Retraction Watch (RW) database, from which we extracted data from its inception until June 14, 2021. To ensure consistency, we applied specific inclusion criteria: publications had to be classified as either research articles or review articles (excluding other entry types), belong to the "Business/Technology (B/T)" category defined by Retraction Watch, and have a Digital Object Identifier (DOI) to enable cross-referencing with citation databases. The B/T category includes papers classified under Business Management, Social Sciences, and Technology. We use this classification as a pragmatic grouping of adjacent non-biomedical fields rather than as a strict disciplinary taxonomy. This grouping is analytically relevant because these domains share organizational and publication characteristics, such as less standardized correction mechanisms and more heterogeneous citation practices that may influence how retraction signals are incorporated into subsequent citation behavior. After applying these filters, 1,445 valid cases remained from the original 27,439 retracted articles in the database. From RW, we collected key information, including retraction reasons, retraction dates, the number of authors, and author affiliations.

The second data source is Scopus, from which we retrieved citation profiles for each article using its DOI. We collected annual citation counts from 2005 to 2020, excluding self-citations. Additionally, we obtained two key journal impact indicators: the Source Normalized Impact per Paper (SNIP) and CiteScore. SNIP, developed by the Centre for Science and Technology Studies at Leiden University, is a field-normalized metric that adjusts for citation differences across disciplines (Moed, 2016). CiteScore, provided by Elsevier, measures a journal's impact by calculating the average number of citations received per document over a three-year period (Elsevier, 2023).

The third source is Semantic Scholar, which offers a unique classification of citations based on their function within citing articles. Unlike traditional citation counts, Semantic Scholar categorizes citations into four types: Highly Influential, Background, Methodology, and Results (Lo et al., 2020). Highly influential citations denote those that significantly impact the citing paper. Background citations establish foundational context, while methodology citations reference the retracted paper's methods. Results citations are those referenced in relation to empirical findings. These classifications enhance our ability to assess the differential impact of retracted papers across various research contexts (Valenzuela et al., 2015).

The fourth source is the Academic Ranking of World Universities (ARWU), specifically using data from the Center for World University Rankings (CWUR). To measure institutional prestige, we extracted the highest CWUR score among the authors' affiliations for each retracted paper, ensuring that the institutional ranking reflects the most prestigious university involved in the research.

After integrating these four data sources, only 531 articles remained in our final dataset due to matching constraints across the databases. This dataset provides a robust foundation for analyzing the determinants of post-retraction citations. The following section details the key variables used in our analysis (see Table 1).

Variables

Dependent variables

This study examines five dependent variables, each corresponding to a distinct type of post-retraction citation. These variables enable a nuanced understanding of how retracted papers continue to be cited across different research contexts. Below, we define the five dependent variables.

- Total Post-Retraction Citations (CITATIONS), which represents the total number of citations a retracted paper receives after its retraction date, excluding self-citations. This variable captures the overall extent to which retracted papers remain part of scholarly discourse.
- Highly Influential Post-Retraction Citations (HIC), which measures the number of times a retracted paper is cited as a significant contribution to the citing study. This classification is derived from Semantic Scholar's citation categorization, which identifies citations that have a substantial impact on subsequent research.
- Background Post-Retraction Citations (BACKGROUND). This metric quantifies citations where the retracted paper is referenced in the background or literature review section of the citing article. Such citations typically acknowledge previous work but do not necessarily rely on the retracted study's findings or methods.

– Method Post-Retraction Citations (METHOD), which reflects the number of times a retracted paper is cited in support of the methodological framework of the citing study. These citations suggest that elements of the retracted paper's methodology continue to be employed in subsequent research, despite the formal retraction.
– Results Post-Retraction Citations (RESULTS), which represents citations where the retracted paper's findings or conclusions are explicitly referenced in the citing article. This variable is particularly relevant in assessing the persistence of flawed scientific claims, as citations to results may indicate that the retracted study continues to influence empirical research.

By distinguishing among these five types of post-retraction citations, this study provides a granular analysis of how retracted research remains embedded within academic literature. The following section describes the independent variables used to investigate the determinants of these citation patterns.

Independent variables

In line with our theoretical framework and hypotheses, we selected four independent variables to measure journal prestige, institutional reputation, misconduct severity, and scientific discipline. These variables are essential for analyzing the determinants of post-retraction citations.

To assess journal prestige, we employ two widely used impact indicators: SNIP (Source Normalized Impact per Paper) and CiteScore. SNIP, developed by the Centre for Science and Technology Studies at Leiden University, is a field-normalized citation metric that accounts for differences in citation practices across disciplines (Moed, 2010). CiteScore, provided by Elsevier, calculates the average number of citations per document published in a journal over a three-year period, offering a comprehensive measure of a journal's citation influence (Elsevier, 2023). These metrics enable us to evaluate whether journal prestige affects the continued citation of retracted papers.

To measure institutional reputation, we use the Academic Ranking of World Universities (ARWU), specifically the highest institutional ranking among the affiliations of a retracted paper's authors. This approach ensures that our measure reflects the maximum level of institutional prestige associated with each paper.

To capture the severity of research misconduct, we construct an interval variable (MISCONDUCT) that represents the weighted aggregated scores of all infractions associated with each retracted paper. This measure is based on the classification framework described in Sect. "Measuring Misconduct Severity", where retractions are categorized according to their degree of misconduct severity.

Finally, to account for disciplinary differences, we include a categorical variable (AREA) that classifies retracted papers into three primary academic fields: Business, Social Sciences, and Technology. Business serves as the baseline category in our regression

Fig. 2 Timeframe for post-retraction citation analysis

Table 1 Definition of the variables used in the analysis variable name definition

Variable name	Definition	Source
CITATIONS	Total number of post-refraction citations (excluding self-citations)	Scopus
HIC	Number of highly influential post-refraction citations	Semantic Scholar
BACKGROUND	Number of post-retraction citations that consider its background	Semantic Scholar
METHOD	Number of post-retraction citations that consider their methods	Semantic Scholar
RESULTS	Number of post-refraction citations that consider their results	Semantic Scholar
SNIP	Source Normalized Impact per Paper	Scopus
CITESCORE	Average citation received per document published in a journal over three years	Scopus
INSTITUTION	Maximum institution's score in the ranking	CWUR
MISCONDUCT	Misconduct severity	Adapted from RW and Hall and Martin (2019)
AREA	Business and Management, Social Sciences, and Technology	RW
TIME	2022-refraction year	RW
CIT_Before	Total citations rate before refraction (excluding self-citations)	Scopus
HIC_Before	Highly influential citations rate before refraction	Semantic Scholar
BACK_Before	Background citations before refraction	Semantic Scholar
MET_Before	Method citations before refraction	Semantic Scholar
RES_Before	Results citations before refraction	Semantic Scholar

models. This classification allows us to examine whether disciplinary variations influence post-retraction citation patterns.

In addition to these independent variables, we incorporate an exposure variable (TIME) to account for the varying duration of time following each paper's retraction. This variable is calculated as:

$$TIME = 2022 - retraction\,year$$

Including this exposure variable is essential for normalizing the citation counts over time, ensuring that differences in citation rates are not driven by variations in the length of post-retraction observation periods. The next section details the control variables incorporated into our models to further refine our analysis.

Control variables

The citation count of a retracted paper is strongly correlated with its citation trajectory prior to retraction. Therefore, to eliminate potential bias, we introduce control variables that account for citation activity before the retraction. However, a key challenge arises from the fact that different papers are retracted at different points in time, which affects their pre-retraction citation counts. To address, this issue, we standardize pre-retraction citations per unit of time, ensuring that citation rates remain comparable regardless of variations in exposure periods. To achieve this, we define the variable TIMEBEFORE (i.e.: time to retraction) as follows:

$$TIMEBEFORE = Retraction\,date - Publication\,date$$

Using this measure, we compute citation rates before retraction for each of the dependent variables, as follows:

$$CIT\_Before = \frac{Citations\,Before}{TIMEBEFORE}$$

$$HIC\_Before = \frac{Highly\,Influential\,Before}{TIMEBEFORE}$$

$$BACK\_Before = \frac{Background\,Before}{TIMEBEFORE}$$

$$MET\_Before = \frac{Method\,Before}{TIMEBEFORE}$$

$$RES\_Before = \frac{Results\,Before}{TIMEBEFORE}$$

where "Citations Before," "Highly Influential Before," "Background Before," "Method Before," and "Results Before" represent the number of each type of citation before the papers are retracted (See Fig.2).

Where *Citations Before, Highly Influential Citations Before, Background Citations Before, Method Citations Before,* and *Results Citations Before* representing the total number of each type of citation received prior to retraction. These standardized variables enable us to control for baseline citation rates, which is both theoretically relevant and statistically justifiable. By incorporating these control variables, we ensure that post-retraction citation patterns are not simply reflections of pre-existing citation trajectories. The next section introduces the instrumental variables employed to further address potential endogeneity concerns.

Instrumental variables

The self-controlled case series approach used in this study inherently controls for time-invariant confounders by employing each article's pre-retraction citations as a baseline. This design ensures that individual fixed effects—such as the quality of the research, author reputation, and field-specific citation norms—are accounted for, mitigating many concerns related to endogeneity.

However, despite these advantages, time-variant confounders could still introduce endogeneity concerns, particularly regarding factors that influence both pre- and post-retraction citation rates. To reinforce methodological rigor, we include an instrumental variable (IV) analysis as a robustness check, addressing potential bias in estimating the effects of journal prestige (CiteScore/SNIP) and institutional reputation (INSTITUTION) on post-retraction citations.

To correct for endogeneity, we employ two instrumental variables: Time to Retraction (TIMEBEFORE) and Number of Authors (N_AUTHORS). These variables are theoretically justified as appropriate instruments because they are strongly correlated with pre-retraction citation rates but are unlikely to directly affect post-retraction citations beyond their indirect influence through prior citation accumulation.

- Time to Retraction measures the time elapsed between a paper's publication and its retraction. Papers that remain in circulation for longer periods before retraction are naturally exposed to more citations. Since this variable affects pre-retraction citations but not post-retraction citation patterns independently, it serves as a valid instrument.
- Number of Authors (N_AUTHORS) is used as a second instrument, as papers with larger author teams typically accumulate more citations due to broader research networks and increased visibility. However, once a paper is retracted, the number of authors should have little direct influence on whether it continues to be cited, making it an appropriate instrument.

While the self-controlled case series approach is the primary method for addressing endogeneity, the IV analysis serves as an additional validation step, ensuring that our findings remain robust to potential confounding factors. The validity of these instrumental variables is assessed through first-stage regression results and the Wald test for instrument strength, confirming their predictive power and exogeneity.

The next section outlines the econometric approach employed to estimate the effects of journal prestige, institutional reputation, and misconduct severity on post-retraction citation patterns.

Methodology

In this study, we adopt a self-controlled case series approach to investigate how citations evolve around the retraction point. Specifically, we use each article's pre-retraction citations as a natural baseline and then apply negative binomial regression for rate modeling to compare citation patterns before and after formal retraction. This design helps account for intrinsic differences between papers—such as topic or author attributes—while highlighting how institutional prestige, journal reputation, and the severity of misconduct may shape ongoing citations.

Econometric model

This study aims to estimate the effects of journal prestige, institutional reputation, and misconduct severity on post-retraction citation patterns. Given that citation counts are discrete, non-negative, and exhibit overdispersion, we employ negative binomial regression for the analysis. Furthermore, since different papers have been retracted at different points in time, the exposure period after retraction varies across observations. To account for these differences, we use rate modeling, incorporating an exposure variable that normalizes citation counts based on the time elapsed since retraction. This approach ensures that our estimates accurately reflect citation dynamics over time, rather than being biased by variations in observation periods.

To select the most appropriate estimation method, we account for two key characteristics of our dependent variables: overdispersion and a high proportion of zero values. Overdispersion occurs when the variance of the dependent variable exceeds its mean, a common issue in citation count data. Additionally, many retracted papers receive no citations after retraction, resulting in an excess of zero counts in the dataset.

We analyzed overdispersion using two approaches. Firstly, we compared the mean and standard deviation of the variables to be modeled. Table 2a presents the five dependent variables' mean, standard deviation, and percentage of zeros. As the means and standard deviations differ, the Negative Binomial regression is recommended.

Secondly, we compared the two models using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to compare model fits. We obtained lower values for both AIC and BIC in the negative binomial regression, as shown in Table 2b.

Therefore, the negative binomial is more suitable than Poisson regression to model these dependent variables.

Regarding the excess of zero counts in the five dependent variables (see Table 2a), two primary modeling approaches are commonly considered: the zero-inflated negative binomial (ZINB) model and the hurdle model. However, as noted by Allison (2002), when zeros

Table 2a Dependent variables overdispersion and zeros

Statistic	CITATIONS	HIC	BACKGROUND	METHOD	RESULTS
Mean	6.65	0.52	2.87	0.90	0.23
Standard Dev	18.01	2.82	10.85	4.66	1.10
Zeros (%)	32.73	81.49	51.78	71.31	89.93
N	999	983	983	983	983

Table 2b Testing overdispersion with information criteria

Model	N	df	AIC	BIC
Poisson	527	7	5635.35	5665.22
Negative Binomial	527	8	2829.23	2863.37

are not generated by a mechanism distinct from that of the non-zero values, the appropriate approach is negative binomial regression without zero inflation. Given the nature of our data—citation counts—we opted for negative binomial regression, as all values, including zeros, originate from the same underlying citation-generating process.

In addition to estimating the determinants of post-retraction citations using negative binomial regression, we apply the self-controlled case series (SCCS) approach to further control for time-invariant confounders at the paper level. The SCCS method is particularly advantageous in this context, as it uses each retracted paper as its own control, thereby accounting for unobserved heterogeneity that may otherwise bias the results.

We apply the self-controlled case series (SCCS) approach to further control for time-invariant confounders at the paper level. The SCCS method uses each retracted paper as its own control, thereby accounting for unobserved heterogeneity that may otherwise bias the results. This approach allows us to isolate the impact of retraction on citation counts by comparing pre- and post-retraction citation rates for the same paper. By controlling for fixed effects, the SCCS model eliminates potential biases stemming from inherent differences in paper quality, author reputation, and field-specific citation norms—factors that remain constant over time. This approach ensures that observed changes in citation behavior can be attributed to the retraction event itself, rather than to intrinsic differences between papers.

All estimations were performed using STATA 15, with robust standard errors to account for potential heteroskedasticity. We estimated two models for each dependent variable: one using SNIP as the measure of journal prestige and another using CiteScore. These models employ rate modeling and negative binomial regression to estimate the determinants of different types of post-retraction citations. The following specification is considered:

$$logE(Y_i) = X_i\beta + Z_i\gamma + C_i\delta + log\left(exposure_i\right) + \varepsilon_i$$

or equivalently:

$$E\left(Y_i\right) = exposure_i \cdot e^{(X_i\beta + Z_i\gamma + C_i\delta + \varepsilon_i)}$$

where $\boldsymbol{Y_i}$ is the count outcome variable (Total citations, HIC, etc.); $\boldsymbol{X_i}$ is a vector of main predictor variables (CITESCORE/SNIP, INSTITUTION, MISCONDUCT); $\boldsymbol{Z_i}$ be a categorical variable used for the disciplines (AREA). $\mathbf{C_i}$ is the vector of control variables (citation rates before), and ***exposure*** represents the exposure variable used to normalize the outcome for varying time after retraction periods (its coefficient is 1). Moreover, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are the vectors of coefficients corresponding to the predictor, categorical, and control variables respectively.[1] Finally, $\boldsymbol{\epsilon_i}$ is the error term that captures the difference between the observed values and the values estimated by the model.

[1] The coefficients in a rate model are interpreted as the log change in the rate of the event for a one-unit change in the predictor variable, holding all other variables constant. Exponentiating the coefficient gives the rate ratio, indicating how many times higher or lower the rate is for a one-unit increase in the predictor variable.

Addressing endogeneity

While the self-controlled case series (SCCS) approach accounts for time-invariant confounders by using each article's pre-retraction citations as a baseline, concerns regarding time-variant unobserved factors may still arise. Specifically, variables such as field-specific trends, journal or institution characteristics could potentially affect post-retraction citation patterns in ways that are not fully controlled within the SCCS framework. To reinforce methodological rigor, we implement an instrumental variable (IV) analysis as a robustness check to further address potential endogeneity concerns.

Two primary sources of endogeneity are considered. First, journal prestige and institutional reputation may be endogenously related to citation patterns, as papers published in high-impact journals or affiliated with prestigious institutions are more likely to attract attention both before and after retraction. Second, misconduct severity could be influenced by factors that also affect citation persistence, such as publicity surrounding high-profile retractions or field-specific retraction policies.

To mitigate these concerns, we employ two instrumental variables: Time to Retraction (TIME_BEFORE) and Number of Authors (N_AUTHORS). These variables serve as exogenous sources of variation, satisfying the two conditions for a valid instrument: they must be strongly correlated with the endogenous predictors but uncorrelated with the error term in the post-retraction citation model.

Time to Retraction (TIME_BEFORE) measures the duration between a paper's publication and retraction. Papers with longer exposure periods before retraction tend to accumulate more citations, making this variable a strong predictor of pre-retraction citation rates. However, it is unlikely to independently influence post-retraction citations beyond its indirect effect through prior citation accumulation, ensuring its validity as an instrument.

Number of Authors (N_AUTHORS) serves as a second instrument, as papers with larger author teams generally receive higher pre-retraction citation counts due to their wider research networks and increased visibility. After retraction, however, the number of authors should have little direct impact on continued citations, reinforcing its role as an exogenous instrument (Sharma, 2021).

We use the Two-Stage Residual Inclusion (2SRI) method which is suitable for count data models with continuous endogenous regressors (Terza, 2018). In the first stage, we estimate the OLS model of the endogenous variable CIT_BEFORE as a function of the instruments and exogenous variables.

$$\begin{aligned} CIT\_BEFORE_i = \beta_0 + \beta_1 CITESCORE_i + \beta_2 INSTITUTION_i + \beta_3 MISCONDUCT_i \\ + \beta_4 TIMEBEFORE + \beta_5 N\_AUTHORS + \hat{u}_i \end{aligned}$$

Then, in the second stage, a negative binomial regression is performed, including the endogenous variable (CIT_BEFORE) and the residuals from the first stage ($\hat{u}_i$).

$$\begin{aligned} E\left(CITATIONS_i\right) = \exp\left[\beta_0 + \beta_1 CITESCORE_i + \beta_2 INSTITUTION_i \right. \\ \left. + \beta_3 MISCONDUCT_i + \beta_4 CIT\_BEFORE_i + \beta_5 \hat{u}_i + \ln\left(TIME_i\right)\right] \end{aligned}$$

We repeat the process for the other type of citations. A significant coefficient for RESIDUAL_CIT_BEFORE suggests that CIT_BEFORE is endogenous. Additionally, we may use the Wald test p-values of the joint IV significance.

To assess the strength and validity of these instrumental variables, we conduct first-stage regression tests and report the Kleibergen-Paap test to ensure that our instruments are not weak. Additionally, we perform the Hansen J-test for overidentification, confirming that the instruments are exogenous to the model's error term.

Overall, while the SCCS approach remains the primary method for addressing potential biases, the IV analysis serves as a secondary robustness check to ensure that our findings are not driven by omitted variable bias or reverse causality.

Results

Descriptive analysis

In the overall sample, approximately 47% of cases were classified as blatant misconduct, 10% as inappropriate, and 32% as questionable. This pattern was consistent across different fields. When excluding cases deemed appropriate, the Business field displayed the highest proportion of papers involved in scientific misconduct, at 93%, followed closely by Technology at 89% and Social Sciences at 87% (Table 3a).

Across all three disciplines, citations before and after retraction generally increase from pre- to post-retraction, but the magnitude of this change varies (Table 3b). In Business, both overall pre-retraction (9.10) and post-retraction (9.80) citation means are the highest, though they also exhibit a large spread (SD ≈ 17–18). Social Sciences starts with notably lower citations before retraction (2.27) yet sees a proportionally large jump afterward (5.39), while Technology lies in between (3.63 before; 6.96 after). A similar pattern appears for "highly influential" citations and background/methods/results subcategories: Business shows consistently higher levels both before and after, Social Sciences exhibits the steepest pre–post increases, and Technology tends to be moderate. With respect to time variables, Social Sciences has the longest average time after retraction (6.19) and the shortest time-to-retraction (2.18), suggesting relatively quicker retraction processes but prolonged post-retraction windows. Business, by contrast, has a slightly longer pre-retraction period (3.02) and a middling post-retraction timeline (5.98), while Technology sits close to Business in time before (2.99) but slightly lower afterward (5.29). Finally, CiteScore and SNIP are highest in Business (6.81 and 2.04, respectively) compared to Social Sciences (5.83 and 1.62) and Technology (6.54 and 1.53), reflecting stronger average journal metrics in Business outlets.

Models with SNIP

Table 4 provides the results of a series of Negative Binomial Regression models, where the dependent variables are different aspects of academic impact, measured through Citations,

Table 3a Distribution of cases by misconduct severity and academic fields

Field	Appropriate	Questionable	Inappropriate	Blatant	Total
Business	8 (6.6%)	39 (32.0%)	16 (13.1%)	59 (48.4%)	122 (100%)
Social Sciences	14 (12.5%)	44 (39.3%)	9 (8.0%)	45 (40.2%)	112 (100%)
Technology	33 (11.3%)	86 (29.4%)	28 (9.6%)	146 (49.8%)	293 (100%)
Total	55 (10.4%)	169 (32.1%)	53 (10.1%)	250 (47.4%)	527 (100%)

Table 3b Summary of means and standard deviations by discipline

Variable	Business n = 125		Soc. Sciences n = 113		Technology n = 294		Definition
	Mean	SD	Mean	SD	Mean	SD	
CITATIONS	9.80	18.49	5.39	9.00	6.96	13.44	Post-retraction citations (excl. self-citations)
HIC	0.84	3.20	0.53	1.54	0.29	1.12	Highly influential post-retraction citations
BACKGROUND	4.77	11.92	2.42	4.61	2.11	5.23	Background post-retraction citations
METHODS	0.70	2.01	1.51	1.37	1.02	2.51	Methods post-retraction citations
RESULTS	0.50	1.84	0.29	1.05	0.13	0.58	Results post-retraction citations
CITESCORE	6.81	4.77	5.83	5.33	6.54	4.62	Journal Citescore
SNIP	2.04	1.18	1.62	1.01	1.53	0.82	Journal SNIP
INSTITUTION	77.94	6.64	75.61	5.95	76.17	5.64	Highest CWUR score
MISCONDUCT	6.22	4.09	4.58	2.91	5.52	3.55	Misconduct severity
TIME	5.98	3.20	6.19	3.92	5.29	3.49	Time after retraction (2022-retraction year)
Time-to-retraction	3.02	2.82	2.18	2.99	2.39	2.49	Time before retraction
Citations Before	9.10	17.37	2.27	7.07	3.63	8.28	Pre-retraction citations (excl. self-citations)
Highly Infl. Before	0.85	2.17	0.16	0.56	0.18	0.57	Highly influential pre-retraction citations
Background Before	4.75	10.64	0.85	2.99	1.18	2.70	Background pre-retraction citations
Methods Before	0.64	1.55	0.24	0.77	0.64	1.79	Methods pre-retraction citations
Results Before	0.54	1.71	0.07	0.32	0.03	0.23	Results pre-retraction citations

Highly Influential Citations (HIC), Background, Method, and Results. The indicator used for measuring the journals' prestige in these models is the SNIP (Source Normalized Impact per Paper). Besides, for each dependent variable, we provide a test to assess the significance of $\widehat{\beta}_{soc\_science} - \widehat{\beta}_{technology}$ analyzing whether these fields exhibit differing citation rates.

The model estimating the number of total post-retraction citations (**CITATIONS**) reveals a positive and significant effect of **SNIP** ($\beta = 0.318$, $p < 0.01$), indicating that higher journal prestige is associated with an increased number of citations (1.4 citations per year increase for a 1-unit rise in **SNIP**). Institutional reputation also shows a positive effect ($\beta = 0.020$, $p < 0.1$), albeit with a smaller magnitude. Prior citations have the strongest effect on current citation counts ($\beta = 0.195$, $p < 0.01$). This result indicates that the main reason a retracted paper is cited is because of its pre-retraction citations. Notably, the model's pseudo-R^2 is 0.068, and the log-pseudolikelihood is −1,407, suggesting a reasonable fit for the data.

In the model predicting Highly Influential Citations after the papers are retracted, **SNIP** remains a significant predictor ($\beta = 0.357$, $p < 0.05$), with institutional reputation also contributing positively ($\beta = 0.047$, $p < 0.1$). Prior highly influential citations exhibit a substantial effect ($\beta = 748.758$, $p < 0.01$), further supporting the path dependency observed in citation dynamics. This model shows a higher pseudo-R^2 (0.087) and a less negative log-pseudolikelihood (−374), indicating a stronger model fit relative to the citations model.

Table 4 Negative Binomial Regression Models with SNIP

VARIABLES	CITATIONS	HIC	BACKGROUND	METHOD	RESULTS
MISCONDUCT	0.002 (0.016)	−0.003 (0.028)	0.009 (0.021)	−0.035 (0.028)	0.035 (0.036)
SNIP	0.318*** (0.056)	0.357** (0.116)	0.246*** (0.077)	0.169 (0.098)	0.100 (0.135)
INSTITUTION	0.020* (0.011)	0.047* (0.027)	0.014 (0.014)	0.016 (0.018)	0.013 (0.021)
CIT_Before	0.195*** 0.024	–	–	–	–
HIC_Before	–	748.758*** (159.801)	–	–	–
BACK_Before	–	–	230.023*** (29.306)	–	–
METH_Before	–	–	–	448.540*** (81.207)	–
RES_Before	–	–	–	–	1.373*** (304.22)
AREA					
Soc.Sciences	0.037 (0.168)	0.555 (0.341)	0.226 (0.213)	0.085 (0.310)	0.664 (0.444)
Technology	0.098 (0.127)	0.143 (0.307)	−0.036 (0.164)	(0.150)	−0.106 (0.383)
Constant	−2.360*** (0.808)	−7.473*** (2.100)	−2.882* (1.074)	−4.117** (1.467)	−5.166** (0.163)
ln(TIME)	1	(exposure)			
$\widehat{\beta}_{soc} - \widehat{\beta}_{tech}$	−0.57 (0.609)	0.21 (0.362)	0.36 (0.698)	−0.68 (0.069)	0.16 (0.072)
n	527	531	531	531	531
Alpha	1.223	2.964	1.732	2.635	3.303
Log-pseudolikelihood	−1,407	−374	−949	−564	−243.768
Pseudo-RÂ^2	0.068	0.087	0.080	0.071	0.091

***p < 0.01, **p < 0.05, *p < 0.1

The model assessing the BACKGROUND citations shows a positive association with **SNIP** (β = 0.246, p < 0.01) and institutional reputation (β = 0.014, p < 0.1). Additionally, the number of this type of citations before retraction is strongly significant (β = 230.023, p < 0.01). The pseudo R^2 of this model is 0.080, with a log-pseudolikelihood of −949, suggesting a good explanatory power.

In the model for METHOD, **SNIP** does not appear to be a significant predictor (β = 0.169, p > 0.1), although prior use of methods shows a strong positive effect (β = 448.540, p < 0.01). The pseudo R^2 is slightly lower at 0.071, with a log-pseudolikelihood of −564.

Finally, the model estimating the impact on RESULTS shows that neither **SNIP** (β = 0.100, p > 0.1) nor institutional reputation (β = 0.013, p > 0.1) are significant predictors. However, prior results exhibit a significant effect (β = 1,373, p < 0.01), highlighting the influence of past work on current outputs. This model has the highest pseudo R^2 (0.091) among the five models, with a log-pseudolikelihood of −243.768, indicating the strongest fit to the data.

Table 5 Negative Binomial Regression Models with CITESCORE

VARIABLES	CITATIONS (1)	HIC (2)	BACKGROUND (3)	METHOD (4)	RESULTS (5)
MISCONDUCT	0.009 (0.016)	0.004 (0.027)	0.012 (0.021)	−0.020 (0.027)	0.035 (0.036)
CITESCORE	0.066*** (0.013)	0.042 (0.030)	0.041* (0.017)	0.020 (0.020)	−0.016 (0.026)
INSTITUTION	0.024* (0.010)	0.053* (0.027)	0.015 (0.014)	0.018 (0.018)	0.019 (0.022)
CIT_Before	0.191*** 0.025	–	–	–	–
HIC_Before	–	756.906*** (141.798)	–	–	–
BACK_Before	–	–	233.644*** (29.289)	–	–
METH_Before	–	–	–	451.516*** (81.774)	–
RES_Before	–	–	–	–	1,444*** (384.077)
AREA					
Soc.Sciences	0.056 (0.167)	0.412 (0.310)	0.158 (0.212)	0.023 (0.301)	0.613 (0.447)
Technology	0.061 (0.122)	−0.012 (0.288)	−0.143 (0.163)	0.462 (0.236)	−0.163 (0.388)
Constant	−2.494** (0.786)	−7.476*** (2.090)	−2.769* (1.064)	−4.026** (1.455)	−5.289** (1.610)
ln(TIME)	1	(exposure)			
$\widehat{\beta}_{soc} - \widehat{\beta}_{tech}$	−0.57 (0.609)	0.21 (0.362)	0.36 (0.698)	−0.68(0.069)	0.16 (0.072)
n	527	531	531	531	531
Alpha	1.221	3.140	1.768	2.679	3.317
Log-pseudolikelihood	−1,406	−378	−951	−565	−243
Pseudo-R^2	0.069	0.078	0.077	0.069	0.091

***p < 0.01, **p < 0.05, *p < 0.1

Across the models, **SNIP** generally shows a positive association with the dependent variables, though its significance varies depending on the specific aspect of academic impact being measured. Institutional reputation (**INSTITUTION**) is consistently positive but varies in significance, highlighting the interaction between journal prestige and institutional standing in influencing academic outcomes. The strong impact of pre-retraction citation rates emphasizes that current retraction practices do not seem to be very effective in changing the citation practices. The models' overall fit, as indicated by the pseudo-R^2 values and log-pseudolikelihoods, suggests that while the models capture significant aspects of the data, there is still unexplained variance that could be explored in future research.

When comparing areas, the non-significance of the coefficients $\widehat{\boldsymbol{\beta}}_{soc\_science}$ and $\widehat{\boldsymbol{\beta}}_{technology}$, along with the results of the test for $\widehat{\boldsymbol{\beta}}_{soc\_science} - \widehat{\boldsymbol{\beta}}_{technology} = 0$, indicate that there are no significant differences in the coefficients regardless the variable used to measure journals prestige (see Tables 4 and 5). This means there are no notable differences between

Social Sciences and Technology compared to Business or between Social Sciences and Technology.

Models with CITESCORE

Table 5 outlines the parameters and statistics for the Negative Binomial Regression models using **CITESCORE** to measure journal prestige. As mentioned earlier, the dependent variables consist of total citations, highly influential citations, background citations, method citations, and results citations, each representing different aspects of academic impact. We also provide for each dependent variable a test to assess the significance of $\widehat{\beta}_{soc\_science} - \widehat{\beta}_{technology}$ analyzing whether these fields exhibit differing citation rates.

Column 1 presents the model predicting the total number of citations. We observe that the journal prestige (**CITESCORE**) has a positive and statistically significant impact ($\beta = 0.066$, $p < 0.01$), indicating that higher **CITESCORE** is associated with an increase in citations. Institutional reputation (**INSTITUTION**) also contributes positively to the number of citations ($\beta = 0.024$, $p < 0.1$). As expected, the strongest predictor remains pre-retraction citation rate (**CIT_Before**), which has a highly significant effect ($\beta = 0.191$, $p < 0.01$). The model's pseudo-R^2 value is 0.069, and the log-pseudolikelihood is −1,406, suggesting a good fit for the data.

The model predicting the highly influential citations is shown in column 2. The journal effect of **CITESCORE** is positive but not statistically significant ($\beta = 0.042$, $p > 0.1$). Institutional reputation shows a marginally significant effect ($\beta = 0.053$, $p < 0.1$), while the impact of prior HIC (**HIC_Before**) is highly significant and substantial ($\beta = 756.906$, $p < 0.01$). This model demonstrates a pseudo-R^2 of 0.078 and a log-pseudolikelihood of −378, indicating a relatively strong model fit.

For the model estimating the Background citations (shown in column 3), **CITESCORE** has a positive and significant impact ($\beta = 0.041$, $p < 0.1$), suggesting that journals with higher **CITESCORE** are more likely to influence the background sections of subsequent papers even when they are retracted. The role of institutional reputation is also positive, albeit with marginal significance ($\beta = 0.015$, $p > 0.1$). The most significant predictor is the background citation rate before retraction (**BACK_Before**) ($\beta = 233.644$, $p < 0.01$). The pseudo-R^2 for this model is 0.077, and the log-pseudolikelihood is −951.

Column 4 shows the results for the model predicting the Method citations. The model reveals that **CITESCORE** does not significantly predict the use of methodological content ($\beta = 0.020$, $p > 0.1$). However, the methodological citation rate before retraction (**METH_Before**) remains a strong predictor ($\beta = 451.516$, $p < 0.01$). The model has a pseudo-R^2 of 0.069 and a log-pseudolikelihood of −565.

Finally, the model for post-retraction citations related to citing paper's findings is presented in column 5. As in the **CITESCORE** is not a significant predictor ($\beta = -0.016$, $p > 0.1$), nor is institutional reputation ($\beta = 0.019$, $p > 0.1$). The only one significant variable is the results citation rate before retraction (**RES_Before**) which strongly influence this type of citations after retraction ($\beta = 1{,}444$, $p < 0.01$). This model exhibits the highest pseudo-R-squared value (0.091) and the best fit among all models, as indicated by the log-pseudolikelihood of −243.

The findings across the models suggest that while **CITESCORE** positively influences the post-retraction citations. Institutional reputation also plays a role, although its influence is often marginal. The most consistent and robust predictors are the pre-retraction citation rates. The pseudo-R-squared values and log-pseudolikelihoods indicate that the models generally provide a good fit for the data, though further research may be necessary to explore unexplained variances and other contributing factors.

Testing for endogeneity

Two stages residual inclusion (2SRI)

We test for endogeneity of **CIT_BEFORE** by using two instrumental variables: **TIMEBEFORE** and **N_AUTHORS**, which we assume are exogenous in the post-retraction citations equation. We use the two-Stage Residual Inclusion (2SRI) method (Terza, 2018). This method is suitable for count data models with continuous endogenous regressors. In the first stage, we estimate the OLS model of the endogenous variable **CIT_BEFORE** as a function of the instruments and exogenous variables:

$$
\begin{aligned}
CIT\_BEFORE_i = \pi_0 + \pi_1 TIMEBEFORE_i + \pi_2 N\_AUTHORS_i + \pi_3 CITESCORE_i \\
+ \pi_4 INSTITUTION_i + \pi_5 MISCONDUCT_i + \pi_7 AREA_i + \pi_8 TIME_i + \pi_9 ui
\end{aligned}
$$

This regression estimates the portion of **CIT_BEFORE** explained by the instruments and exogenous variables. The residuals capture the unexplained variation, which may be correlated with the error term in the second-stage regression. Next, in the second stage, we include the endogenous variable (**CIT_BEFORE**) and the residuals from the first stage (**RESIDUAL_CIT_BEFORE**) in the negative binomial regression. This adjusts for the endogeneity of **CIT_BEFORE.** A significant coefficient for **RESIDUAL_CIT_BEFORE** suggests that **CIT_BEFORE** is endogenous. Additionally, we report the Wald tests p-values of the joint IV significance. Tables 6a and 6b present the second-stage models for predicting the five types of citations including the IV and the residuals. In Table 6a, the **SNIP** is used as the explanatory variable for journal prestige, and in Table 6b, **CITESCORE** is utilized.

The instrumental variable (IV) analysis in Table 6a indicates that the IV residuals are not significant for any model, confirming the absence of endogeneity. Additionally, the Wald test supports the non-significance of residual coefficients. A similar conclusion can be drawn from Table 6b. In conclusion, the IV analysis confirms that our model provides reliable and unbiased estimates, effectively addressing potential endogeneity concerns.

Robustness analysis

In this section, we report the results of some robustness checks to validate the stability of our results, including multicollinearity and alternative specifications, and subsample analysis. Regarding multicollinearity, we computed the Variance Inflation Factor (VIF) values in the model for CITATIONS (Table 7). The VIF values are well below the commonly used thresholds (e.g., 5 or 10), indicating that multicollinearity is not a significant issue in our models. As a result, the estimated coefficients can be considered reliable.

Next, we estimated alternative versions of our model by replacing one of the variables with its logarithmic transformation. We obtained similar results. Furthermore, we estimated the model in two subsamples, considering the retraction year. We estimated the model for papers retracted until 2015 and a second one comprising de retractions after 2015. We obtained similar results to those we got in the whole sample. These results confirm the robustness of our models.

Table 6a Negative Binomial Regression Models with IV (SNIP)

VARIABLES	CITATIONS	HIC	BACKGROUND	METHOD	RESULTS
MISCONDUCT	0.004 (0.019)	0.013 (0.028)	0.027 (0.025)	−0.013 (0.029)	0.009 (0.045)
SNIP	0.322*** (0.058)	0.446* (0.177)	0.352*** (0.107)	0.114 (0.117)	−0.078 (0.222)
INSTITUTION	0.021* (0.012)	0.054 (0.029)	0.025 (0.017)	0.004 (0.022)	0.001 (0.022)
CIT_Before	0.178*** (0.087)	–	–	–	–
Resid_Cit_Before	0.019 (0.092)	–	–	–	–
HIC_Before	–	−1.333 (953.221)	–	–	–
Resid_HIC_Before	–	764.086 (967.449)	–	–	–
BACK_Before	–	–	75.334 (119.845)	–	–
Resid_BACK_Before	–	–	163.783 (125.537)	–	–
METH_Before	–	–	–	892.993** (373.898)	–
Resid_METH_Before	–	–	–	−468.382 (384.010)	–
RES_Before	–	–	–	–	3394 (1848)
Resid_RES_Before	–	–	–	–	−2067.855 (1853.951)
AREA					
Soc.Sciences	0.039 (0.168)	0.550 (0.336)	0.218 (0.211)	0.122 (0.301)	0.681 (0.447)
Technology	0.099 (0.127)	0.103 (0.306)	−0.049 (0.164)	0.575** (0.246)	−0.082 (0.384)
Constant	−2.443*** (0.935)	−8.048*** (2.288)	−3.841*** (1.317)	−3.280* (1.741)	−4.002** (1.738)
ln(TIME)	1	(exposure)			
n	527	531	531	531	531
Wald's test p-value	0.000	0.000	0.000	0.000	0.000
Alpha	1.223	2.953	1.729	2.618	3.267
Log-pseudolikelihood	−1,407	−374	−948	−563	−243
Pseudo-RÂ^2	0.068	0.087	0.080	0.072	0.093

***p < 0.01, **p < 0.05, *p < 0.1

Conclusion and limitations

In this study, we examined post-retraction citations in three academic fields: Business, Social Sciences, and Technology, using a sample of retracted papers identified by Retraction Watch. We employed a self-controlled case series (SCCS) approach, using each paper's pre-retraction citation count as a baseline to analyze post-retraction citation patterns. Our

Table 6b Negative Binomial Regression Models with IV (CITESCORE)

VARIABLES	CITATIONS	HIC	BACKGROUND	METHOD	RESULTS
MISCONDUCT	0.009 (0.019)	0.013 (0.033)	0.035 (0.026)	−0.011 (0.028)	0.006 (0.047)
CITESCORE	0.066*** (0.014)	0.052 (0.029)	0.065** (0.023)	0.003 (0.029)	−0.031 (0.033)
INSTITUTION	0.024** (0.012)	0.057 (0.029)	0.030 (0.017)	0.008 (0.022)	0.003 (0.023)
CIT_Before	0.191*** (0.085)	–	–	–	–
Resid_Cit_Before	0.001 (0.090)	–	–	–	–
HIC_Before	–	404.102 (992.701)	–	–	–
Resid_HIC_Before	–	360.170 (933.197)	–	–	–
BACK_Before	–	–	54.302 (120.224)	–	–
Resid_BACK_Before	–	–	190.520 (125.627)	–	–
METH_Before	–	–	–	832.784** (412.299)	–
Resid_METH_Before	–	–	–	−400.486 (423.656)	–
RES_Before	–	–	–	–	3395.789 (1815.903)
Resid_RES_Before	–	–	–	–	−1999.852 (1815.65)
AREA					
Soc.Sciences	−0.056 (0.168)	0.410 (0.306)	0.150 (0.209)	0.048 (0.296)	0.629 (0.453)
Technology	0.061 (0.123)	−0.032 (0.296)	−0.161 (0.163)	0.467** (0.233)	−0.133 (0.394)
Constant	−2.498*** (0.915)	−7.756*** (2.301)	−3.937* (1.343)	−2.279** (1.778)	−4.004** (1.766)
ln(TIME)	1	(exposure)			
n	527	531	531	531	531
Wald’s test p-value	0.000	0.000	0.000	0.000	0.000
Alpha	1.223	3.13	1.732	2.667	1.188
Log-pseudolikelihood	−1,407	−379	−950	−565	−243.768
Pseudo-R^2	0.068	0.078	0.078	0.070	0.092

***$p<0.01$, **$p<0.05$, *$p<0.1$

findings indicate that higher journal recognition (measured by Source Normalized Impact per Paper [SNIP] and CiteScore) and prestigious author affiliations are associated with increased post-retraction citations. Furthermore, our analysis of citation motivations reveals that these effects are particularly pronounced for background citations and, even more notably, for highly influential citations. These results expand upon previous research by Fang et al. (2012) and Furman et al. (2012), who observed that journal prestige and

Table 7 Variance inflation factor (VIF) for CITATIONS with CITESCORE

Variable	VIF	1/VIF
MISCONDUCT	1.07	0.94
CITESCORE	1.05	0.96
INSTITUTION	1.08	0.93
CIT_Before	1.09	0.92
Soc. Sciences	1.57	0.63
Technology	1.53	0.65
Mean VIF	1.23	0.81

author prominence shape the extent to which retracted papers continue to be cited. Notably, our study found no significant disciplinary differences across the three fields analyzed.

As research on scientific misconduct transitions from observational studies to hypothesis-driven inquiries, it is imperative to move beyond simply describing patterns or frequencies and instead investigate the causes and effects of flawed research. We address this gap by leveraging the four citation categories defined by Semantic Scholar (i.e., Highly Influential Citations, Background, Method, and Results) to identify the factors influencing post-retraction citation behavior. Our findings suggest that retracted papers across these three fields continue to exert a substantial influence on subsequent research, particularly through background and highly influential citations. Our results are consistent with multiple mechanisms. Persistent post-retraction citations may reflect incomplete awareness of retraction information (Xu et al., 2023), particularly when retraction notices are difficult to access, poorly disseminated, or not clearly linked to the original article. They may also reflect prestige bias, in which authors grant disproportionate credibility to work published in high-status journals or authored by researchers affiliated with prestigious institutions. A third possibility is that some authors continue to cite retracted work because they perceive residual methodological, historical, or contextual value in the article. Our design does not allow us to disentangle these mechanisms empirically; therefore, we interpret our findings as consistent with these pathways rather than as evidence of a single behavioral mechanism.

A more encouraging finding is that citations classified under "Results" appear to be driven primarily by pre-retraction citation patterns, with no significant effect from journal or institutional prestige.

Finally, by adopting our citation-type modeling approach, scholars in other disciplines can conduct scientometric studies to better understand how flawed research influences subsequent scholarship. This approach is particularly valuable in fields such as Business Education, where retractions can have far-reaching consequences (Hall & Martin, 2019). Additionally, our methodology can be applied to Medicine and other disciplines where flawed research may pose serious real-world risks.

Policy implications

Our findings support several policy recommendations to mitigate the persistence of post-retraction citations. First, academic journals and funding bodies could consider implementing penalties for authors who cite retracted papers without justification, such as desk rejections or delays in manuscript processing. However, legitimate citations, such as those for meta-research or scientometric analysis, should be exempt from such restrictions if they are clearly indicated outside formal reference lists. Without such measures, ongoing citations risk unjustifiably reinforcing the prestige of journals and institutions that published retracted work. Strengthening editorial oversight and improving awareness of retractions through a comprehensive public database documenting all retracted papers would further help curb their influence. Such a resource would also provide a valuable foundation for future studies seeking to track and mitigate the effects of retracted research.

Limitations and future research directions

Despite these contributions, several limitations warrant further investigation.

First, the non-significance of misconduct severity should not be interpreted as evidence that the seriousness of misconduct is irrelevant. Rather, it may indicate that the formal severity of the retraction is not sufficiently visible or interpretable to later citing authors. Retraction notices vary in clarity, accessibility, and specificity, and the severity classifications used in this study are constructed analytically from Retraction Watch reasons rather than necessarily observed directly by citing authors. Therefore, the absence of a significant severity effect may reflect limitations in the transmission of retraction information rather than the absence of concern about misconduct.

Second, citation trajectories are known to follow a life-cycle pattern, and retractions may occur at different stages of this trajectory. To mitigate this concern, our models incorporate exposure-adjusted post-retraction citation rates and control for pre-retraction citation intensity, defined as citations accumulated before retraction divided by the time from publication to retraction. This approach reduces the risk that post-retraction citation patterns simply reflect differences in the accumulation phase of each paper. Nevertheless, our design does not fully estimate the counterfactual citation trajectory each retracted paper would have followed had it not been retracted. Matched-control designs could address this question more directly, but they require strong assumptions about the comparability of retracted and non-retracted papers. We therefore present our analysis as an internally controlled study of heterogeneity in post-retraction citation patterns, rather than as a full causal estimate of the effect of retraction itself.

Third, we acknowledge that article accessibility may confound post-retraction citation patterns. Open Access articles may be more visible and therefore more likely to be cited, independently of journal prestige. The Retraction Watch database includes a Paywalled field; however, this variable should not be interpreted as a formal Open Access indicator for the original article. Rather, it captures accessibility of the retraction notice or related information. Accordingly, we treat accessibility as a potential visibility mechanism and discuss it as a limitation. Future research should incorporate article-level OA status from dedicated sources, such as *Unpaywall* or *OpenAlex*, to distinguish formal OA status from the accessibility of retraction information.

Finally, regarding the institution's prestige, we use the highest CWUR score among the authors' affiliations to capture peak prestige. This choice reflects the idea that academic attention and credibility may be shaped disproportionately by the most salient institutional signal associated with a paper. In the context of retracted research, a highly prestigious affiliation may continue to confer visibility or perceived authority even after formal retraction. This measure is therefore conceptually distinct from collaboration breadth, institutional diversity, or average institutional prestige. We acknowledge, however, that multi-institutional collaborations may generate additional dissemination effects. Future research should compare alternative institutional measures, including average prestige, the number of institutions, and institutional diversity.

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